Methodology for Climate Central’s WeatherPower™ (Wind and Solar Electricity Forecaster), version 3.1

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1. Overview

WeatherPower™ (v3.0), Climate Central’s wind/solar electricity forecaster, provides estimates of the amount of electricity generated by solar-PV and wind-turbine installations yesterday, today, and tomorrow across each Nielson Designated Market Area (DMA) in the U.S., as well as for each state, county, congressional district, and EPA eGRID region. The estimates are generated using spatially-resolved hourly actual-observed (for “Yesterday”) or forecast (for “Today” and “Tomorrow”) wind speeds and solar irradiance, together with spatially-resolved estimates of installed wind turbine and solar PV capacities. The weather data are estimated for each point on a uniform 0.05° latitude by 0.05° longitude grid across the continental U.S., Alaska, and Hawaii. WeatherPower makes electricity generation estimates for solar-PV and wind-turbine installations using weather data from their closest respective grid points. These estimates are then aggregated into totals for larger regions. To put the electricity generation estimates in perspective, several metrics are calculated and reported, including the equivalent number of households in a region that could be powered each day by the estimated amounts of solar or wind generated electricity. The tool also estimates the amount of CO₂ avoided by not generating the electricity from CO₂-emitting power plants and compares the avoided CO₂ emissions with activities that either emit or avoid emitting equivalent amounts of CO₂, including driving a car and planting trees. Additionally, a “Wind Power Index” (WPI) and “Solar Power Index” (SPI) are calculated. These indices reflect how “good” the day was (“Yesterday”) or is expected to be (“Today” and “Tomorrow”) in terms of solar or wind electricity generation. This document details the methodologies, assumptions, and input data sources used by WeatherPower™ version 3.0.

2. Weather Parameters at 0.05° x 0.05° Grid Cell Resolution

Hourly wind speed and solar irradiance estimates on a 0.05° lat x 0.05° lon grid are provided by MESO.¹ Specifically, MESO provides observed (historical) and forecast wind speed at 80-meter elevation (m/s) and global horizontal irradiance (GHI) at the earth’s surface, plus its direct and diffuse components, and a clear-sky GHI (all in W/m²). Historical observed values and values forecast for the next 48 hours are estimated for the continental U.S. from the hourly analysis (i.e., the 0-hour forecast) dataset from the 3-km grid of the High-Resolution Rapid Refresh (HRRR) weather forecasting model² and from the 13-km grid of the Rapid Refresh (RAP)
model for Alaska and Hawaii. Forecast values beyond 48 hours are from the hourly 0.25° degree pressure level dataset from the Global Forecast System (GFS) weather forecasting model. The values from the HRRR, RAP, and GFS datasets are interpolated to the 0.05° grid by the bilinear interpolation scheme contained in National Centers for Environmental Prediction’s “degrib” software package. The data from MESO are downloaded and processed at Climate Central every six hours starting at 00:00 UTC. These data include observed weather data from the previous 24 hours, as well as forecasted weather data for the following 96 hours. These data are used to construct forecast for “Yesterday,” “Today,” and “Tomorrow” and two days after "Tomorrow".

3. Estimating Solar and Wind Electricity Generation

The weather parameter values at the 0.05° grid level are used together with estimates of installed generating capacity of solar PV (from data available July 2020) and wind turbines (from published data as of June 2, 2020) to estimate the solar and wind electricity generation for each hour for which estimated or forecasted values are provided. Hourly estimates are summed to get daily values, and the daily values for different regional aggregations of power generators — i.e., DMAs, states, counties, and congressional districts — are then reported as outputs.

3.1. Installed Solar-PV Generating Capacity

Estimates of installed solar-PV generating capacity are developed from a combination of several data sources to cover both utility-scale and residential installations.

3.1.1. Solar utility-scale generators

All electricity generators in the U.S. with installed capacity of 1 MWAC or more, including solar-PV generators, submit information about their operations to the Energy Information Administration, which reports these collectively on form EIA860. We used the Early Release EIA 860 data available June 2, 2020. For each solar-PV generator reporting on form EIA860, we extract the following data: the EIA-assigned utility ID number, plant ID number, generator ID number, nameplate capacity in AC, net capacity in DC under standard test conditions, type of tracking (fixed, east-west fixed, single-axis, or dual axis), tilt angle, and generator location (latitude, longitude, zip code, and state).
3.1.2. Solar residential rooftop generators

For residential-scale solar-PV installations (less than 1 MW\textsubscript{AC} of installed capacity), we combine data from two sources: the Lawrence Berkeley National Laboratory’s *Tracking the Sun* (TTS) 2019 report,\textsuperscript{13} and Google’s *Project Sunroof* (PS).\textsuperscript{14,15} The TTS report includes capacities for only 27 states and the District of Columbia, and in 6 of the 27 states (CO, IL, MD, MN, RI, and UT) more than 50% of the reported installations are missing zip codes so cannot be precisely located. The capacity for these six states and for states not covered in TTS are estimated using the PS database. Additionally, we compare each state’s total installed residential PV capacity between the two databases. If a state’s capacity as estimated using PS is 20% or more than the capacity given by TTS for that state, we assume PS represents a more accurate accounting and we use that data. In total, WeatherPower uses data from TTS for the District of Columbia and 13 states: AZ, CA, CT, DE, MA, MO, NH, NJ, NM, NY, OH, PA, and VT. For all other states, WeatherPower estimates are based on data from PS.

3.1.2.1. Tracking the Sun

From the TTS dataset, we extract for each reported solar installation its DC capacity rating and zip code. To avoid duplications of EIA860 data, we eliminate any installations from TTS that report capacities greater than 1 MW\textsubscript{AC}.\textsuperscript{16} We assume a DC-to-AC capacity ratio of 1.3 for this step.\textsuperscript{17} We assign installations from the TTS dataset to specific 0.05° grid cells using the following methodology. TTS installations report their location by zip code, but zip codes are, strictly speaking, associated with postal delivery routes rather than geography, so they cannot be used directly to determine precise physical locations. However, the U.S. Census groups zip codes into geographic regions called zip code tabulation areas (ZCTA, Figure 1).\textsuperscript{18} We use an online tool, UDS Mapper,\textsuperscript{19} to determine which ZCTA is associated with each zip code. Thus, by assigning zip codes to ZCTAs and then summing the capacities of all TTS solar installations in a given ZCTA, we are able to estimate the total residential solar capacity installed in each ZCTA. We then use population data from the 2010 Census to apportion fractions of the ZCTA capacity to individual census tracts. ZCTAs typically include portions of multiple census tracts, so we break each ZCTA capacity into smaller quantities assumed to be installed where ZCTAs and census tracts intersect. The US Census reports the ratio of the population of each intersected area of a census tract to that of the ZCTA it intersects.\textsuperscript{20} We multiply the ZCTA’s installed capacity by this ratio to approximate the capacity installed in that intersection of a census tract. We then
estimate the total capacity of a census tract by summing the estimated capacities of each intersection included in that census tract. This approach distributes the installed capacity in the ZCTA according to population density. For a given census tract \( X \),

\[
\text{Solar capacity in census tract } X = \sum_{i=1}^{N} \left( \frac{\text{population of census tract } X}{\text{population of ZCTA}_i} \cdot \text{solar capacity of ZCTA}_i \right)
\]  

