A comparison of high-resolution modeled wind speed driven by different forcing datasets over Bohai and Yellow Sea

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Motivation & Objectives

- Despite numerous researches and publications devoted to climate change of areas like North Sea, Baltic Sea using Regional Climate Model (RCM), however, few attention has paid on the Chinese marginal sea Bohai and Yellow Sea.
- A monsoon climate regime is dominant in Bohai and Yellow Sea regional, which is charaterized by complex physiography and scarce observation network.
- RCM reconstruction is a ideal alternative of global or regional reanalysis data in climate research with many advantages (Feser et al. 2011, Weisse and von Storch, 2010):
  a) much simpler and less computational consumption;
  b) with higher temporal and spatial resolution, regional-scale climate variability and change might be better described, high-resolution reliable condition can be provided for ocean wave, storm surge and sea level;
  c) various applications such as wind energy and potential risk assessment.
- Marine surface wind is of great importance to various processes in the earth system.
- Assess the skill of RCM in reproducing surface wind with different forcing conditions; a basic step for long-term hindcast over Bohai and Yellow Sea.

Methodology

COSMO-CLM V4.14 (CCLM)

- Three simulations with 7-km resolution over Bohai and Yellow Sea (Fig. 1.) for the year 2006.
- Different forcing datasets : CCLM 55km (hourly output, 0.5°, downscaled from NCEP1 1.8°); NCEP-CFSR (~ 55 km); ERAinterim (~ 80 km).
- Runge-Kutta scheme ; Convection scheme Tiedtke (1989); Spectral nudging technique (von Storch et al. 2000);

Comparison with observational data

9 land stations, including 8 airport stations; 8 offshore stations.

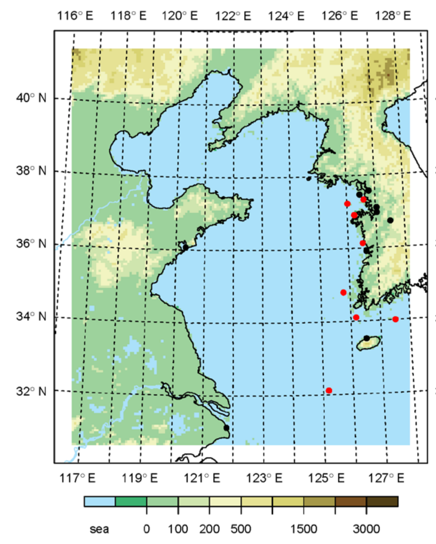

Fig. 1. Orography and station locations

Table 1. Statistical metrics and their definition

BIAS	$\overline{x_m}-\overline{x_o}$
Ration of short term Standard Deviation (RSD)	σ_{fm}/σ_{fo}
Normalized Mean Square Error (NMSE)	$MSE(x_m,x_o)/(\sigma_m\ \sigma_o)$
Correlation Coefficient (R)	$COV(x_m,x_o)\ /(\sigma_m\ \sigma_o)$
Brier Skill Score (BSS)	$1-MSE(x_m,x_o)\ /MSE(x_r,x_o)$
Standard Deviation Error (STDE)	$\sqrt{MSE(x_m,x_o)-BIAS^2}$

Results

Evaluation of the wind speed time series

Table 2. Statistical measures of modeled and observed wind speeds.

	CCLM 7km	CCLM-CFSR	CCLM-ERAint	CCLM 55km	CFSR	ERAint	NCEP1
	Land stations						
BIAS	1.06	0.31	0.41	-0.13	-0.05	0.30	0.54
RSD	1.06	0.83	0.87	0.85	0.77	0.76	0.82
NMSE	1.19	0.87	0.77	0.84	0.79	0.81	1.51
R	0.58	0.61	0.67	0.64	0.68	0.67	0.50
BSS	0.01	0.44	0.49	0.42	0.49	0.45	0
	Offshore stations						
BIAS	1.56	0.44	0.56	0.63	0.39	0.21	0.46
RSD	0.95	0.79	0.80	0.92	0.77	0.73	0.73
NMSE	1.13	0.67	0.68	0.87	0.65	0.66	0.95
R	0.57	0.72	0.72	0.61	0.76	0.74	0.60
BSS	-0.45	0.30	0.29	-0.11	0.33	0.32	0

- Positive biases at offshore stations;
- RSD < 1 except for CCLM 7km at land stations;
- Downscaled results add short term variability ($RSD_{dyndown}$>RSD_{global});
- Generally lower R values for downscaled results;
- Lower BSS values after downscaling in most cases.

