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Evaluation of the climate change impact on wind resources in Taiwan Strait

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ABSTRACT

A new statistical downscaling framework is proposed to evaluate the climate change impact on wind resources in Taiwan Strait. In this framework, a two-parameter Weibull distribution function is used to estimate the wind energy density distribution in the strait. An empirically statistical downscaling model that relates the Weibull parameters to output of a General Circulation Model (GCM) and regression coefficients is adopted. The regression coefficients are calculated using wind speed results obtained from a past climate (1981–2000) simulation reconstructed by a Weather Research and Forecasting (WRF) model. These WRF-reconstructed wind speed results are validated with data collected at a weather station on an islet inside the strait. The comparison shows that the probability distributions of the monthly wind speeds obtained from WRF-reconstructed and measured wind speed data are in acceptable agreement, with small discrepancies of 10.3% and 7.9% for the shape and scale parameters of the Weibull distribution, respectively. The statistical downscaling framework with output from three chosen GCMs (i.e., ECHAM5, CM2.1 and CGCM2.3.2) is applied to evaluate the wind energy density distribution in Taiwan Strait for three future climate periods of 2011–2040, 2041–2070, and 2071–2100. The results show that the wind energy density distributions in the future climate periods are higher in the eastern half of Taiwan Strait, but reduce slightly by 3% compared with that in the past climate period.

1. Introduction

The impact of climate change due to increased greenhouse gas emissions has fostered the development of renewable energy sources. With the features of maturity, good competitiveness and nature friendship, wind power is experiencing swift growth among the energy sources. Wind resources around Taiwan are abundant since the wind climate, including the Asia monsoon and tropical cyclones during the summer season and the northeast trade winds during the winter season, induces high winds in many areas. In particular, winds inside Taiwan Strait seem speed-up due to the blockage effect and the water depths within the strait area are shallow less than 100 m, normally with a range of water depths from 40 to 80 m in the most offshore area. Thus, Taiwan Strait is considered to be a quite potential area for the development of offshore wind energy. In spite of such great potential in the strait area, the deployment of wind turbines in Taiwan has progressed only on onshore areas in the last decade [1,2], and has been gradually rejected by the public in recent years. The total installed capacity of wind energy has reached 596 MW with 302 onshore wind turbines by 2012. To extend the development of wind energy, the Taiwan government recently strived to pass three green laws (i.e., Renewable Energy Development Bill, Greenhouse Gas Reduction Law and Energy Tax Law) and built up the Thousand Wind Turbines Project to proclaim the decision of energy-economizing and carbon-reducing. Through the project, the installed capacity of wind energy will reach a total of 4200 MW with 1050 wind turbines installed on both onshore and offshore areas, with an aim of installing offshore wind turbines producing a total capacity of 3000 MW in the next 20 years [3].

Although the expectable expansion of installed capacity of wind energy in Taiwan Strait will reduce greenhouse gas emissions for mitigating anthropogenic climate change [5,6], variability of wind speed and temperature due to climate change may still affect meteorological variables as well as renewable energy sources [7,8]. Particularly, wind power is susceptible to climate change

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because of the cubic relationship between wind speed and wind power. Changes of wind speed statistics (e.g., mean wind speeds and wind speed distributions) related to climate mutation affect the amount of wind energy extracted from atmospheric flows. In general, sea areas are expected to possess higher wind speeds since the kinetic energy of the flow is less dissipated by the homogeneous surface of sea. However, meteorological data collected above sea areas are lack, which hinders the understanding of wind speed characteristics, the prediction of future climates, and the development of wind energy technology within the sea areas. To reduce the risk of loss from investment of offshore wind energy, it is necessary to investigate the impact of climate change on offshore wind energy within Taiwan Strait in the future.

General Circulation Models (GCMs), adopted in the intercomparison project by Intergovernmental Panel on Climate Change (IPCC), can be used to assess the likely climate response to increasing carbon dioxide levels in a future climate prediction. The output results are with regional-scale grid resolutions that are generally greater than 2.0 degree for both latitude and longitude [8]. Both dynamical and statistical (empirical) downscaling approaches are commonly used to downscale GCM predictions to local surface variables. The dynamical downscaling approach with RCMs is theoretically preferable to the statistical one [6], whereas the dynamic downscaling approach needs much more computational cost than the statistical one. Previous works [7–10] have successfully applied the statistical downscaling approach to examples of downscaling wind resources.

