Opportunities and challenges in assessing climate change impacts on wind energy— a critical comparison of wind speed projections in California

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Abstract
Future climate change is expected to alter the spatial and temporal distribution of surface wind speeds (SWS), with associated impacts on electricity generation from wind energy. However, the predictions for the direction and magnitude of these changes hinge critically on the assessment methods used. Many climate change impact analyses, including those focused on wind energy, use individual climate models and/or statistical downscaling methods rooted in historical observations. Such studies may individually suggest an unrealistically high level of scientific certainty due to the absence of competing projections (over the same region, time period, etc). A new public data archive, the North American Regional Climate Change Assessment Program (NARCCAP), allows for a more comprehensive perspective on regional climate change impacts, here applied to three wind farm sites in California.

We employ NARCCAP regional climate model data to estimate changes in SWS expected to occur in the mid-21st century at three wind farm regions: Altamont Pass, San Gorgonio Pass, and Tehachapi Pass. We examined trends in SWS magnitude and frequency using three different global/regional model pairs, focused on model evaluation, seasonal cycle, and long-term trends. Our results, while specific to California, highlight the opportunities and limitations in NARCCAP and other publicly available meteorological data sets for energy analysis, and the importance of using multiple models for climate change impact assessment. Although spatial patterns in current wind conditions agree fairly well among models and with NARR (North American Regional Reanalysis) data, results vary widely at our three sites of interest. This poor performance and model disagreement may be explained by complex topography, limited model resolution, and differences in model physics. Spatial trends and site-specific estimates of annual average changes (1980–2000 versus 2051–71) also differed widely across models. All models predicted changes of <2% at each site, but the direction of the change varies. However, decreases of <2% in resources at Altamont Pass are agreed upon by each NARCCAP model used. This lack of model agreement suggests uncertainty in future changes, and a potentially high degree of risk for future investors in wind-generated electricity. More broadly, our study highlights the need for multiple calculation approaches to help distinguish between robust and method-dependent results.

Keywords: climate change, NARCCAP, wind energy, California

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1. Introduction

Like temperature, rainfall, and other climate variables, surface wind speeds (SWS) change on time scales of hours, months, years, and decades. Studies to date have found a negative trend in observed SWS since the 1970s over the US (Pryor *et al* 2009, Pryor and Barthelmie 2010), Australia (McVicar *et al* 2008), and the mid-latitudes (McVicar and Roderick 2010, Mearns *et al* 1999, Vautard *et al* 2010). The expectation of long-term change through the 21st century is supported by a large body of research, summarized most recently by the United Nations Intergovernmental Panel on Climate Change (IPCC 2007). These projections pose both risks and opportunities for wind-generated electricity, as the distribution, timing, and magnitude of wind resources may change over the projected 30-year lifetime of a wind turbine installation (EPRI 1997).

Any projection of future climate hinges fundamentally on the methods and models chosen for analysis. Wind, in particular, is more sensitive to model formulation than other variables like temperature and pressure. Here, we evaluate SWS change at the three largest sites in California using publicly available output from three regional climate models (RCMs), generally considered the best available tools for climate projection on regional scales (e.g. Caldwell 2010, Steiner *et al* 2010, Wang *et al* 2009). Similar RCM inter-comparison studies have been completed (e.g. Project PRUDENCE[5], CECILIA[6], and EMSEMBLES[7]), but none have yet assessed wind resources.

In the context of wind energy production, even small changes in wind speed magnitude can have a major impact on the productivity of a wind farm, as the wind power potential ($P_{pot.}$) function is directly proportional to the cube of the wind speed. This relationship is shown below where V is the speed of the wind going through the rotor (m s^{-1}), A is the cross sectional area of the turbine rotor (m^2), and ρ is the density of the ambient atmosphere (kg m^{-3}). However, this relationship is not continuous, as there exists a minimum and maximum speed of the wind that is required to begin and cease power production; the latter to avoid damage operating in high winds. Additionally, Betz's Law states that no wind turbine may extract more than 59.3% of this energy from the wind (Betz 1966).