Eqn. 1

where the summation is over all ZCTAs intersected by census tract \( X \). The population center of each census tract (as defined by the U.S. Census\(^2\)) is assigned as the location of the total installed capacity for that census tract, and solar electricity generation is forecast for that tract using weather data from the 0.05° grid cell closest to the population center.

3.1.2.2. Project Sunroof

For residential capacity estimated using \( PS \) data, we use a similar method as with \( TTS \). Using satellite imagery, \( PS \) estimates total potential rooftop PV capacity (in kW DC) for census tracts. It also reports an estimate of the number of buildings in the tract that have solar panels installed, as well as the total number of buildings judged to be capable of having solar panels installed. For each census tract, we multiply \( PS \)'s estimated potential PV capacity by the ratio of the number of buildings it estimates have solar panels to total number of buildings capable of having solar panels. This gives an estimate of the installed solar PV capacity by census tract. As with the \( Tracking the Sun \) calculations, the population center of each census tract is assigned as the location of the total installed capacity for that census tract, and solar electricity generation is forecast for that tract using weather data from the 0.05° grid cell closest to the population center.

3.1.2.3. State-level adjustments

One additional data source is used to make a final adjustment in the residential installed solar capacities described above. The additional data source is the Solar Energy Industry Association’s (SEIA) published state-level installed solar PV capacity estimates, which are updated quarterly and reported in MW\(_{\text{DC}}\).\(^{22}\) We found that state totals of utility-plus-residential capacities calculated as described above were nearly universally lower than the total installed PV capacity for that state reported by SEIA. SEIA’s in-house estimates of installed capacity rely on EIA860 and various other sources of information, including direct communications with a number of utilities and other entities involved with solar electricity generation.\(^{23}\) Thus, to arrive at the final estimates of installed solar capacity used by WeatherPower v3.0, we multiplied the capacity of
each residential installation from TTS or PS by a scaling factor \((A - B) / C\), where \(A\) is the total installed DC capacity as reported by SEIA for a given state, \(B\) is the total installed DC capacity reported in EIA860 for that state, and \(C\) is the sum for that state of installed DC capacity calculated as described above from TTS or PS data (Table 1). This adjustment assumes that the EIA860 database accurately reflects utility-scale PV capacity. It assumes that the difference between the SEIA and EIA860 totals for a state is SEIA’s estimate of installed residential capacity in the state, and that this represents a better-informed estimate of installed residential capacity than estimates derived from TTS or PS. However, in rare cases where the EIA860 total for utility-scale PV capacity exceeds the SEIA combined utility-plus-residential capacity, we do not scale the estimate of residential capacity from TTS or PS.

In the two years since WeatherPower v1.0 was introduced, the estimated total nationwide installed solar-PV capacity used in the tool’s calculations has increased by 55%, from 54,644 to 84,648 MWDC.

3.2. Installed Wind Turbine Capacity

To determine installed wind turbine capacity in the United States, we used the US Wind Turbine Database (USWTDB) maintained by the Lawrence Berkeley National Laboratory, the US Geological Survey, and the American Wind Energy Association. The version of the USWTDB used for WeatherPower 3.1 includes data on 63,794 turbines. The oldest turbines in the dataset were installed prior to 1990, and the most recent ones became operational in the spring of 2020. For each wind turbine in the database, we extract a number of different parameter values, including the turbine’s state, county, latitude, longitude, and installed AC generating capacity.

The national total wind capacity included in the WeatherPower 3.1 database (107,968 MW) represents a 12% increase over the previous WeatherPower database update one year earlier.
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4. Electricity Generation Calculations

We use the hourly weather parameter values and the installed solar and wind generating capacity values to calculate the estimated actual (previous day) and forecasted (current and next day) hourly electricity generation within a given region. For each wind turbine, solar PV utility generator, and census tract population center used for estimating residential solar PV capacity, we use weather data from the closest 0.05° grid cell to estimate electricity generation based on the installed AC capacity. We sum the hourly values for each 24-hour period to estimate daily electricity generation.

4.1. Solar Electricity Generation

We calculate solar electricity generation separately for the residential dataset (*Tracking the Sun* or *Project Sunroof*), and utility-scale dataset (EIA860).

4.1.1. Residential solar

For installations reported in the residential dataset, we assume these are all distributed roof-top installations, with compass-direction orientations and tilt angles varying from installation to installation in a given census tract. For a set of such distributed PV installations, the collective electricity generation can be correlated with the global horizontal irradiance (GHI) and expressed as a fraction of the collective installed capacity (Figure 2).\(^{28}\) The following equation describes the curve in Figure 2:

\[
y = -7.0778 \times 10^{-10} GHI^3 + 7.1347 \times 10^{-7} GHI^2 + 8.7895 \times 10^{-4} GHI + 7.9739 \times 10^{-3}
\]

Eqn. 2

where GHI is in watts/m\(^2\) and \(y\) (dimensionless) is the fraction of installed AC capacity that would be generating power at the given GHI. To calculate hourly electricity generation in a given census tract, the forecast GHI for that cell in that hour is used in Eqn. 2. The resulting fraction is multiplied by the installed kW_{AC} capacity to get the kWh generated in that hour. (To convert residential PV capacity data from kW_{DC} to kW_{AC} for this calculation, we assumed a DC-to-AC ratio of 1.3.)

