

Updated Wind Resource Assessment for the Outer Continental Shelf off the Coast of California

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Background

- 1. A new wind resource data set for the Outer Continental Shelf (OCS) off the coast of California has been produced by NREL
- 2. This data set, called CA20, replaces NREL's 2013 WIND Toolkit (WTK) for this region
- 3. Both data sets were produced using the Weather Research and Forecasting (WRF) numerical weather prediction model
- 4. CA20 is being used by NREL to update its floating offshore wind cost analysis for the OCS
- 5. CA20 leverages extensive R&D advancements over the last 7 years, extends the period of record to a full 20 years (2000-2019), and includes uncertainty information for 100-m wind speeds

New Data Set



• Highest wind resource in the northern OCS, consistent with WTK

Mean annual wind resource for the OCS based on the new 20-year data set

New Data Set shows an Increase in Modeled Resource

Comparison of Mean 100-m Wind Speeds from Both Data Sets



| Call Area | Mean Wind Speed $(m \cdot s^{-1})$ | | Change | |
|---------------|------------------------------------|------------------|----------------------|------|
| | WIND Toolkit | Updated Data Set | (m·s ^{−1}) | (%) |
| Humboldt | 9.41 | 10.41 | 1.00 | 10.6 |
| Morro Bay | 8.20 | 9.52 | 1.32 | 16.1 |
| Diablo Canyon | 7.70 | 9.18 | 1.48 | 19.2 |

Mean 100-m Uncertainties



Key Questions

- What validation was performed?
- What is leading to the increased modeled wind resource in CA20?
- How did we determine uncertainty metrics?
- How is the data set made available to the public?

Validation





Observation stations





Atmospheric forcing

- ERA-5
- MERRA-2

Planetary Boundary Layer (PBL) scheme

- MYNN
- YSU



Sea surface temperature

- NCEP RTG
- Default in reanalysis product

Land surface Model (LSM)

| • | NOAH |
|---|---------|
| • | NOAH-MP |

Unbiased Root-Mean-Squared-Error (RMSE)

Average across all sites



Bias

Average across all sites



Earth Mover's Distance

Average across all sites



Validation Conclusions

Final WRF Component Selection for New 20-Year Wind Resource Data Set for the OCS

| Model Component | Selection for New 20-Year Data Set |
|--------------------|------------------------------------|
| Reanalysis product | ERA5 |
| PBL scheme | MYNN |
| SST product | OSTIA |
| LSM | Noah |

Explaining the Increased Modeled Wind Resource



Factors affecting increase in wind resource

| | PBL* Scheme | Reanalysis Product | SST Product | Time Period | WRF Version |
|-----------------|----------------|-----------------------|--|-------------------------|----------------|
| WIND Toolkit | YSU | ERA- interim | NCEP RTG 1/12 degree | 7 years (2007-2013) | 3.4 |
| BOEM 20-year | MYNN | ERA-5 | OSTIA 0.25 degree (pre-2007) HadISST2 0.25 degree (post-2007) | 20 years (2000-2019) | 4.1 |

*PBL - Planetary Boundary Layer

PBL Scheme is critical in influencing modeled wind profiles

Example: Hot Summer Day

- Surface heats up
- Lower warmer air *less dense* than upper colder air
- Warmer air moves up aloft
- Colder air comes down to replace it
- Cycle results in strong large-scale vertical convection
- Termed 'unstable' conditions
- Effect is to mix high momentum air aloft (i.e., high wind speeds) down to the surface
- Leads to even distribution of momentum in column, i.e., similar wind speeds or **low shear**



Example: Following Summer Night

- Now surface cools
- Lower colder air *more dense* than upper warmer air
- Vertical mixing is now suppressed
- Termed **'stable' conditions**
- Effect is to keep high momentum air aloft (i.e., high wind speeds)
- Leads to uneven distribution of momentum in column, i.e., **high shear**



planetary-sciences/wind-profiles



os.uiuc.edu/(Gh)/wwhlpr/fcst_temps_winds.rxml

Summary on Stability Regimes



Role of PBL Schemes

- This vertical mixing is a form of turbulence
- Turbulence: unsteady, chaotic movement of a fluid
- Too computationally expensive to model directly in WRF
- Rather, models like WRF parameterize that mixing in terms of measurable quantities (e.g., wind shear)
- Such parameterizations are called PBL schemes, and WRF currently has 9 of them!