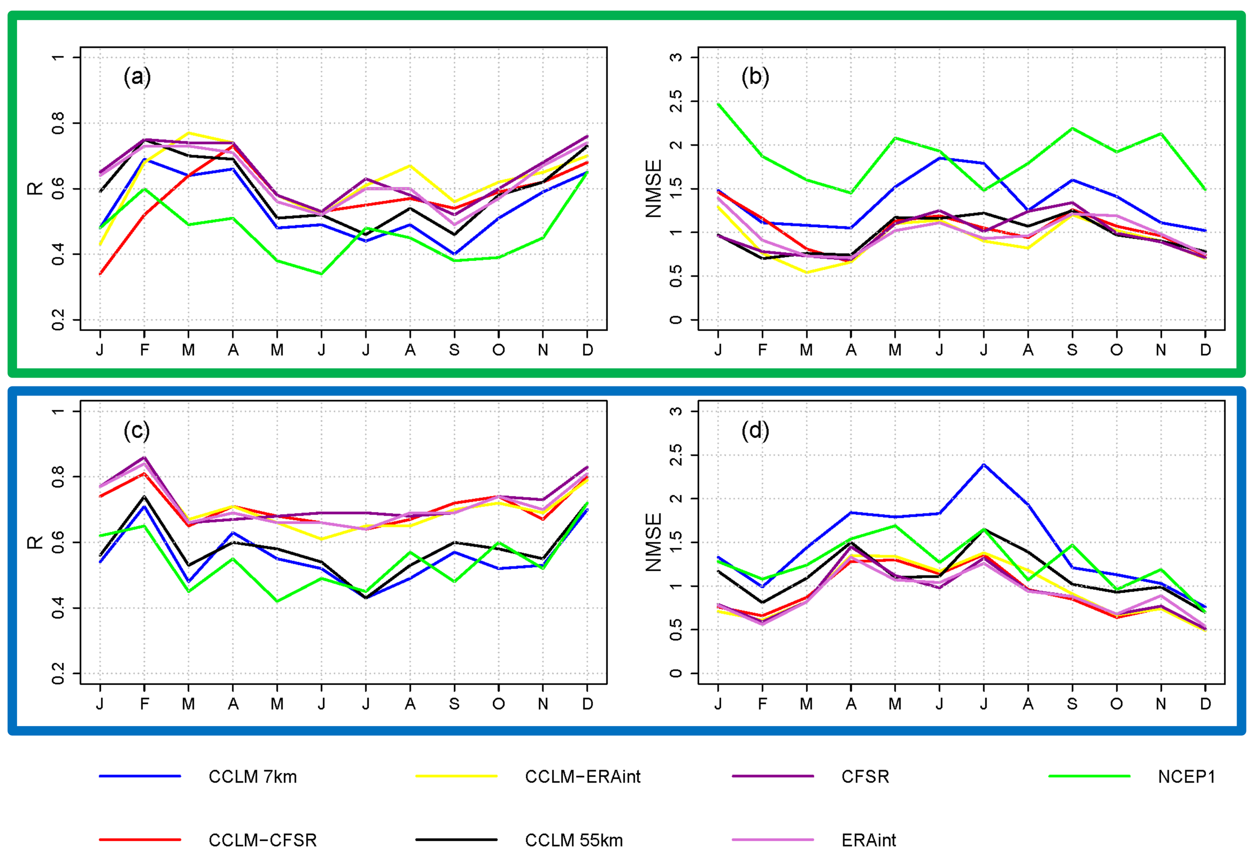

Fig. 2. Monthly R and NMSE between modeled and observed wind speed: (a,b) land stations, (c,d) offshore stations.