$$P_{Pot.} = \tfrac{1}{2}\rho A V^3.$$

We selected sites in California because the state has passed both a renewable portfolio standard and a greenhouse gas reduction policy (Nunez 2006, Wong Kup *et al* 2009). Both are sufficiently ambitious that, in combination, they will lead to new capacity on the scale of gigawatts (GW). That wind farms are concentrated in just a few locations in the state makes our selected sites especially relevant to future wind farm development. In early 2011, California was home to the US's third largest installment of wind turbines at 3177 megawatts (MW) out of a US total of 40,180 MW (AWEA 2011) and global total of nearly 200 GW[8]. Detailed analysis is performed

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[5] http://prudence.dmi.dk/.
[6] http://www.cecilia-eu.org/index.htm.
[7] http://ensembles-eu.metoffice.com/index.html.
[8] World Wind Energy Association, http://www.wwindea.org.

for Altamont Pass (AP, 562 MW), San Gorgonio Pass (SGP, 710 MW), and Tehachapi Pass (TP, 359 MW) (Yen-Nakafuji 2005). The state has over 30 years of experience of integrating this intermittent power source and is considered a pioneer in the development of wind-generated electricity (e.g. Righter 1996a, 1996b).

1.1. Estimating future climate

Wind speed and direction vary on small scales, and respond in complex ways to changes in large-scale circulation, surface energy fluxes, and topography. Thus, whereas multiple climate models often agree qualitatively on temperature projections (e.g. Gordon *et al* 2000, Pope *et al* 2000, IPCC 2007, Spak *et al* 2007), wind estimates are less robust (e.g. Pryor and Barthelmie 2010). The spatial variability of wind and its sensitivity to model structure suggest that higher resolution models and multi-model comparisons are particularly valuable for wind energy projections.

Global general circulation model (GCM) output has been used to estimate future climate impacts on wind (Breslow and Sailor 2002, Mansbach and Cayan 2010), with Breslow and Sailor (2002) finding an overall decrease of 1–4.5% in SWS across the US over the 21st century. However, Sailor *et al* (2008) found that GCMs to not well represent observed SWS at specific sites in the Pacific Northwest region of the US, and we would not expect GCMs to resolve winds in mountainous regions like AP, SGP, and TP. To meet local climate information needs, GCM results may be 'downscaled', a process by which GCM projections are combined with additional information—either historic measurement data ('statistical downscaling' e.g. Pryor *et al* 2005c, Sailor *et al* 2000, Sailor *et al* 2008), a higher resolution regional climate model (RCM, 'dynamical downscaling', as discussed here), or hybrid approaches ('statistical–dynamical downscaling' Frey-Buness *et al* (1995)). Work to date shows a strong sensitivity to choice of GCM and downscaling method (e.g. Mearns *et al* 1999, Pryor *et al* 2005a, 2005b, 2005c, 2005d, 2006). Pan *et al* (2004) found that the improved horizontal resolution of atmospheric dynamics in RCMs had a positive influence on the ability of a model to simulate a climate over a given domain. Because RCMs explain why and how future climate may change, they are often viewed as preferable in principal to statistical downscaling.

RCMs have been used to assess SWS in the past, but no comparison among RCM results has been conducted, typically due to the high cost of running multiple scenarios on multiple RCMs. Garreaud and Falvey (2009) estimate SWS increases of 15% or more along the west coast of South America. Segal *et al* (2001) found decreases in wind power potential between 0 and 30% over much of the United States, but increases of up to 30% in localized regions. Ensemble regional climate studies on the European continent have shown disagreement among results (Frei *et al* 2006, Hirschi *et al* 2007), and a strong sensitivity to the GCM output that drives the simulations (Pryor *et al* 2005a). Thus, comparing among models is critical to avoid over-confidence in any one RCM. To support climate impacts analysis with multiple RCMs, an international

initiative called the North American Regional Climate Change Assessment Program (NARCCAP) began in 2005 to archive multiple RCM projections for public use (Mearns *et al* 2009).

2. Models used for analysis

Of the twelve planned RCM–GCM combinations for the NARCCAP data archive (six planned RCMs, each coupled with two of four planned GCMs[9]), at the time this study commenced three RCM–GCM combinations were available. RCM-calculated values for past time periods typically agree better with observations than GCM-values (e.g. Anthes *et al* 1989, Giorgi and Mearns 1991, 1999, Laprise 2006).

We used all three available future RCM simulations, with data provided on 50 km × 50 km grids and over 40 atmospheric and land-cover variables outputted every 3 h. All NARCCAP model runs available at the time of study assume emissions consistent with the Special Report on Emissions Scenarios (SRES) A2 scenario: heterogeneous economic growth and technological change, and a global population of 11.3 billion by 2050, 15.1 billion by 2100 (IPCC 2000).