PBL Schemes

Two most popular schemes:

- YSU (simple, fast), used in WIND Toolkit
- MYNN (more complex, expensive), used in new 20-year data set
 - Becoming global standard
 - Used in operational weather prediction models
 - Used by wind industry consultants
 - Focus of previous and ongoing research (A2e's Wind Forecast Improvement Projects)
 - New European Wind Atlas

For offshore California, they produce VERY different results

Direct MYNN vs YSU Comparison, 2017



Other Factors Affecting the Increase

- WRF Version, reanalysis product, SST product and time period do not significantly change the modeled wind resource between WTK and CA20
- PBL scheme is by far the largest driver
- But still a lot of the increase is left unexplained:



Other Factors Affecting the Increase

- Other differences that might explain the increase include
 - Different domain sizes (WTK was run for the whole U.S.)
 - o Updated terrain and land use data
- More analysis is required to fully account for differences

Interannual Variability (IAV) Comparison:

IAV = expected variability in annual mean wind resource from year to year



CA20 has significantly higher IAV values. Why?

IAV Comparison:





2007-2013 WTK period just happened to be very consistent in many parts of the OCS

Uncertainty Metric Approach





Use of Ensembles

- Recall the 16 WRF model setups used in the validation analysis
- We can quantify sensitivity in WRF model by exploring spread between those "ensemble members"





Specifying an Uncertainty Metric

- Running 16 different simulations for 20 years is too computationally expensive
- Instead we run them for the 2017 year only
- Quantify uncertainty at each time step as the standard deviation divided by the mean, i.e., the coefficient of variation, or CoV
- Focus only on the 100-m wind speeds



Extrapolating Uncertainty

- Train a machine learning model to predict uncertainty (grey) from atmospheric variables in 20-year run (orange)
- Apply that model to full 20-year run to extrapolate uncertainty to full 20-year period



How are We Sharing the Data?



Wind Prospector



Wind Prospector

 Ideal for downloading data at a single location

| Offshore CA | Wind Toolkit | | | | | | |
|--|---------------------|---|---|---|---|---|---|
| Offshore Ca | alifornia Wind Data | Select Year | s Select All | Clear All | | | |
| onshore ca | | □ 2000 | 2001 | 2002 | 2003 | 2004 | □ 2005 |
| The Offshore CA Dataset is a 20-year wind resource dataset for offshore Cali- fornia. Produced in 2020, this data set re- places NREL's Wind Integration National Dataset (WIND) Toolkit for offshore Cali- fornia, which was produced and released publicly in 2013 and is currently the prin- cipal data set used by stakeholders for wind resource assessment in the conti- nental United States. Both the WIND Toolkit and this new data set are created using the Weather Research and Fore- casting (WRF) numerical weather predic- tion model (NWP). The Offshore CA shares many of the same attributes as the WIND Toolkit, including | | 2006 | 2007 | 2002 | 2009 | 2010 | □ 2003 |
| | | 2012 | 2013 | 2014 | 2015 | 2016 | 2017 |
| | | Wind Di 10m Wind Di 80m Wind Di Select Dow | rection at rection at rection at mload Optic | Wind 40m Wind 100m Wind | Direction at Direction at Direction at All Clear All | Vind D 60m Wind D 120m Wind D | irection at irection at irection at |
| Contact | Documentation | Include Lease | ap Day | Cor | nvert UTC to Loca | L Time 60 | ect Interval (Minu) 🗸 |

Python-based API

- Need Python familiarity
- Better for downloading regions of data and applying any processing (e.g., monthly means)

```
# Extract time-series data for a single site
import h5pyd
import pandas as pd
```

```
# Open .h5 file
with h5pyd.File('/nrel/wtk/conus/wtk_conus_2010.h5', mode='r') as f:
    # Extract time index and convert to datetime
   # NOTE: time index is saved as byte-strings and must be decoded
    time_index = pd.to_datetime(f['time_index'][...].astype(str))
    # Initialize DataFrame to store time-series data
   time_series = pd.DataFrame(index=time_index)
    # Extract 100m wind speed, wind direction, temperature, and pressure
    for var in ['windspeed 100m', 'winddirection 100m',
                        'temperature_100m', 'pressure_100m']:
        # Get dataset
        ds = f[var]
        # Extract scale factor
        scale_factor = ds.attrs['scale_factor']
        # Extract site 100 and add to DataFrame
        time_series[var] = ds[:, 100] / scale_factor
```

https://github.com/NREL/hsds-examples

Thanks!

www.nrel.gov

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