# Evaluating the Methodology of Assessing Inter-Annual Variability of Wind Speed

**Joseph C. Y. Lee*,+, M. Jason Fields* and Julie K. Lundquist*,+**
*National Renewable Energy Laboratory, Golden, Colorado, USA, joseph.lee@nrel.gov
+Department of Atmospheric and Oceanic Sciences, University of Colorado Boulder, Boulder, Colorado, USA

## Abstract
Because wind resources vary from year to year, the inter-annual variability (IAV) of wind speed is a key component of the overall uncertainty in the wind resource assessment process and causes challenges to wind-farm operators and owners. The length of the analysis period influences the resulting IAV estimate. Since many approaches of calculating IAV exist, we present a review of these methods and apply each of the methods to the same wind speed and energy production time series to highlight their differences. We then assess the accuracy of the IAV calculations by comparing the wind speed IAV estimates to the IAV of actual wind-farm power production. Finally, we recommend a systematic approach for estimating IAV.

**Keywords:** *Inter-annual variability, Statistics, Wind resource assessment, Uncertainty quantification*

## Introduction
Inter-annual variability (IAV) of wind resources contributes to the overall uncertainty of the wind resource assessment process. Despite the importance of IAV, the wind energy industry lacks a systematic method to quantify IAV. The goal of this study is to identify the methods most appropriate for different situations, such as duration of data availability and wind speed distributions. We provide an overview and evaluation of various methods in calculating IAV, as well as recommendations on the choice of methods.

## Data and Methods
In this study, we use multi-year time series of wind speed and wind energy production in the United States to calculate the IAV of wind resources as well as the IAV of energy generation. We derive the monthly-average hub-height wind speed data from NASA's MERRA2 reanalysis dataset [1], for 21 years (1996-2016). We also use the net monthly energy production of wind farms from the Energy Information Administration (EIA) from 2003 to 2016.

To exclude low-production data due to factors such as curtailment and maintenance, we linearly regress energy production on the MERRA2-modelled wind speed at the closest grid point to each wind farm. We then filter the time series based on the coefficient of determination ($R^2$), which describes the confidence of the regression. Since some farms lack years of complete generation data, we extend the energy production time series to 21 years using the same linear models with an $R^2$ larger than 0.75. We further filter the data based on the correlation (Pearson's r) between predicted and actual power.

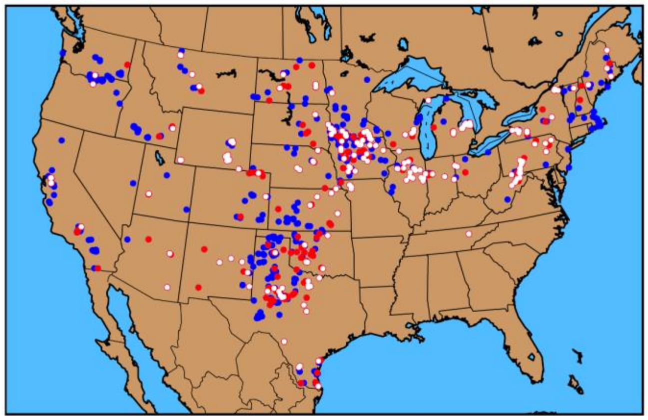

Figure1: Map of wind farms: The pre-filter EIA wind farms are in blue, the $R^2$-filtered wind farms are in red, and the r-filtered wind farms are in white.

To describe the spread of the data from the filtered wind farms, we test numerous combinations and variations of existing methods based on statistical robustness to non-Gaussian distributions and statistical resistance to outliers. We quantify IAV using methods such as the Coefficient of Variation (CoV, standard deviation divided by mean; neither robust or resistant) [2,3] and the Robust Coefficient of Variation (RCoV, mean absolute deviation divided by median; robust and resistant) [4]. We calculate the IAVs via different metrics on the extended time series of wind speed and energy production with different time frames: 1 year, 2 years, up to 21 years for each wind farm. An IAV method is considered useful when the resultant wind speed IAV correlates well with the resultant energy production IAV across wind farms.

**Results**

When using statistically robust and resistant methods, the results yield higher correlations between wind speed IAV and energy production IAV, as robust methods do not assume Gaussian wind speed distributions and resistant methods are insensitive to wind speed extremes. Although different IAV methods are appropriate in different conditions, depending on the meteorological data availability, terrain complexity, etc., robust and resistant methods are the most applicable to estimate IAV in general.

Moreover, the correlation between energy IAV and wind speed IAV changes when the analysis time frame changes. For all the methods, the correlation coefficients converge to the 21-year value within a certain time span. For example, the resultant correlations using CoV asymptotes by year 8, which means one needs 8 years of wind speed data in order to confidently infer the energy production IAV of a particular wind farm using CoV.

**Conclusions**

This study highlights the importance of a rigorous method to estimate inter-annual variability (IAV). To search for the suitable ways to quantify this uncertainty under different conditions, we investigate 29 combinations of methods for estimating IAV. We evaluated the methods for robustness to non-Gaussian distributions and resistance to extreme values, in contrast to the common practice in the industry. We find that within the United States, statistically robust and resistant methods more accurately predict IAV in wind resources. Depending on the exact method chosen, data for 3-11 years are generally required for accurate IAV estimates.

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