- CFSR, ERAint and their downscaled results have similar R and NMSE values, and generally better than NCEP1 and its downscaled results, especially for offshore stations;
- Apparent seasonal variability at offshore stations, with winter being better; land stations are less so.

Representation of wind speed distribution

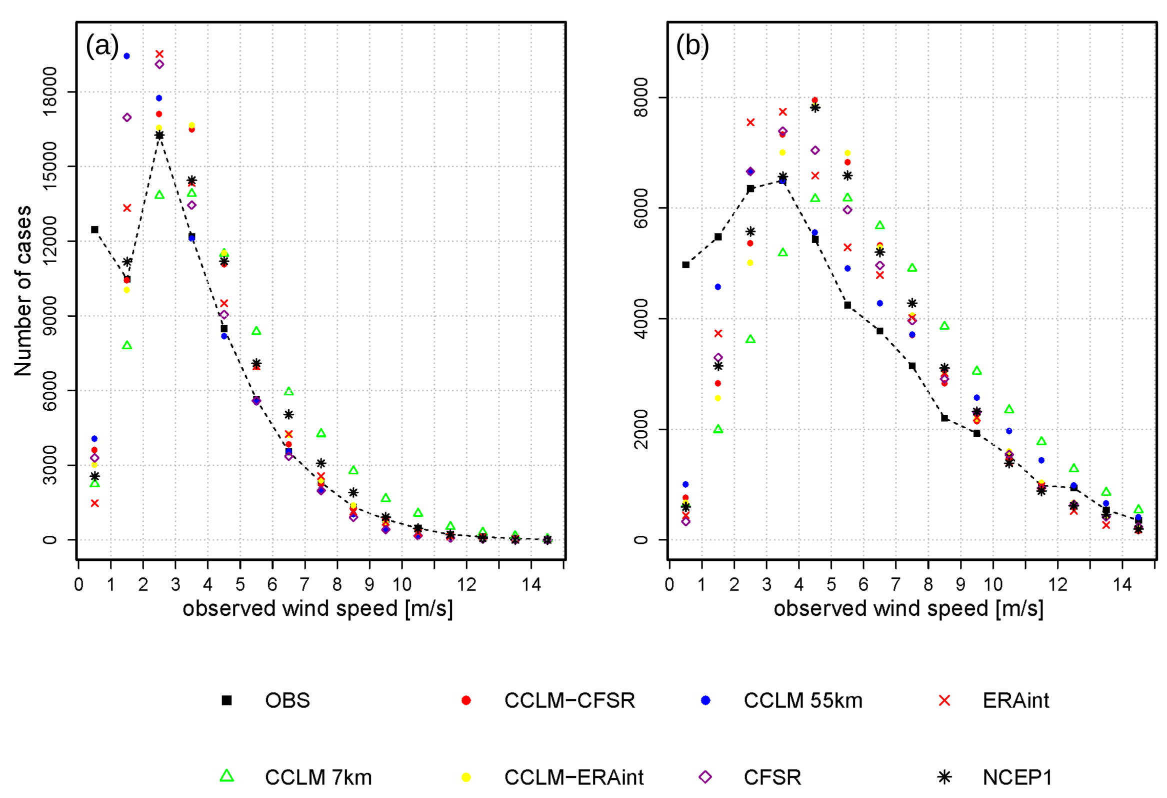

Fig. 3. Frequency distribution of wind speeds for (a) for land stations and (b) for offshore stations.

Is there added value to forcing datasets?