In addition to the RCM–GCM past and future estimates, each of the three RCMs were coupled with the National Centers for Environmental Prediction (NCEP)—Department of Energy (DoE) Reanalysis 2 (NCEP2). NCEP2 is a global scale dataset with T62 horizontal resolution (about 210 km) and 28 vertical levels. Data is available for 1979–2006, with most variables reported every 6 h. Observed surface winds are not assimilated, but are extrapolated from the lowest model level to 10 m (Kanamitsu *et al* 2002). Coupling with GCMs allows for evaluating future change, whereas RCM–NCEP2 coupling allows for direct comparison with historic measurement data.

Nine separate NARCCAP data products were available for our evaluation: three RCM–GCM pairs ran for future conditions (2051–71, assuming SRES A2 emissions scenario); the same pairs for historic conditions (1980–2000); and the three RCMs coupled to NCEP2 for historic conditions (1980–2000). For our assessments of future climate change, we compared future RCM estimates with the RCM–GCM pairs for historic conditions.

In addition to three-dimensional wind components characteristic of atmospheric models (u, v, w), NARCCAP models report 10 m wind speed (two-dimensional, every 3 h and maximum daily value) and zonal and meridional 10 m SWS (two-dimensional, every 3 h)[10]; both generated in post-possessing by extrapolating winds from the lowest vertical model level to 10 m. The u and v wind components may be used, with substantial interpolation, to calculate turbine-level SWS. Here, we calculated scalar SWS from the reported zonal and meridional 10 m SWS as pre-calculated 10 m SWS were not available from all models for all time periods. Limiting our analysis to 10 m values represents a more easily reproducible approach and focuses on metrics more appropriate for comparison with weather station data.

Here we discuss the models contributing to NARCCAP employed for this study:

- *The Canadian Regional Climate Model (CRCM) and the Coupled Global Climate Model (CGCM3.1).* The horizontal resolution of the CRCM is 45 km × 45 km and its vertical resolution is variable using a terrain following coordinate. The CRCM is a fully non-hydrostatic, grid point model; the non-hydrostatic effects are not resolved at this resolution, but are used to justify the claim that the dynamical core could be used at all spatial scales (Laprise 2006). The land surface parameterization intended to simulate energy transfer between the surface and the atmosphere is the Canadian Land Surface Scheme (CLASS 2.7) (Laprise 2006, Music and Caya 2007). The CGCM3.1, like the CRCM, was developed and created by the Canadian Centre for Climate Modeling and Analysis (CCCMA). The CGCM3.1 used to constrain the CRCM was run with the T47 resolution. Its land surface grid resolution is 3.75° × 3.75° and is 31 levels deep in the vertical. The resolution over water is 1.85° × 1.85° and has 29 vertical levels (Flato *et al* 2000).

- *The Abdus Salam International Centre for Theoretical Physics Regional Climate Model 3 (RegCM3) and Geophysical Fluid Dynamics Laboratory (GFDL) CM2.1.* The RegCM3 is a third-generation RCM run by the University of California, Santa Cruz. The RegCM3 dynamic core is based on the hydrostatic mesoscale model fifth-generation (MM5) developed by Pennsylvania State University and the National Center for Atmospheric Research. It is a primitive equation, compressible, sigma vertical coordinate model with a horizontal resolution of 50 km × 50 km and a vertical resolution of 18 levels (Pal *et al* 2007). The GFDL CM2.1 was coupled with the RegCM3 RCM. The resolution of the land and atmospheric components is 2° latitude × 2.5° longitude and the ocean resolution is 1° in latitude and longitude. The GFDL CM2.1 has 24 vertical levels in the atmosphere, and 50 vertical levels in the oceans to accommodate mixed and surface layer physics (Delworth *et al* 2006).

