ADDENDUM

Addendum: Observation-based solar and wind power capacity factors and power densities (2018 Environ. Res. Lett. 13 104008)

Lee M Miller 1,3,4 and David W Keith 2,1

1 School of Engineering and Applied Sciences, Harvard University, Cambridge, MA 02139, United States of America
2 Harvard Kennedy School, Cambridge, MA 02138, United States of America
3 now at Atmospheric and Environment Research (AER), 131 Hartwell Avenue, Lexington, MA 02421
4 Author to whom any correspondence should be addressed.

E-mail: lmiller@aer.com

Keywords: wind power, power density, photovoltaics

Abstract

‘Observation-based solar and wind power capacity factors and power densities’ (Miller and Keith 2018 Environ. Res. Lett. 13 104008) contained a methodological error in how we estimated wind plant area, leading to an underestimate of wind power densities. The method and revised results were published as a Corrigendum (Miller and Keith 2019 Environ. Res. Lett. 14 079501). Given the importance of these estimates to energy policy, here in this Addendum, we expand on these corrected results, while also describing the public release of data to allow verification by third-parties. Specifically, here we: (1) illustrate our method by showing in greater detail how it works for the 2 wind power plants from figure 1 of the original study, (2) identify potential selection biases in the sampling of wind power plants used in our study, (3) provide a comparative overview of the various prior published estimates in graphical form, and, (4) conclude with a description of the data we are releasing publicly.

Figure 1 shows the Bull Creek and Fenton wind power plants. Bull Creek (Plant_Code = 56956) is comprised of 180 Mitsubishi MWT62/1.0 turbines, with a per-turbine rated capacity of 1.0 MWi and 69 m hub-height. Based on our Methods (main text and supplemental information of Miller and Keith 2018a, 2019), we calculated a Voronoi polygon around each wind turbine location. Each Voronoi polygon delineates the area closer to an individual turbine than to any other wind turbine in the entire USGS data set (Hoens et al. 2018). As shown in figure 1(C), some Voronoi polygons are unrealistically large if considered as estimates of their wind turbine footprint. Indeed, a wind plant consisting of a single isolated turbine would have a huge Voronoi polygon area. This is the reason our method uses the area of the median Voronoi polygon as the basis for estimating the area of the wind plant which is computed by multiplying the median area (in this case 0.22 km²) by the number of turbines (180) to yield an estimate for the total area (39.2 km²).

Our method provides an estimate of the wind plant area, but it does not provide a unique outline of that area. As an aid to visualizing and understanding our results, we can compute an outline that contains the same total area as our estimate while having a constant minimum offset between each turbine and the perimeter. This is computed by constructing disks of equal radii around each turbine, dissolving their overlapping area to prevent double counting, and adjusting the radii until the total area inside one or more disks is equal to the area we computed. The resulting perimeter for Bull Creek is shown in figure 1(A). This is a useful illustration of a wind-plant perimeter, particularly as compared to methods that use a fixed radius from each turbine.

The same approach was used for Fenton (Plant_Code = 56617). Fenton is comprised of 137 GE1.5-77 turbines, with a per-turbine rated capacity of 1.5 MWi and an 80 m hub-height. Just like the method for Bull Creek, Fenton’s median Voronoi polygon area of 0.53 km² was multiplied by the turbine count, yielding a total area of 73.2 km² (figure 1(D)). This equivalent area is shown around the Fenton wind turbines in figure 1(B).

We investigated the impact of selection bias in our sample of wind plants. In the 2016 data, for example,
total capacity of wind plants that passed our quality-assurance filters was only 51% of the total capacity reported by EIA at the end of 2016. How representative is our sub-sample of the full data set? We first examine spatial sampling. Figure 2 shows the map of the all wind power plants from the EIA Power Plants (US Energy Information Administration EIA 2018a) and our subset (see public data release below:}

**Figure 1.** Wind power plants at Bull Creek (A), (C) and Fenton (B), (D). For Bull Creek, (A) the turbine locations and equivalent total area are shown in red, with the same for Fenton (B) in green. In (C), (D), the Voronoi polygon areas of individual turbine locations are shown as well as percentiles noted in text. In each case locations of turbines that are in another wind plant are shown in yellow.

**Figure 2.** Showing locations of all wind power plants from the EIA Power Plants (US Energy Information Administration EIA 2018a), with those in black used in this study.
MillerKeith2018Data1.csv). Some locations, like Massachusetts appear to be missed. Upon further analysis, many of these 'plants' are actually 1 or 2 wind turbines, which because of their rated capacity >1 MW are included in the Power Plants dataset, but were excluded from our analysis because the Voronoi polygons containing these wind power plants were large, so the filter for capacity densities ≤0.1 MWi km$^{-2}$ excluded these wind plants.

Figure 3 compares the capacity cumulative distribution of wind plant size in the full data and our subset. Our sample is biased towards larger wind power plants. This highlights the fact that our method is not applicable to very small wind plants.

Assuming, as seems likely, that continued expansion of wind power will be associated with larger wind plants, then our under-sampling of small wind plants does not impact the applicability of our estimates.

Moreover, the uncertainty or arbitrariness of the median-Voronoi method decrease with increasing scale. For a single turbine, we know of no unambiguous way to define the area over which it is extracting power. Calculating power density for small wind plants is inherently arbitrary, as the benefits of being isolated on a ridgeline or in a coastal region are clear, but the ability to later deploy additional wind turbines downwind is often limited. But the methodological errors in estimating the power density of medium sized wind power plants (30–200 km$^2$) using the median-Voronoi method are small as these plants typically contain 10–100 s of wind turbines all co-located into one region, often in rows (e.g. figure 1).