4.1.2. Utility-scale solar

For solar installations in the utility-scale dataset, we assume that the tracking capability or fixed tilt angles are designed to provide more optimal solar exposure than with distributed PV
systems discussed in the previous paragraph. To calculate the power generated from each installation in the EIA860 dataset, we used the relationship plotted in Figure 3 and described by the following expression:\textsuperscript{28}

\[
GEN = -7.3045 \times 10^{-10} \times POA^2 + 7.2772 \times 10^{-7} \times POA^2 + 9.7863 \times 10^{-4} \times POA + 0.01505
\]

Eqn. 3

where \(GEN\) is the fractional AC generation, and \(POA\) is the Plane of Array irradiance in watts/m\(^2\). POA is calculated from the direct normal irradiance (DNI) and diffuse irradiance (DIFFI) components of the GHI. Different models are available for estimating DNI and DIFFI from GHI,\textsuperscript{29} but differences in the results from different models are small compared with other uncertainties in WeatherPower’s results. DNI and DIFFI are calculated by MESO using an internally developed polynomial curve-fit to measured direct and diffuse data that employs the clear sky GHI (CS-GHI) and the clear sky index (CSI) as input variables. The CS-GHI is calculated using the “pvlib-python” software module from Sandia National Laboratory.\textsuperscript{30} CS-GHI represents the global solar irradiance that would reach a horizontal plane at a specified geographical location on the earth’s surface under cloudless conditions and an assumed set of reference clear sky atmospheric conditions (e.g. optical path length due to aerosols and water vapor). The CSI is the ratio of the actual GHI to CS-GHI. The DNI and DIFFI values are transmitted along with the CS-GHI as part of the daily download from MESO of hourly weather parameters for each grid cell. We then calculate POA from the following sequence of relationships:\textsuperscript{31}

\[
POA = (DNI \cdot \text{corfac}) + DIFFI
\]

Eqn. 4

where,

\[
\text{corfac} = \sin(r \cdot \text{dec}) \cdot \sin(r \cdot \text{lat}) \cdot \cos(r \cdot \text{tilt}) - \sin(r \cdot \text{dec}) \cdot \cos(r \cdot \text{lat}) \cdot \sin(r \cdot \text{tilt})
\]

\[
+ \cos(r \cdot \text{dec}) \cdot \cos(r \cdot \text{lat}) \cdot \cos(r \cdot \text{tilt}) \cdot \cos(r \cdot \text{HRA})
\]

\[
+ \cos(r \cdot \text{dec}) \cdot \sin(r \cdot \text{lat}) \cdot \sin(r \cdot \text{tilt}) \cdot \cos(r \cdot \text{HRA})
\]

with,

\[
r = \frac{\pi}{180} \text{ radians conversion}
\]

\[
\text{tilt} = \text{tilt angle of the PV array}
\]

\[
\text{dec} = \text{solar declination angle} = -23.45 \cdot \cos \left( r \cdot \frac{360}{365} \cdot (d + 10) \right)
\]

\[
d = \text{day number (January 1 = 1)}
\]
\[
\text{\texttt{lat} = latitude of PV array location} \\
\text{\texttt{HRA} = hour angle = 15^\circ \cdot (SH - 12)} \\
\text{\texttt{SH} = solar hour = } \frac{SS}{3600} \\
\text{\texttt{SS} = solar second = } ST \text{ in seconds} \\
\text{\texttt{ST} = solar time = } LT - (60 \cdot EoT) \\
\text{\texttt{LT} = local time = UTC + (lon \cdot 12 \cdot \frac{3600}{180})} \\
\text{\texttt{lon} = longitude of PV array locations} \\
\text{\texttt{EoT} = Equation of time} \\
\text{\texttt{EoT} = 9.87 \cdot \sin(2B) - 7.53 \cdot \cos(B) - 1.5 \cdot \sin(B)} \\
B = r \cdot \frac{360}{365} \cdot (d - 81)
\]

For a PV array with dual-axis tracking, \texttt{corfac} = 1. Arrays that are fixed or have single-axis tracking are calculated assuming a tilt angle equal to the latitude.

Eqn. 3 (Figure 3) was derived from a regression analysis of actual measured data from utility-scale solar generation facilities in California. Figure 4 lends confidence to our approach for utility-scale calculations. In that figure, we compare results from Eqn. 3 with actual performance results (measurements every 15 minutes) from one specific facility in California. For that facility, the POA irradiance was measured using an onsite pyranometer, which gives a point value, while the reported generation corresponds to an area-weighted value. This accounts for some of the scatter – especially the points well below the main band. In those cases, the pyranometer was recording cloud effects much greater than the cloud impacts on the larger facility area.

4.2. Wind Electricity Generation

To calculate wind electricity generation, we assume each turbine performs according to the power curve shown in Figure 5. This is a composite facility-scale curve developed by analysts at MESO. The curve is not as sharp as a power curve for a specific individual turbine because it accounts for the partially uncorrelated behavior of the generation among a set of turbines (due to
wind speed differences from wakes and other factors, as well as performance variations). Also, the maximum generation is less than 100% which represents the fact that, on average, a turbine or two is offline for maintenance or other issues. Furthermore, the high speed shut down is gradual (from 20 to 25 m/s) to reflect variations in wind speed experienced by individual turbines (some will shut down sooner than others). The curve in Figure 5 can be represented analytically as follows, where \( x \) is wind speed (m/s) and \( y \) is wind power output expressed as fraction of installed AC generating capacity:

\[
\begin{align*}
0 < x < 2.5 \text{ m/s:} & \quad y = 0 \\
2.501 < x < 13.5 \text{ m/s:} & \quad y = A x^6 + B x^5 + C x^4 + D x^3 + E x^2 + F x + G \\
13.501 < x < 20 \text{ m/s:} & \quad y = 0.9646 \\
20.001 < x < 25 \text{ m/s:} & \quad y = -0.1929 x + 4.8232 \\
x > 25.001 \text{ m/s:} & \quad y = 0
\end{align*}
\]

Eqn. 5

where the coefficients \( A, B, C, D, E, F, \) and \( G \) are as given in Table 2.

To calculate hourly wind electricity generation for a given turbine, the forecast wind speed at the closest weather grid cell in that hour is used in Eqn. 5. The resulting fraction is multiplied by the capacity (MW\(_{AC}\)) of the turbine to give MWh generated in that hour.

To help assess the accuracy of the above methodology, we compared wind electricity generation estimates using this methodology with data on actual wind electricity generation in the jurisdiction of the Electric Reliability Council of Texas (ERCOT), which operates a grid delivering electricity to some 24 million customers and which makes data available on actual hourly wind electricity generated. The initial results of this comparison (detailed in the Appendix) indicate that WeatherPower estimates of daily wind generation are on average about 10% higher than ERCOT-reported data, but with day-to-day variations. Thus, on average WeatherPower wind generation estimates are close to actual generation.