- *Providing Regional Climates for Impacts Studies (PRECIS) model (referred to in this study as the HRM3) and the Hadley Centre Climate Model 3 (HadCM3).* HRM3 was developed at the Hadley Centre at the UK Meteorology Office (Wilson *et al* 2005) and derived from the HadCM3's atmospheric parameterization, but with greatly modified model physics (Jones *et al* 2004). HRM3 is a hydrostatic, primitive equation model with a 50 km × 50 km horizontal resolution and 19 vertical model levels, the lowest at 50 m (Cullen 1993, Jones *et al* 2004). Terrain following sigma coordinates are used for the bottom four vertical levels (Simmons and Burridge 1981). The HadCM3's atmospheric component has 19 vertical levels, and a horizontal resolution of 2.5° × 3.75°. The ocean resolution has 20 levels and a horizontal resolution of 1.25° × 1.25° (Pope *et al* 2000).

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[9] http://www.narccap.ucar.edu/about/plan.html#rcm-gcm.

[10] http://www.narccap.ucar.edu/data/data-tables.html; note that the documentation describes these winds as 'surface', which refers to 10 m per the netCDF meta-data definitions, and consistent with other documentation on the NARCCAP site. Here we refer to these variables as 10 m for clarity.

Table 1. Multi-year (1980–2000) average historical 10 m SWS (m s^{-1}) at each wind farm location (AP, SGP, and TP) as estimated by five different historic data sources. Observed data are taken from nearby weather stations presented in text; NARR data are high resolution reanalysis data; CRCM, RegCM3, and HRM3 are NARCCAP data from the unconstrained GCM–RCM simulations. Standard deviations (m s^{-1}) of annual mean SWS are given next to the 1980–2000 mean SWS in parentheses.

Data set	Altamont	San Gorgonio	Tehachapi
Observed	5.40 (0.37)	4.32 (0.48)	3.02 (0.27)
NARR	2.07 (0.15)	2.58 (0.26)	3.26 (0.27)
CRCM	3.98 (0.13)	6.93 (0.21)	4.50 (0.15)
RegCM3	3.87 (0.11)	3.91 (0.13)	4.49 (0.12)
HRM3	3.41 (0.09)	4.23 (0.11)	3.73 (0.11)

3. Model comparison with measurements and reanalysis data

Although observations from weather stations are the gold standard for model evaluation, often measurements are not available at site of interest. Indeed, none of the three California wind sites in this study have publicly available wind data for comparison. The closest weather stations to each site were identified from records at Lawrence Livermore National Laboratory (LLNL) and the DS35305 data set from the National Climate Data Center (NCDC), representing stations 722868 (Palm Springs International Airport; 30 km east of SGP), 723840 (Meadows Field Airport, 90 km west of TP), and LLNL Site 300 (in remote rolling terrain 10 km south of AP).

Table 1 presents these observation sites compared with the unconstrained RCM estimates for 1980–2000. At AP, observations are nearly 20% higher than even the highest of the RCM SWS estimates. At TP, observations are 15% lower than even the lowest of the RCM SWS estimates. The models appear to significantly underestimate interannual variability, as measured by the standard deviation of the annual average SWS values. At all sites, year-to-year variability is at least twice as high in the observations as it is in any of the RCMs at the corresponding site. These findings are consistent with (Wang *et al* 2009) who found that NARCCAP RCMs do not correctly reproduce historical interannual variability for precipitation. Furthermore, Pryor *et al* (2009), Pryor and Barthelmie (2010), Höglund *et al* (2009) both found that RCMs driven by reanalysis data do not capture the highly variable spatial characteristics of wind. To check whether grid box location significantly affected performance against observations, all RCM estimates were recalculated with the inclusion of including the eight neighboring grid boxes. No significant improvement was seen, except for an improved representation of the seasonal cycle in the RegCM3.

When weather station data are not available an oft-used substitute is the North American Regional Reanalysis (NARR) data product (Mesinger *et al* 2006). NARR is based on the NCEP Eta model, with observations integrated using the 3D-Var Data Assimilation System (EDAS). It has a horizontal resolution of 32 km × 32 km and 45 vertical layers with corrections for stability and terrain applied to the extrapolation of winds from the lowest vertical layer to 10 m (Lobocki 1993, Chuang *et al* 2001, Pryor *et al* 2009, Pryor and Barthelmie 2010).