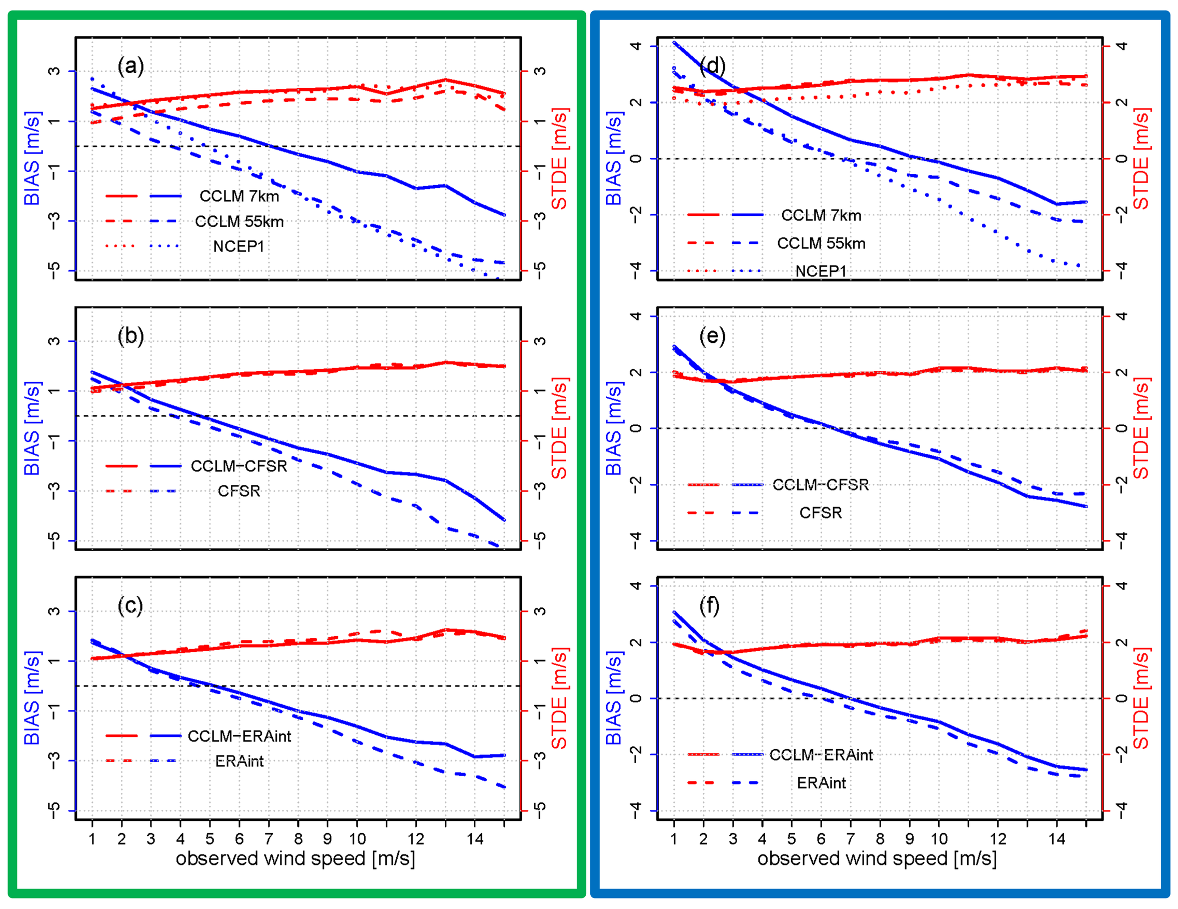

Fig. 4. Comparison of wind speed bias (blue) and STDE (red) between forcing datasets and downscaled results: (a, b, c) for land stations and (d, e, f) for offshore stations.

Which one rank the best among forcing datasets and among downscaled results?