<table>
<thead>
<tr>
<th>Coefficient</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>3.06931757575758 x 10^6</td>
</tr>
<tr>
<td>B</td>
<td>-1.13803311616162 x 10^4</td>
</tr>
<tr>
<td>C</td>
<td>1.43270635919192 x 10^3</td>
</tr>
<tr>
<td>D</td>
<td>-7.74205866202020 x 10^3</td>
</tr>
<tr>
<td>E</td>
<td>3.18455940779798 x 10^2</td>
</tr>
<tr>
<td>F</td>
<td>-7.33994638234343 x 10^2</td>
</tr>
<tr>
<td>G</td>
<td>5.96417544920202 x 10^2</td>
</tr>
</tbody>
</table>
5. Spatial Aggregation of Results

Calculated solar and wind electricity generation for wind turbines, solar utility generators, and residential solar locations (census tracts) were aggregated into larger regions of interest. In WeatherPower 3.0, results are reported for Nielsen Designated Market Areas (DMA, Figure 6), states, counties, congressional districts, and Emissions and Generation Resource Integrated Database (eGRID) regions (Figure 7). eGRID is a database maintained by the Environmental Protection Agency that includes environmental characteristics of almost all electric power generators in the U.S. Among other applications, the eGRID database is widely used for estimating greenhouse gas emissions associated with the consumption of electricity, i.e., emissions that occurred when the consumed electricity was originally generated. In practice, the source of a consumed electron on the grid is difficult to determine precisely. The eGRID database assigns individual power plants to an eGRID region within which the electricity generated is judged likely to also be consumed in that region.

Wind turbines are assigned to states and counties based on the USWTDB. Solar utility generators were similarly assigned to the states and counties they are associated with in the EIA860 dataset. Residential solar installations are assigned to states and counties that contain the census tracts with which the installations are associated.

For the remaining regions (DMAs, congressional districts, and eGRID regions), we assigned wind and solar generators based on whether their geographic coordinates fell within the boundaries of the region.

A small number of generators fell outside all region boundaries for a particular region type. In such cases, we assigned solar installations to the region lying within the same state as the generator and with a border not more than 1 km from the generator. To account for offshore turbines (of which there are very few), we assigned turbines to the region lying within the same state and within 10 km of the location specified in the USWTDB. The very few generators that could not be assigned to a region using these criteria were excluded from aggregations for that region type.

6. WeatherPower 3.1 Reporting Metrics

WeatherPower 3.1 reports several solar and wind electricity metrics for “Yesterday,” “Today,” and “Tomorrow” for each DMA, eGRID, state, county, and congressional district. (When the geographic area of a DMA, state, county, or congressional district overlaps multiple
eGRID regions, we associate that DMA, state, county, or congressional district with the eGRID region that contains its centroid.) By associating each geographic entity with an eGRID region, we implicitly assume that wind power generated in the eGRID region is consumed in the geographic entity.

6.1. Solar Electricity Metrics

Table 3 lists the metrics calculated for solar electricity generation. There are two primary metrics and six comparative (derived) metrics. Comparative metrics #3, #4, and #5 put in perspective the amount of solar electricity generated, and #6, #7, and #8 put in perspective the greenhouse gas emissions avoided by generating electricity using the sun instead of CO2-emitting generators.

Table 3. Solar electricity metrics reported by WeatherPower 3.0. These metrics are reported for each DMA, eGRID, state, county, and congressional district.

<table>
<thead>
<tr>
<th>SOLAR ELECTRICITY</th>
<th>Yesterday</th>
<th>Today</th>
<th>Tomorrow</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRIMARY METRICS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Electricity Generated (MWh)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Solar Power Index (SPI)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>COMPARATIVE METRICS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Percent of Homes Powered</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Percent of Daily Cost Saved</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Smartphones charged (1000s)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. CO₂ emissions avoided (metric tons)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Car miles driven</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Trees planted</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

6.1.1. Metric #1: Electricity Generated

Metric #1 is the electricity generated (or forecast to be generated) over each 24-hour period for the region of interest. It is the sum of electricity generated with each sub-unit of the region of interest. The units are megawatt-hours (or megawatt-hours per day).

6.1.2. Metric #2: Solar Power Index

Metric #2 is the dimensionless solar power index (SPI). The SPI indicates how the solar electricity that was (or is forecast to be) generated compares with the maximum amount of solar generation that could be expected with a clear sky. WeatherPower first calculates the maximum
possible power output (under clear sky conditions) for each residential\textsuperscript{38} and utility-scale\textsuperscript{39} solar generator for each hour of a particular day within the local time zone. It sums the resulting maximum hourly output values for the given day to get the maximum daily output for that generator, and then calculates the ratio of its observed or forecasted output to its estimated daily maximum. Finally, the resulting daily maximums for all generators in a region (e.g., DMA or state) are summed to arrive at the daily maximum output for that region. The SPI value for a given day is ten times the ratio of the actual solar output calculated for all generators (residential plus utility) for that day divided by the maximum possible output for the same region. The factor of ten is included such that the range in possible SPI values is 0 to 10.\textsuperscript{40}

6.1.3. Metric #3: Equivalent Homes Powered

Metric #3 is the equivalent number of households that could be served in a region (DMA, state, county, congressional district) by the amount of solar electricity generated divided by the total number of households in the region. The denominator (total number of households in a region) was determined from 2010 U.S. Census estimates.\textsuperscript{41,42} DMAs are a collection of counties, and so the number of households in a DMA was determined by summing the households in the counties constituting that DMA.\textsuperscript{43,44} The equivalent number of households that could be served in a region is calculated as the total solar electricity generated in the region divided by $HHelec$, where $HHelec$ is the average total electricity consumption per day per residential customer in the state in which the region is located.\textsuperscript{45} The $HHelec$ values are based on 2018’s annual average household electricity consumption as reported by the Energy Information Administration (EIA).\textsuperscript{46,47} Daily consumption by the household ($HHelec$) was assumed to be the same each day throughout the year for purposes of calculating this metric.

6.1.4. Metric #4: Home Energy Savings

Metric #4 is an estimate of the fraction of a hypothetical household’s electricity expenditures that would have been saved if the household had a PV-based generation system operating that day. For this calculation, we assume an average household PV array has a generating capacity of 5.5 kW\textsubscript{DC}, which several sources suggest is a reasonable estimate for the current U.S. residential roof-top solar PV fleet.\textsuperscript{48,49,50} We calculate the hourly generation from this hypothetical 5.5 kW\textsubscript{DC} array at the population center of each census tract using the methodology described in Section 4.1.1, then sum the hourly values to get daily generation, and then find the average of the daily
generation across all census tracts in the region, weighted by the population of each census tract. This weighted-average value is divided by the average daily household electricity consumption in the region ($HHelec$) to arrive at the fraction of the electricity bill saved.