As shown in table 1, NARR does not agree with observations nor with the NARCCAP RCMs. Qualitatively consistent with Mesinger *et al* (2006), NARR values are lower than observed at AP and SGP, and similarly at TP. NARR captures interannual variability better than the RCMs, but still underestimates variability relative to observations, except at TP. Because NARR are not observed data, but rather represent both observations and model simulation, they have been shown to have errors in certain regions. Mesinger *et al* (2006) report a small (<1 m s^{-1}) negative bias in NARR SWS relative to recorded observations. Lazić *et al* (2010) found positive SWS biases from Eta forecast verification projects in Sweden on the order of 0.5 m s^{-1} (Eta forecast SWS were also analyzed by O'Connor *et al* (1999)). Through enhancements in the land surface physics and tropospheric circulation, the NARR data have shown significant improvement over the NCEP2 in SWS bias and fits to rawinsonde observations.

These discrepancies are consistent with past studies. (Chin *et al* 2010) found RCM SWS forecast errors to be dependent upon the physics scheme used. Pryor *et al* (2009), Pryor and Barthelmie (2010) found disparate reproductions of historical SWS from a grid model (MM5) and a spectral model (RSM) based on each model's founding dynamics and/or the boundary layer scheme[11]. Additionally, Pryor *et al* (2009), Pryor and Barthelmie (2010) found that the surface energy balance at each grid box is a relevant factor in the simulation of circulation below the model's lowest vertical level; when extrapolating model winds to the surface, the stability in the modeled surface layer would consequently be misrepresented. A positive bias in the RegCM3 reproducing surface sensible heat fluxes has also been seen (Takle *et al* 2007).

Model representation of processes occurring on the sub-grid scale should also be considered in explaining the significant differences among observations, reanalysis, and RCM SWS estimates. The inconsistency in terrain and surface roughness among each model's grid box that contains each wind farm location strongly affects the SWS produced. Additionally, it has also been seen that SWS gusts on the sub-grid scale are not well represented by RCMs (Goyette *et al* 2003, Höglund *et al* 2009).

To compare spatial patterns between NARR and NARCCAP models, figures 1(a)–(d) compares JJA average historical SWS. We focus on summer, the season of peak electricity demand across most of the United States (Lu *et al* 2009). For current conditions, all models show similar spatial patterns with the highest SWS over the Pacific. A tight wind speed gradient exists along the California coast in all models, relaxing near the Channel Islands. The highest interior SWS exist in the southern half of the state with isolated areas of high wind speeds both along the northern California Coast and in close proximity to San Francisco Bay. Because of spatial interpolation methods used in figures 1(a)–(g), we caution in considering values at any local site to be absolute.

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[11] It should be noted that the RCMs compared by Pryor *et al* (2009), Pryor and Barthelmie (2010) were also provided by the NARCCAP archive.
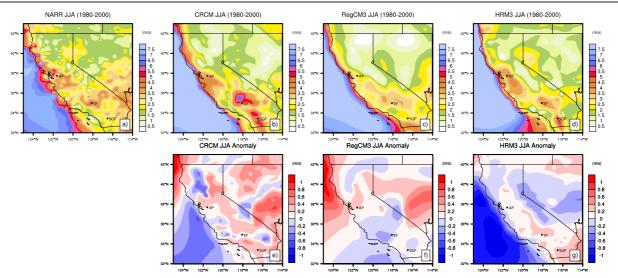
Figure 1. (a)–(g) Spatial patterns in June, July, August (JJA) average wind speeds over California and surrounding areas. (a) JJA 1980–2000 average 10 m wind speed (m s^{-1}) from the NARR data; (b) same as (a) except for the CRCM historic simulation from NARCCAP; (c) same as (b) except for RegCM3; (d) same as (b) but for HRM3; (e) future 10 m wind speed anomalies (m s^{-1}), representing future (2051–71) minus historical (1980–2000) from the NARCCAP-archived results for CRCM, calculated as future simulation minus the GCM–RCM historic simulation; (f) same as (e) except the RegCM3; (g) same as (e) except the HRM3.

4. Future projections

Before discussing these results, it is useful to pose a thought experiment. Imagine that we were reporting data from a single RCM, say the CRCM shown in figures 1(b) and (e). If we had limited the result to this single RCM for JJA, results would be very clear: future summer wind increases off the coast of Northern California and the middle interior of the state. With other RCMs available for comparison, we see that the results of the CRCM are not consistent across the other results presented in figure 1. A study with this—or any—single RCM might lead to an erroneously high degree of confidence in future wind resources.