Sailor et al. [7] developed neural network to relate local wind speed observations to GCM predictions and then downscale GCM output to predict surface wind speed for three sites in Texas and California. Sailor et al. [8] used statistical downscaling approach, tree-structured regression, to investigate scenarios of climate change impacts on wind power generation potential in a five-state region within the Northwest United States. Pryor et al. developed empirical downscaling approach, based on multiple linear regression, to estimate near-surface wind speed and energy density at 46 stations in Northern Europe [9,10]. The key step of the statistical downscaling approach is to acquire near-surface wind speed observations on a time scale of decades, and then construct a downscaling model between the near-surface measured data and the variables of GCMs under control period. On the other hand, due to the lack of long-term measured wind speed data or sufficient offshore meteorological stations, offshore wind energy studies [4,11,12] mostly target on the characterizations or distributions of offshore wind power, but the predictions of near-surface wind data under future period. Li et al. used wind data observed at a wind farm in the Taiwan Strait from 2006 to 2008 to compute the Weibull parameters for wind characterization analysis [11]. Oh et al. analyzed marine buoy dataset measured at 5 positions over the period of 12 years, QuikSCAT satellite data measured over 9 years, and a numerical wind map based on meteorological data measured for 4 years to provide a summary of the offshore wind resources of the Korean Peninsula [12]. Jiang et al. used QuikSCAT level-2 satellite measurements at a 0.5-degree horizontal resolution over 9 years to study the distribution of offshore wind power in China [4]. Among the aforementioned wind energy researches, only the on-land areas have long-term measured wind speed data for training downscaling model.

To fill this gap and surmount the shortage of offshore wind speed data, the main objective of the study is to develop a new statistical downscaling framework using Weather Research and Forecasting Model (WRF) to regenerate wind speed data and use near-surface hourly mean wind speed data (1981–2000) of meteorological station on the offshore islet, Tungchitao, to calibrate the model. This study selects three GCMs, ECHAM5 (the European Centre Hamburg Atmospheric Model, version 5), CM2.1 (the Second Generation Coupled Global Climate Model), and CGCM2.3.2 (the Second Generation Coupled General Circulation Model) to perform a statistical downscale, and combines wind speed data regenerated from WRF to evaluate the impact of climate change on offshore wind energy potential in Taiwan. In addition, wind speed and wind energy density of three periods (2011–2040, 2041–2070 and 2071–2100) with A1B emission scenario represented the lower middle range of growth in CO_2 emissions developed from the Special Report on Emissions Scenarios (SRES) are selected to compare those of control period (1981–2000).

2. A statistical downscaling framework

In this study, we propose a new statistical downscaling framework to evaluate accessible wind resources of an area in a future climate period. In particular, the development of the framework aims at predicting spatial distributions of wind speed and wind energy density in a windy area (e.g., open sea areas) where only a few meteorological data are available.

In general, wind energy density per unit area is a common measure to quantify how much electricity is attainable by wind energy conversion systems. It can be estimated using a probability distribution fitting to a set of wind speed data (e.g., Weibull distribution or Rayleigh distribution) [13,17–21]. Considering that the natural distribution of measured wind speeds often matches a Weibull shape, a two-parameter Weibull density function is used to assess wind energy density in the framework and is written as follows:

$$f(V) = \frac{k}{c}\left(\frac{V}{c}\right)^{k-1} e^{-(V/c)^k}, \tag{1}$$

where V is the wind speed, c is the scale parameter related to the mean of the wind speed distribution, and k is the shape parameter related to the "peakedness" of the distribution. The cumulative distribution function $F(V)$ is expressed by

$$F(V) = 1 - e^{-(V/c)^k}. \tag{2}$$

The mean wind speed and the wind energy density at a local site are given by

$$\overline{V} = c\Gamma\left(\frac{k+1}{k}\right), \tag{3}$$

and

$$\frac{E}{A} = \frac{1}{2}\rho c^3 \Gamma\left(\frac{k+3}{k}\right), \tag{4}$$

respectively. Here, Γ denotes the Gamma function and ρ is the air density. The maximum likelihood method [1,14] is used to compute the scale and shape parameters through numerical iterations using the following equations:

$$k = \left(\frac{\sum_{i=1}^{n} V_i^k \ln(V_i)}{\sum_{i=1}^{n} V_i^k} - \frac{\sum_{i=1}^{n} \ln(V_i)}{n}\right)^{-1}, \tag{5}$$

$$c = \left(\frac{1}{n}\sum_{i=1}^{n} V_i^k\right)^{1/k}. \tag{6}$$

In order to predict wind resources of a local site in a future climate period, an empirically statistical downscaling model [9,22] with independent variables that are obtained from a General Circulation Model (GCM) simulation is involved in the framework. The downscaling model includes a multiple linear regression function which relates the site-specific Weibull parameters to three GCM output variables and their associated regression coefficients. The three GCM output variables, regarded as predictors in the