6.1.5. Metric #5: Smartphones Charged

Metric #5 is the number of smartphones that could be charged using an amount of electricity equal to WeatherPower’s calculated daily solar generation in a region. According to the EPA, a common smartphone would use 14.17 Watt-hours of electricity over a 24-hour period to charge a fully depleted battery and then maintain the battery at full charge throughout the day. Additionally, the battery requires 2 hours to reach full charge, and the amount of power consumed once the battery is fully charged and the phone remains plugged in is 0.14 W. Based on these assumptions, the amount of electricity needed to charge a common smartphone is:

$$\frac{MWh}{smartphone\ charge} = \frac{(14.17Wh - (22\ hours \times 0.14Watts)) \times \frac{1\ MWh}{1,000,000\ Wh}}{0.000011}$$

Dividing the MWh of solar generated electricity calculated by WeatherPower for a given day in a region by this value provides an estimate of the number of smartphones that could be charged with the solar electricity produced that day.

6.1.6. Metric #6: CO2 Avoided

Metric #6 is an estimate of the CO2 emissions avoided by generating solar power, assuming that the power instead would have been generated elsewhere on the grid by generators having CO2 emissions equivalent to the annual average emissions per MWh generated by electricity producers in the state in which the solar generator is located. WeatherPower calculates the avoided emissions for each generator using state-wide annual average emissions per MWh of electricity generated (Table 4) for the state in which the generator is located:

$$CO2\ avoided\ (metric\ t/day) = power\ generated\ (MWh/day) \times state\ factor\ (metric\ tCO2/MWh)$$

WeatherPower then finds the amount of CO2 avoided for a region (DMA, eGRID, state, county and congressional district) by summing the CO2 avoided by all generators in that region.

6.1.7. Metric #7: Car Miles

Metric #7 is an estimate of the number of miles an average car in the U.S. drives to emit the amount of CO2 calculated as metric #6. WeatherPower derives this estimate using the same
assumptions as used in the EPA’s greenhouse gas equivalency tool: a weighted average combined city/highway fuel economy of light duty vehicles, which includes cars, vans, pickup trucks and SUVs, of 22 miles/gallon; an amount of CO₂ emitted in burning a gallon of gasoline of $8.89 \times 10^{-3}$ metric tons; and a ratio of total GHG emissions (in CO₂-equivalents, CO₂e)

Table 4. Annual average CO₂ emission rates for electricity generation by state (metric tonnes CO₂ per MWh) in 2018, as reported by the Energy Information Administration.

<table>
<thead>
<tr>
<th>State</th>
<th>Emissions (tCO₂/MWh)</th>
<th>State</th>
<th>Emissions (tCO₂/MWh)</th>
<th>State</th>
<th>Emissions (tCO₂/MWh)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Alabama</td>
<td>0.387</td>
<td>Kentucky</td>
<td>0.841</td>
<td>North Dakota</td>
<td>0.734</td>
</tr>
<tr>
<td>Alaska</td>
<td>0.543</td>
<td>Louisiana</td>
<td>0.497</td>
<td>Ohio</td>
<td>0.619</td>
</tr>
<tr>
<td>Arizona</td>
<td>0.418</td>
<td>Maine</td>
<td>0.195</td>
<td>Oklahoma</td>
<td>0.400</td>
</tr>
<tr>
<td>Arkansas</td>
<td>0.564</td>
<td>Maryland</td>
<td>0.407</td>
<td>Oregon</td>
<td>0.137</td>
</tr>
<tr>
<td>California</td>
<td>0.223</td>
<td>Massachusetts</td>
<td>0.367</td>
<td>Pennsylvania</td>
<td>0.358</td>
</tr>
<tr>
<td>Colorado</td>
<td>0.627</td>
<td>Michigan</td>
<td>0.53</td>
<td>Rhode Island</td>
<td>0.400</td>
</tr>
<tr>
<td>Connecticut</td>
<td>0.243</td>
<td>Minnesota</td>
<td>0.484</td>
<td>South Carolina</td>
<td>0.291</td>
</tr>
<tr>
<td>Delaware</td>
<td>0.512</td>
<td>Mississippi</td>
<td>0.412</td>
<td>South Dakota</td>
<td>0.231</td>
</tr>
<tr>
<td>District of Columbia</td>
<td>0.540</td>
<td>Missouri</td>
<td>0.771</td>
<td>Tennessee</td>
<td>0.359</td>
</tr>
<tr>
<td>Florida</td>
<td>0.441</td>
<td>Montana</td>
<td>0.553</td>
<td>Texas</td>
<td>0.482</td>
</tr>
<tr>
<td>Georgia</td>
<td>0.424</td>
<td>Nebraska</td>
<td>0.690</td>
<td>Utah</td>
<td>0.725</td>
</tr>
<tr>
<td>Hawaii</td>
<td>0.735</td>
<td>Nevada</td>
<td>0.353</td>
<td>Vermont</td>
<td>0.005</td>
</tr>
<tr>
<td>Idaho</td>
<td>0.097</td>
<td>New Hampshire</td>
<td>0.128</td>
<td>Virginia</td>
<td>0.351</td>
</tr>
<tr>
<td>Illinois</td>
<td>0.384</td>
<td>New Jersey</td>
<td>0.252</td>
<td>Washington</td>
<td>0.091</td>
</tr>
<tr>
<td>Indiana</td>
<td>0.807</td>
<td>New Mexico</td>
<td>0.564</td>
<td>West Virginia</td>
<td>0.895</td>
</tr>
<tr>
<td>Iowa</td>
<td>0.540</td>
<td>New York</td>
<td>0.211</td>
<td>Wisconsin</td>
<td>0.634</td>
</tr>
<tr>
<td>Kansas</td>
<td>0.459</td>
<td>North Carolina</td>
<td>0.370</td>
<td>Wyoming</td>
<td>0.954</td>
</tr>
</tbody>
</table>

associated with burning the gallon of gasoline of 1.012 times the CO₂ emissions alone (due to some non-CO₂ greenhouse gas emissions that occur as a result of burning the gasoline). With these assumptions, the greenhouse gases (CO₂e) emitted per mile driven is

$$0.00089 \frac{\text{metric CO}_2}{\text{gal}} \times 1.012 \frac{\text{tCO}_2}{\text{tCO}_2} \times \frac{1}{22 \text{ miles}} = 0.000409 \frac{\text{metric CO}_2e}{\text{mile}}$$
and the number of car-miles corresponding to the amount of CO₂ avoided by solar generation is

\[
\frac{\text{miles}}{\text{day}} = \frac{\text{metric } tCO₂ \text{ avoided/day}}{\text{day}} \times \frac{1}{0.000409 \frac{\text{metric } tCO₂}{\text{mile}}}
\]

where the \( \text{metric } tCO₂ \text{ avoided/day} \) is the calculated value of metric #6 above.