In considering the results of all models taken together, most areas in California show some change in summertime SWS by mid-21st century relative to the 1980–2000 average (figures 1(e)–(g)). All three NARCCAP models project a decrease or no change in resources off the coast of California roughly south of Monterey Bay to the California and Mexico border. Additionally, SWS decrease in the northern California interior. It is likely that the CRCM produces more spatial variability at smaller scales than the RegCM3 and HRM3 due to the spectral nudging of horizontal wind (von Storch *et al* 2000). Similar plots for the December, January, and February (DJF) period (not shown) revealed changes in wind speeds greater than ± 1 m s^{-1} in certain areas of the state, but little spatial agreement across the RCM ensemble. On a continental scale (not shown) some points of agreement emerge among these NARCCAP RCMs, such as small annual average decreases, <1 m s^{-1}, in the Northwestern US and small increases, <0.3 m s^{-1}, in Texas, but no spatially consistent patterns even at the continental scale larger than 1 m s^{-1}.

Figure 2 compares current and future seasonal cycles among model estimates, with observations added to identify errors in assessing current conditions. Seasonality is key to

Table 2. Future 10 m SWS multi-year (2051–71) average per cent change over multi-year (1980–2000) unconstrained historical average 10 m SWS at each wind farm location (AP, SGP, and TP) as estimated by three GCM–RCM simulations. Standard deviations (m s^{-1}) of the annual mean future (2051–71) SWS are given next to per cent changes in parentheses.

Data set	Altamont	San Gorgonio	STehachapi
CRCM	−0.41% (0.16)	1.39% (0.37)	0.37% (0.13)
RegCM3	−1.06% (0.10)	0.31% (0.10)	−0.18% (0.13)
HRM3	−1.65% (0.11)	−0.83% (0.15)	0.86% (0.14)

the viability of wind energy investments, especially without large-scale storage in place, to compare patterns in production with concurrent patterns in demand, and to plan for integration with other renewable energy products (e.g. solar, hydro). The dot–dash–dot red line represents future winds at each site, and that pattern should be compared with the dashed black line, showing RCM–GCM coupled results for 1980–2000. For all models and sites, no significant trend in seasonal cycle or magnitude of monthly mean SWS is calculated. As in Pryor *et al* (2005a), there is more variability among the models at each site; between RCM–GCM and RCM–NCEP2 historic simulations; and between the RCM estimates and NARR than between present and future estimates.

These changes are summarized in terms of annual percentage change in table 2 comparing 1980–2000 SWS values with 2051–71. All models estimate a decrease in winds at AP, with HRM3 estimating the largest change (1.65%) and the other two models both estimating a decrease of about 1% or less. Models differ in direction of change for the other two sites. Changes are smallest at TP, $<\pm 1\%$ from all models, but in different directions. Standard deviations of mean annual wind speeds for future conditions are given in parentheses, which may be compared with analogous standard
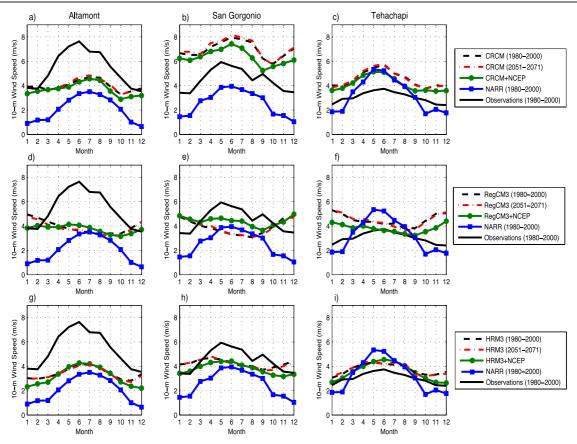
Figure 2. (a)–(i) Time series plots of monthly average historic (1980–2000) and future (2051–71) 10 m wind speeds (m s^{-1}) for all three sites from all three NARCCAP-archived models. Dashed black line represents historic RCM estimates for GCM-coupled simulations; NCEP2-coupled simulations shown as solid green with circles; dot–dash–dot red line represents the RCM future simulations; solid blue line with squares represents the NARR historic simulation; solid black line represents historic observations. Each row reflects a NARCCAP model: (a)–(c) CRCM; (d)–(f) RegCM3; (g)–(i) HRM3.

deviation values given for each model in table 1. As a metric of interannual variability in mean wind speeds, the values suggest little change between current and future conditions, although the HRM3 shows increased variability in future SWS at all sites.