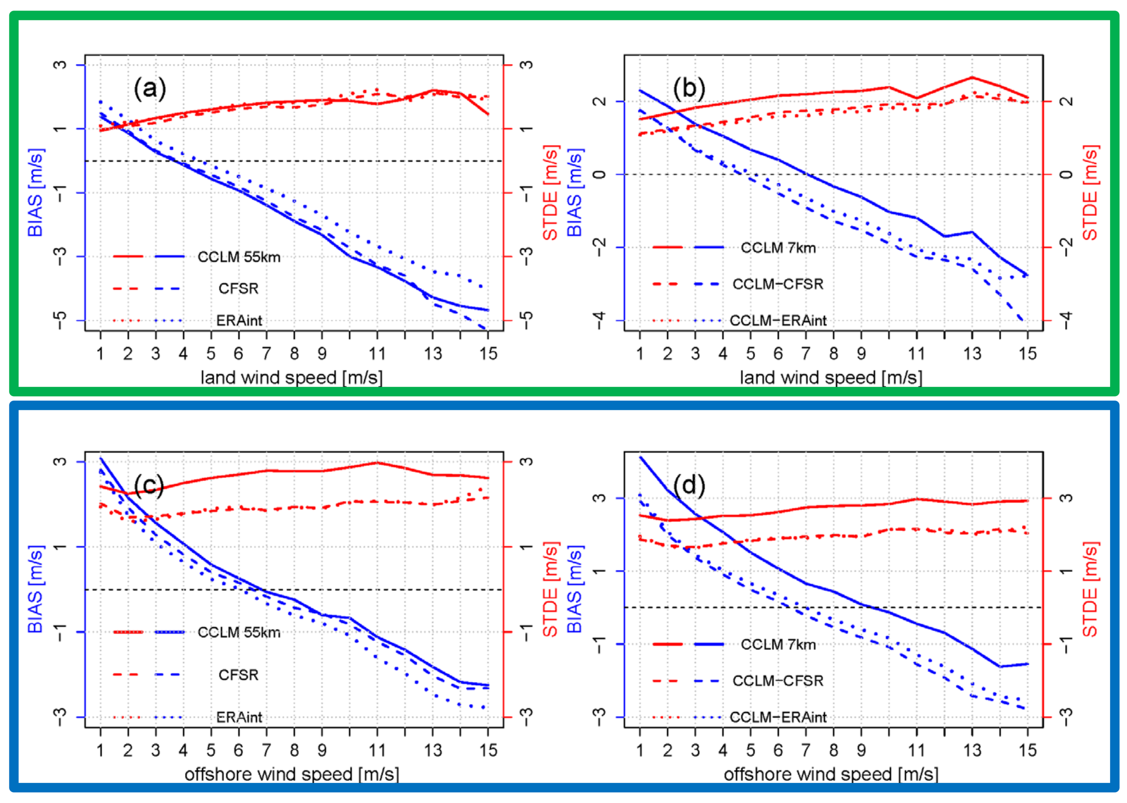

Fig. 5. Inter-comparisons of different forcing datasets and their downscaled wind speeds: (a, b) for land stations and (c, d) for offshore stations.

- Fig. 3 shows that modeled wind speeds underestimate the records of observed wind 0.0 m s^{-1} -1.0 m s^{-1}, and fit to the observation at high wind speeds.
- The bias for high wind speeds at land stations is strongly reduced by all downscaled results (Fig. 4). For high wind speeds of offshore stations, large bias reduction is generated for NCEP1 downscaled simulations CCLM 55km and CCLM 7km, and is reduced slightly by downscaling ERAint; but CCLM-CFSR generated larger bias. Error variance is not reduced by all downscaled results.
- Fig. 5 shows that CCLM 55km exhibits a somewhat less precision (standard deviation) than the other driving analyses at offshore stations; CCLM-CSFR and CCLM-ERAint products are rather similar, and have much higher precision than CCLM 7km. CCLM-ERAint is slightly better than CCLM-CFSR.

Conclusions

- The downscaling simulations driven by ERAint and CFSR are consistent with each other in reproduction of local wind speeds, with the one driven by ERAint slightly better. They generate local wind estimates superior to the one driven by CCLM 55km.
- Due to dynamical downscaling the short term variability of wind speed is added, and the biases are much reduced at land stations for high wind speeds while at offshore stations the reduction of biases are not so much as the one at land stations.
- The error variance is not reduced by downscaling.

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