6.1.8. Metric #8: Trees Planted

Metric #8 is an estimate of the number of trees planted and grown for 10 years that would photosynthetically absorb an amount of CO₂ (stored as carbon in tree biomass) equal to the avoided CO₂ calculated as metric #6. WeatherPower derives this estimate using the same assumptions as used in the EPA’s greenhouse gas equivalency tool: tree seedlings (11% medium growth coniferous and 89% medium-growth deciduous) are raised in a nursery for one year before being planted with wide spacings in suburban or urban areas; taking into account tree “survival factors”, coniferous trees absorb and store an average of 23.2 lbs of CO₂ and deciduous trees absorb and store 38.0 lbs of CO₂ per tree over the 10-year period. The absorption and storage of CO₂ per average tree planted is then:

\[
\frac{tCO₂ \text{ avoided}}{\text{tree planted}} = \left( 0.11 \frac{\text{coniferous trees}}{\text{all trees}} \times 23.2 \frac{\text{lbs CO₂}}{\text{coniferous tree}} \right) + \left( 0.89 \frac{\text{deciduous trees}}{\text{all trees}} \times 38.0 \frac{\text{lbs CO₂}}{\text{deciduous tree}} \right) \times \frac{\text{metric } tCO₂}{2,046.8 \text{ lbs}} = 0.060 \frac{tCO₂}{\text{tree planted}}
\]

and the number of trees planted that corresponds to the amount of CO₂ avoided by solar generation is

\[
\frac{\text{trees planted}}{\text{day}} = \frac{tCO₂ \text{ avoided/day}}{\text{day}} \times \frac{1}{0.060 \frac{tCO₂}{\text{urban tree planted}}}
\]

where the \( \text{metric } tCO₂ \text{ avoided/day} \) is the calculated value of metric #6 above.

6.2. Wind Electricity Metrics

Except for the Wind Power Index (WPI), the wind electricity metrics (Table 5) are calculated analogously to the solar electricity metrics described in the previous section.

The WPI is calculated only for eGRID regions, since smaller geographic units (state, county, DMA, and congressional district) may often have little or no wind generation installed within its boundaries, but will still be consuming electrons generated by wind in the associated
eGRID region. The WPI is ten times the ratio of actual wind generation in the eGRID region for a given 24-hour period divided by the maximum possible wind generation if all turbines in the region were operating at their rated capacity at all times. The factor of ten is included such that the possible range of WPI is 0 to 10. The maximum generation is calculated at the grid cell level using Eqn. 5 assuming a wind speed of 14 m/s at all times, the speed at which the wind power curve (Figure 5) indicates turbine output is maximized. The maximum output for all turbines in each eGRID region are then summed to give total maximum possible generation in each region.

Table 5. Wind electricity metrics reported by WeatherPower 3.0. Except for the Wind Power Index (WPI), these metrics are calculated for each DMA, state, county, congressional district, and eGRID region. The WPI is calculated only for eGRID regions, and that value is assigned to each DMA, state, county, and congressional district associated with the eGRID region.

<table>
<thead>
<tr>
<th>WIND ELECTRICITY</th>
<th>Yesterday</th>
<th>Today</th>
<th>Tomorrow</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRIMARY METRICS</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Electricity Generated (MWh)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Wind Power Index (WPI)*</td>
<td></td>
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<tr>
<td>COMPARATIVE METRICS</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>3. Percent of Homes Powered</td>
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<tr>
<td>4. Smartphones charged (1000s)</td>
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<tr>
<td>5. CO₂ emissions avoided (metric tonnes)</td>
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<td></td>
<td></td>
</tr>
<tr>
<td>6. Car miles driven</td>
<td></td>
<td></td>
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<td>7. Trees planted</td>
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* The WPI metric is calculated only for eGRID regions.
Figures

Figure 1. ZCTA regions as represented by GIS shapefile.54

Figure 2. Aggregated distributed solar-PV curve.28 The curve is the result of regression analysis of actual measurement data from individual roof-top systems and measured solar radiation data in an urban area of Hawaii. The measurements were for a substation-scale aggregate of residential and commercial (predominantly roof-top) PV systems.
Figure 3. Power curve for utility-scale solar facilities. This curve is from a regression analysis of actual measured data from solar generation facilities in California. The input is plane of array (POA) irradiance in watts/m², and the output is power production as a fraction of AC capacity. The curve assumes a DC/AC capacity ratio of 1.3.

Figure 4. Comparison of generic power curve for utility-scale solar facilities (Figure 3) with actual data for a 45 MWAC capacity dual-axis tracking solar facility in California with a DC/AC ratio of about 1.33. The data points are 15-minute generation data, some of which have been adjusted to account for curtailments or equipment outages. [Actual production is impacted by weather conditions as well as outages and curtailments. The outages (number of panels or inverters offline) and curtailment (due to max generation limits imposed by the grid operator) are reported by the facility, and this information was used to scale the measured (reported) generation to an estimate of what would have occurred if there were no outages or curtailments.]
Figure 5. Representative facility-scale wind turbine electricity generation curve.\textsuperscript{28}

Figure 6. Nielsen Designated Market Areas (DMA).\textsuperscript{55}
Because of their small size, WeatherPower aggregates NYLI and NYCW with NYUP and HIOA with HIMS.
Appendix: WeatherPower wind power comparisons with actual wind generation

We compared wind electricity generation estimated using the methodology of WeatherPower version 2.0 against actual wind electricity generation data to assess the accuracy of WeatherPower estimates. This comparison exercise was carried out for the geographic region corresponding to the jurisdiction of the Electric Reliability Council of Texas (ERCOT), where more wind electricity is generated annually than in any other independent system operator (ISO) region of the US.