Large wind power plants (>300 km$^2$) should also be easily defined in the future, but as today’s wind plants are just now growing to these dimensions via adjacent deployment in windy locations, we suspect that our results for these large wind power plants are also not perfect. In our analysis, the power densities associated with these large wind power plants are quite low (figure 7(B) of Corrigendum), leading us to believe that these are regions with very low capacity densities rather than low power densities resulting from wind plants operating upwind. As these regions are built-out with turbines, we would expect the area estimate for large wind plants to improve as well.

Finally, figure 4 compares results from this study with earlier estimates of wind’s power density. The power densities from this study are consistent with physically-based models, and inconsistent with wind resource estimates that ignore interactions between wind turbines and the atmosphere.

To facilitate independent validation of these results, we have placed 2 datasets on OpenEI, a public
data repository developed and maintained by the US Department of Energy’s National Renewable Energy Laboratory. Two files are provided: http://openei.org/datasets/dataset/miller-keith-2018-windplantdata.

- MillerKeith2018Data1.csv; 430 wind power plants used in this study, initially based on the Power Plant locations released by the US Energy Information Administration

Plant_Code—from EIA Power Plants (US Energy Information Administration EIA 2018a)—used to link to electricity generation

Longitude—from EIA Power Plants

Latitude—from EIA Power Plants

InstCapMWi—from EIA Power Plants

AreaKM2: total area of the wind plant (km²), based on our calculations in Wind Methods

NetGENe_2016_MWe—from EIA Bulk Data (US Energy Information Administration EIA 2018b)

USWTDB_ID—from US Wind Turbine Database (USWTDB, Hoen et al 2018); unique text name (match to MillerKeith2018_Data2.csv)

- MillerKeith2018Data2.csv; 26 659 unique wind turbine locations
Acknowledgments

We thank one anonymous reviewer for constructive comments on the manuscript. This work was supported by the Fund for Innovative Climate and Energy Research.

ORCID iDs

Lee M Miller @ https://orcid.org/0000-0001-5527-3194

References

Adams A S and Keith D W 2013 Are global wind power resource estimates overstated? Environ. Res. Lett. 8 015021
Archer C L and Jacobson M Z 2005 Evaluation of global wind power J. Geophys. Res. 110 1–20
Dabirij O 2011 Potential order-of-magnitude enhancement of wind farm power density via counter-rotating vertical-axis wind turbine arrays J. Renew. Sustain. Energy 3 1–12
Fitch A C 2015 Climate impacts of large-scale wind farms as parameterized in a global climate model J. Clim. 28 6160–80
Gustavsson M R 1979 Limits to wind power utilization Science 204 13–7
Hoen B D, Diffendorfer J E, Rand J T, Kramer L A, Garrity C P and Hunt H E 2018 United States Wind Turbine Database (US Geological Survey, American Wind Energy Association, and Lawrence Berkeley National Laboratory data release: USWTDB V1.0 (19 April 2018)(https://eerscmap.usgs.gov/uswtdb)) (Accessed: 10 April 2019)
IPCC 2012 IPCC Special Report on Renewable Energy Sources and Climate Change Mitigation (Cambridge: Cambridge University Press) ch 7
Jacobson M Z and Archer C L 2012 Saturation wind power potential and its implications for wind energy Proc. Natl Acad. Sci. 109 15679–84
Jacobson M Z et al 2018 Sustain. Cities Soc. 42 22–3
Kammen D M and Sunter D A 2016 City-integrated renewable energy for urban sustainability Science 352 922–8 (https://science.sciencemag.org/content/352/6288/922)
Keith D W, Decarolis J F, Denkenberger D C, Lenschow D H, Malyshev S L, Pacala S and Rasch P J 2004 The influence of large-scale wind power on global climate Proc. Natl Acad. Sci. 101 16115–20
Lopez A, Roberts B, Heimiller D, Blair N and Porro G 2012 US Renewable Energy Technical Potentials: A GIS-Based Analysis NREL/TP-6A20-51946 (https://nrel.gov/docs/fy12osti/51946.pdf) (Accessed: 10 April 2019)
MacKay D J C 2013 Could energy-intensive industries be powered by carbon-free electricity Phil. Trans. R. Soc. A 371 20110560
Miller L M, Brunsell N A, Mechem D B, Gans F, Monaghan A J, Vautard R, Keith D W and Kleidon A 2015 Two methods for estimating limits to large-scale wind power generation Proc. Natl Acad. Sci. 112 11169–74
Miller L M, Gans F and Kleidon A 2011 Estimating maximum global land surface wind power extractability and associated climatic consequences Earth Syst. Dyn. 2 1–12
Miller L M and Keith D W 2018a Observation-based solar and wind power capacity factors and power densities Environ. Res. Lett. 13 104008
Miller L M and Keith D W 2018b Climatic impacts of wind power J. Environ. Res. Lett. 13 104008
Miller L M and Keith D W 2019 Corrigendum: observation-based solar and wind power capacity factors and power densities Environ. Res. Lett. 14 079951
Miller L M and Kleidon A 2016 Wind speed reductions by large-scale wind turbine deployments lower turbine efficiencies and set low generation limits Proc. Natl Acad. Sci. 113 13570–5
Rogner H et al 2000 Energy resources World Energy Assessment. Energy and the challenge of sustainability United Nations Development Programme (New York: United Nations Department of Economic and Social Affairs, World Energy Council)
US Dept. of Energy 2014 Wind Vision: a new era for wind power in the United States (http://energy.gov/sites/prod/files/WindVision_Report_final.pdf) (Accessed: 18 May 2018)
US Energy Information Administration (EIA) 2018a Power Plants Shapefile
US Energy Information Administration (EIA) 2018b Bulk Electricity Data (https://eia.gov/opendata/) (Accessed: 10 April 2019)