Wind speed distributions from SGP for January and July in figure 3 further illustrate some of the same patterns discussed above: disagreement among data sources is greater than change between current and future estimates. The CRCM overestimates variability in January, and overestimates mean values in July, whereas RegCM3 and HRM3 perform fairly well against observations for January, but underestimate variability in July.

5. Conclusion

The disparity among SWS estimates for current conditions limits the value of quantitative wind energy assessment based on NARCCAP model results in these regions of complex terrain. Since trend estimates do not agree, the models do not suggest a clear direction of future change at these specific sites, even on a qualitative basis. Still, knowing where climate projections agree, and where they differ, is essential for informed decision-making and risk assessment.

The poor agreement for current conditions occurs because surface airflows at these sites are unresolved by the 50 km × 50 km RCM simulations evaluated here—despite the fact that these simulations are considered high resolution over such a large area (continental United States and most of Canada). For example, SGP has a width of only a few kilometers, smaller than the resolution of even relatively fine-grid RCMs. Chin *et al* (2010) found SWS forecast error from a non-hydrostatic model at AP to decrease with increasing grid size (converging near 1 km×1 km), so some error may be attributed to resolution alone. In addition, near-neighbor weather stations may not represent typical wind patterns over the 50 km × 50 km region, and significant variability exists among the RCMs due to their varying modeling schemes (e.g. spectral versus grid box modeling, spectral nudging of variables, number of vertical layers, etc). Although local observations at the study sites were not available for this analysis, such data could contribute significantly to the validation of model results.

We have shown that projections of future wind availability depend critically on the model chosen for assessment. By comparing current and future estimates across models, now possible through the use of NARCCAP data, more robust risk analyses are possible, although even these data may not be appropriate for sub-grid scale assessments of highly
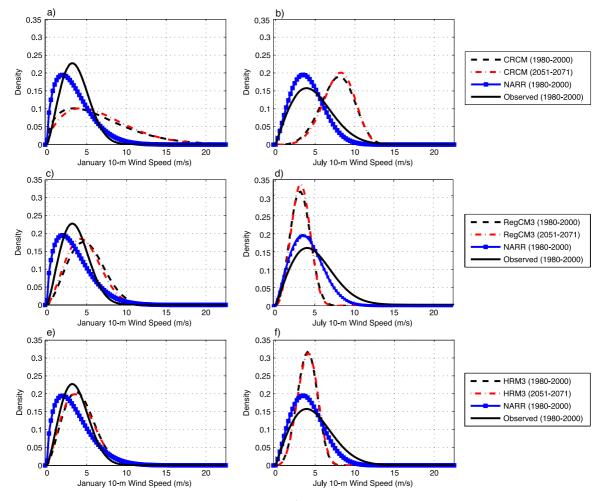
Figure 3. (a)–(f) San Gorgonio: 10 m wind speed distributions (m s^{-1}) for January (left: (a), (c), (e)) and July (right: (b), (d), (f)). Dashed black line represents historic RCM estimates for GCM-coupled simulations; dot–dash–dot red line represents the RCM future simulations; blue solid line with squares represents the NARR; solid black line represents observations from Palm Springs International Airport. Each row reflects a NARCCAP model: (a) and (b) CRCM; (c) and (d) RegCM3; (e) and (f) HRM3.

varying climatic variables. By comparing multiple estimation methods—whether they agree or not—climate assessment moves toward a rigorous standard for estimating risk in light of all available information.

Despite model limitations, we find that spatial wind speed patterns in California do change under future climates, but the impact of these changes on wind-generated electricity at the major generation sites cannot be stated with confidence based on the models examined in this study. The choice of climate model has a significant effect on the projections that are produced as model physics, dynamics, terrain parameterizations, and the driving reanalysis data or parent GCM all affect results.

The 'ideal' assessment would include an ensemble of RCMs over each site with resolution in the order of 1 km × 1 km to better resolve complex terrain and to parameterize fundamental sub-grid scale processes relevant to surface wind, such as wind gusts. Additionally comparing RCM results with statistical downscaling estimates may help identify whether relationships between local and large-scale processes are expected to remain constant into future, or if and how they may change with changing atmospheric conditions. As more

evaluation and application of model-based wind projections are employed, these metrics will likely improve and support long-term decision-making for US and global renewable energy investments.

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