Actual wind electricity generation in Texas (ERCOT)

ERCOT makes available 15-minute average wind electricity generation (MW) for each individual wind generation facility in its region. ERCOT reports both average actual 15-minute output in MW from a wind facility and the expected output in MW if all turbines in the facility were operating without restrictions. ERCOT refers to the latter as the high-sustained limit (HSL) generation. [At any given time, some turbines may be down for unscheduled (e.g., component malfunction) or scheduled maintenance. Other turbines may be deliberately turned off or operated at less than design capacity at ERCOT’s request, i.e., curtailed, due to an over-supply of electricity on the grid at that time.] Because WeatherPower calculations assume all turbines in its database are always operating without restrictions, for this exercise we compare WeatherPower estimates with ERCOT’s HSL values, although the differences between HSL values and actual generation are currently small. For each ERCOT wind facility, we averaged the 15-minute HSL output values to get hourly average output in MW and then summed the hourly values over 24-hour periods to get daily HSL energy production values (MWh). The latter were aggregated into five ERCOT sub-regions, as described below, and compared with WeatherPower’s daily MWh estimates for the same groupings of wind generators. WeatherPower’s power production estimates were made using local estimated actual hourly average wind speeds (as described below) and the rated capacities of the wind facilities in the WeatherPower v2.0 database.

WeatherPower estimates of ERCOT wind electricity generation

To ensure that WeatherPower estimates for this comparison exercise were made for the installed wind generation capacities corresponding to ERCOT’s HSL wind power estimates,
ERCOT’s published listing of wind-farm locations and capacities were used in lieu of the wind turbine characteristics in WeatherPower’s database. Each month ERCOT reports the location by region (Coastal, South, North, West, and Pan Handle) and installed capacity of each operating wind generation facility in its system. A spreadsheet containing ERCOT’s reporting for March 2019 was downloaded. The “Resource to Region” tab in that spreadsheet lists every wind facility (grouping of wind turbines) operating each day during March 2019. Several steps were then involved to determine the latitude and longitude of the centroid of each wind facility for the purpose of assigning the facility to a WeatherPower grid cell. To determine the wind facility centroids for about half the facilities, a KML file available from ERCOT was used. For wind facilities not shown in the KML file, a listing of US wind facility locations maintained by the National Renewable Energy Laboratory was consulted. Finally, for farms not listed in the KML file or the NREL listing, the USWTDB was used to identify the location of each turbine in a facility. With the latter data source, latitudes and longitudes of turbines within a facility were averaged to establish a centroid for that facility.

Observed hourly wind speeds for each WeatherPower grid cell in the ERCOT region for the months of January, March, and April 2019 were provided by MESO, and were used with the installed wind facility capacities described immediately above to generate WeatherPower estimates of hourly wind electricity generation by grid cell. Hourly values were summed to generate daily values, and daily values for each grid cell were summed across grid cells corresponding to the five sub-regions of ERCOT (Coastal, South, North, West, and Pan Handle) to produce estimates to compare with ERCOT-reported daily HSL generation.
Comparison of results

Figure 8 plots ERCOT’s reported system-wide daily HSL wind generation from wind facilities for January, March, and April 2019 against WeatherPower’s calculated daily ERCOT system-wide wind generation for all days for which calculated and reported HSL generation data were available. A linear regression curve fit yields a correlation coefficient squared ($R^2$) of 0.87, meaning WeatherPower’s estimates account for 87% of the variability in daily wind generation across the full ERCOT region.

We might expect lower $R^2$ values for sub-regions, since greater small-scale variability is captured in the HSL values than in WeatherPower’s grid-cell averaged calculations. However, as shown in Table 6, $R^2$ values for sub-regions are still 0.80 or higher for the full 3-month data set, with the exception of the North region for which $R^2$ is 0.77. Table 6 also shows $R^2$ values for each month and sub-region. For any given region, there is month-to-month variability in $R^2$, but a consistent trend of improved correlation in going from January to March to April. This trend is likely related to the generally increasing wind capacity utilization across these months.65

The ratios of daily WeatherPower-calculated to ERCOT-reported-HSL wind generation values are plotted in Figure 9. The mean value is 1.1, and two-thirds of the values fall within one standard deviation of the mean. About 70% of all values are above 1.0, indicating that the majority of WeatherPower-calculated values exceed the ERCOT-reported values. Table 7 reports mean values of the WeatherPower/ERCOT-HSL ratios for each sub-region and each month.
This initial WeatherPower wind generation comparison exercise for the ERCOT region suggests that WeatherPower estimates are reasonably accurate.\textsuperscript{66} Statistical corrections, as are commonly applied in commercial wind-energy forecasts to address discrepancies between forecast and actual generation, may be considered for a future update of the WeatherPower tool.
References and Notes


6. GFS forecasts are released by NOAA four times each day (at approximately 02:20, 08:20, 14:20, and 20:20 UTC).

7. “Yesterday” = 24 hours beginning at 00:00 local time of the day prior to the day of graphic download. “Today” = 24 hours starting from 0:00 local time on the day of the graphic download. “Tomorrow” = 24 hours starting from 0:00 local time of the day after the day of graphic download.

8. WeatherPower does not include estimates for concentrating solar power generation (CSP). There are 21 currently operational CSP plants in the US with a total installed capacity of 1749 MW (https://www.nrel.gov/csp/solarpaces/index.cfm). In 2018 solar-PV and solar-CSP generation totals across the U.S. were 92,555 GWh, and 3,592 GWh, respectively (Energy Information Administration).


10. WeatherPower 3.1 uses EIA860 2019 data.

11. Given the small number of east-west oriented installations in the EIA860 database (5 of 3955 installations report having an east-west orientation), we assume for purposes of the forecasting tool that all fixed and single-axis tracking installations have south-facing orientations. In practice, east-west oriented arrays will generate less total electricity annually than south-facing arrays, but may produce more electricity per day at certain times of the year. [See endnote 12.]


15. WeatherPower v1.0 and v2.0 used Stanford University’s Deep Solar project (http://web.stanford.edu/group/deepsolar/home) as a data source for residential installations to complement data from Tracking the Sun. However, Deep Solar data were for 2018 and
have not been updated. Project Sunroof data are more current, so this data source is used in WeatherPower 3.1 in lieu of Deep Solar.

16. The capacity of some Tracking the Sun entries were larger than 1 MW\textsubscript{AC}. To avoid duplicating capacity data in EIA860, we removed all Tracking the Sun installations with capacity larger than 1 MW\textsubscript{AC}. Total capacity of the 877 installations removed from the database was 1863 MW\textsubscript{AC}.

17. The ratio of 1.3 is arrived at using the EIA860 dataset discussed earlier. That dataset reports both MW\textsubscript{DC} and MW\textsubscript{AC} for most installations, and the average MW\textsubscript{DC} to MW\textsubscript{AC} ratio among all listed installations listing both values was found to be 1.3.


24. SEIA reports state capacities in MW\textsubscript{DC}, so in calculating the ratio, (A - B) / C, we had to first ensure that our utility and residential capacities were all expressed in MW\textsubscript{DC}. Residential capacities were reported in MW\textsubscript{DC} or calculated to be in MW\textsubscript{AC}. The EIA860 reports both MW\textsubscript{DC} and MW\textsubscript{AC} for most installations. For those reporting only AC, we calculated the value of DC capacity assuming a DC-to-AC ratio of 1.3, the source of which is described in endnote 17.

25. In WeatherPower 2.0, both utility-scale and residential PV capacity in a state were up-scaled using the ratio of total SEIA capacity to Climate Central’s estimated utility plus residential capacity. The change in methodology for version 3.1 reflects the assumption that most of the uncertainty in estimates of installed PV capacity for a state are in the residential capacity.


27. For each turbine, the parameter values that we extract and have in our database for possible future use are location related: state, county, fips number, and longitude and latitude coordinates, and turbine related: manufacturer, model, capacity (MW\textsubscript{AC}), hub height, rotor diameter, rotor swept area, and total height.


34. Congressional district boundaries as of May 1, 2018 (latest available data as of June 2019).


37. Metrics for “Yesterday”, “Today, and “Tomorrow” are calculated from the RAP and HRRR models, whereas the GFS model is used for the forecast period beyond 48 hours. This may result in some inconsistencies in metric values at the intersection of these forecast periods.

38. For residential solar generators, the maximum possible hourly output is calculated by replacing GHI with the clear-sky GHI (CS-GHI) in Eqn. 2.

39. To calculate the maximum possible hourly output for utility-scale solar generators, we first calculate the ratio between the maximum possible output and actual output of a virtual solar panel deployed at the generator location at a given hour. This ratio is then multiplied by the generator’s actual output during that hour to get the generator’s maximum possible output.

40. The estimate of CS-GHI, from which maximum generation values are calculated, assumes reference clear sky conditions, with typical amounts and vertical profiles of aerosols, water vapor and other atmospheric gases that determine the degree of transmission of solar radiation through a cloud-free atmosphere. The reference atmospheric conditions for estimates of CS-GHI are assumed to be the same at all locations and dates in version 3.1 of the tool. Thus, the actual GHI could exceed CS-GHI if the actual atmospheric conditions are more favorable for irradiance at the earth’s surface than the assumed reference clear sky conditions. This would produce SPI values greater than 10. In such cases, the tool reports the SPI value as 10.


42. Ten U.S. congressional districts were added after the 2010 Census, so the populations of households in those districts are not available. For this reason, WeatherPower 3.1 does not report on those 10 congressional districts.
43. U.S. Census Bureau, “Cartographic Boundary Shapefiles – Counties,”
https://www.census.gov/geo/maps-data/data/cbf/cbf_counties.html

44. All except one of the more than 200 DMAs include multiple counties, and DMA boundaries
   correspond to county boundaries. The Palm Springs DMA is unique in being wholly
   contained within a single county and not even covering the whole county. For this DMA, the
   number of households was estimated to be the number of television-owning households in
   the DMA. (personal communication from Sean Sublette, Climate Central, August 2018.)

45. Some DMAs overlay multiple states. In these cases, the average of HHelec value for the
   multiple states involved was used.

46. Energy Information Administration, “2018 Average Monthly Bill - Residential,”
https://www.eia.gov/electricity/sales_revenue_price/.

47. Data for 2019 are scheduled for release by EIA in October 2020.


49. “Solar Photovoltaic Technology,” SEIA, accessed July 26, 2019,


51. Environmental Protection Agency, “Greenhouse Gases Equivalencies Calculator -
Calculations and References,” Data and Tools, US EPA, August 10, 2015,
https://www.epa.gov/energy/greenhouse-gases-equivalencies-calculator-calculations-and-
references.

52. Energy Information Administration, Form EIA-923.

53. This is an underestimate of miles driven because only CO2 emissions avoided at power plants
    are considered in the calculation. In reality, avoided emissions would include CO2 and some
    non-CO2 greenhouse gases associated with extraction and delivery of fossil fuels to power
    plants. We have neglected these additional avoided greenhouse gas emissions in this
    calculation, i.e., we equate avoided CO2 with avoided CO2e here.

54. US Census Bureau, “Geography Program,” accessed July 26, 2019,
https://www.census.gov/programs-surveys/geography.html.

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57. Filename: 60d_SCED_Gen_Resource_Data-xxx, downloaded via the 60-Day SCED
Disclosure Reports link accessed via the Report Explorer link at
http://mis.ercot.com/misapp/. These data are available on a 60-day delay basis, with a rolling
8-day archive: each day, data for the day 60 days prior to the current day become available
while data for the oldest day in the 8-day archive is deleted. Climate Central downloads the
data each day to build a longer time-series archive.
58. Daily actual generation varied from HSL generation by an average of only 3.2% on an ERCOT-wide basis across the full 3 months for which data were available for our comparison exercise. The average differences by sub-region were 4.1% in the West, 2.0% in the Pan Handle, 3.5% in the Coastal, 2.4% in the South, and 3.4% in the North.


63. USGS, LBNL, and AWEA, “The U.S. Wind Turbine Database,” version uswtdb_v2_0_20190424.

64. Much of the wind speed data for February was unavailable as a result of a loss of data at MESO due to a technical issue. For January, March, and April, only a small number of hourly wind speeds were missing from the MESO data. To fill in missing hours, the calculated wind electricity generation in the hour before and the hour after the missing hour were averaged and assigned to the missing hour.

65. Wind generation in ERCOT typically peaks in April or May. This implies that there is a shift in the numbers of hours that turbines spend operating in different segments of their power curves going from January to April. In January, for example, there are more hours in the steeply-sloped part of the power curve where the generation estimate is most sensitive to wind speed estimation error. During a higher capacity month (e.g., April) there are more hours at the flat top part of the power curve where there is much lower sensitivity to wind speed estimation error.

66. Possible sources of bias include: (i) a bias in the HSL values – in theory these account for all outages and curtailments but in practice they may not; (ii) wind direction (wake) effects – there are noticeable wake effects at many of the wind facilities for certain wind directions so power would be below what would be estimated from wind speed alone; (iii) variations in turbine power curves – there are many types of turbines in ERCOT, with systematic variations from oldest to newest, which may introduce bias; (iv) variations in hub heights – older turbines tend to have lower hub heights than newer ones, but WeatherPower uses wind speed estimates for 80-m for all turbines; and (v) bias in the HRRR wind speeds – these are a blend of measured and modeled speeds and somewhat dependent on the local surface properties (e.g., roughness) which probably have bias/misrepresentations.