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# *Statistical Modelling of Wind Plant Power Production: Contrasting Different Machine Learning Algorithms and Atmospheric Features*

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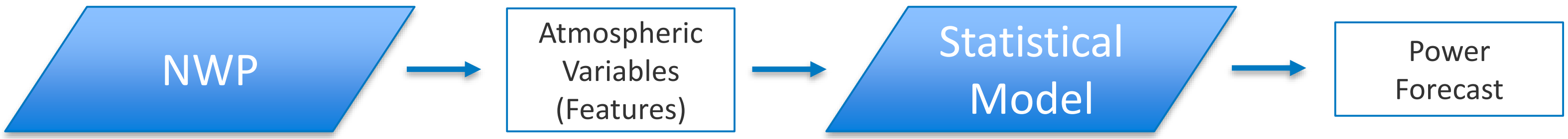
# State of Literature

- Machine learning (ML) is now a standard step in wind power forecasting




- Extensive literature with a large range of datasets, algorithms, input variables, timescales, forecast horizons, and error metrics

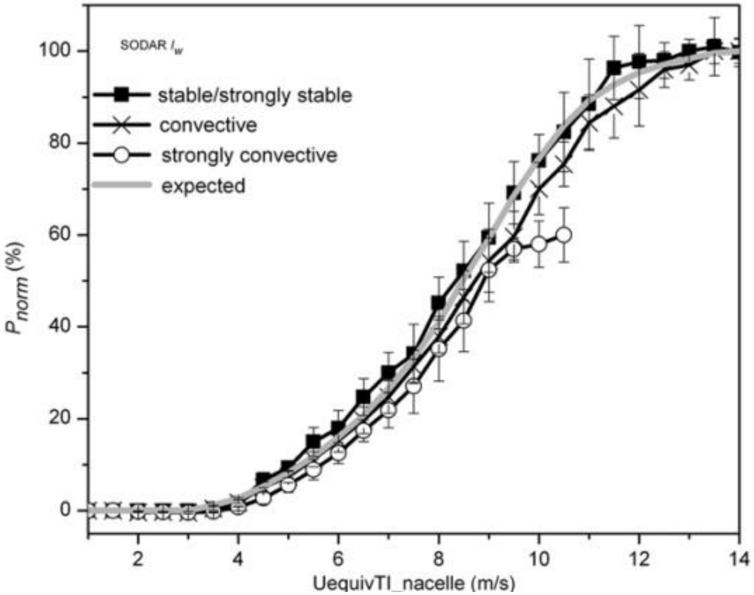
- **No clear consensus on best practices, no standardized methods to assess**

| Algorithms | Counts |
|---|---|
| Neural network | 14 |
| Neuro-fuzzy inference system | 6 |
| K-means clustering | 5 |
| Support vector machine | 4 |
| Regression tree approaches | 4 |
| Gaussian processes | 2 |
| Particle swarm optimization | 2 |
| Principle component analysis | 1 |
| Markov chain approaches | 1 |
| Bayesian learning | 1 |

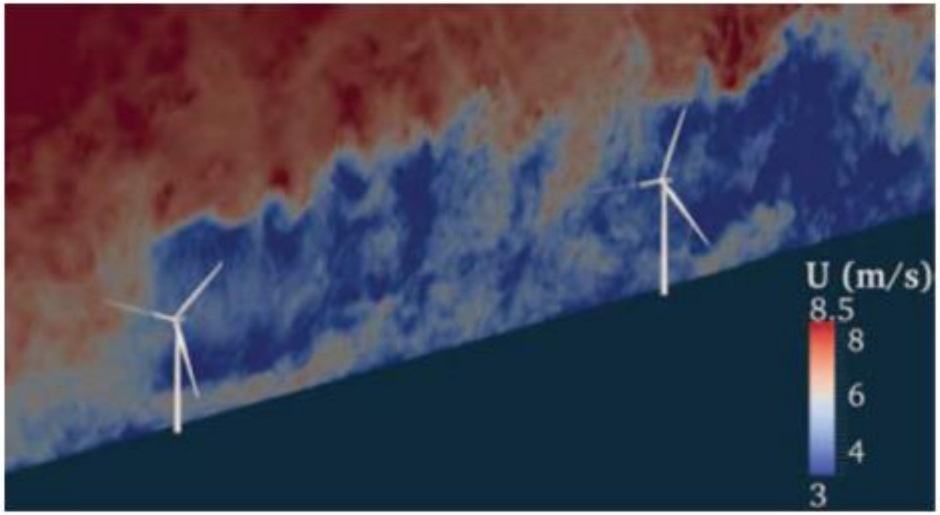
| Atmospheric Input | Counts |
|---|---|
| Wind speed | 22 |
| Wind direction | 10 |
| Temperature | 8 |
| Air pressure | 4 |
| Humidity | 3 |
| Air density | 1 |
| Potential temperature gradient | 1 |

# Turbulence and Stability

- Significant impacts on both turbine and plant power
  - Laminar vs. turbulent flow
  - Effect of wind shear
  - Turbine wake propagation and dissipation
- Almost never considered in ML models for wind power forecasting




Wharton and Lundquist (2012). Env. Res. Let., **7** (1)

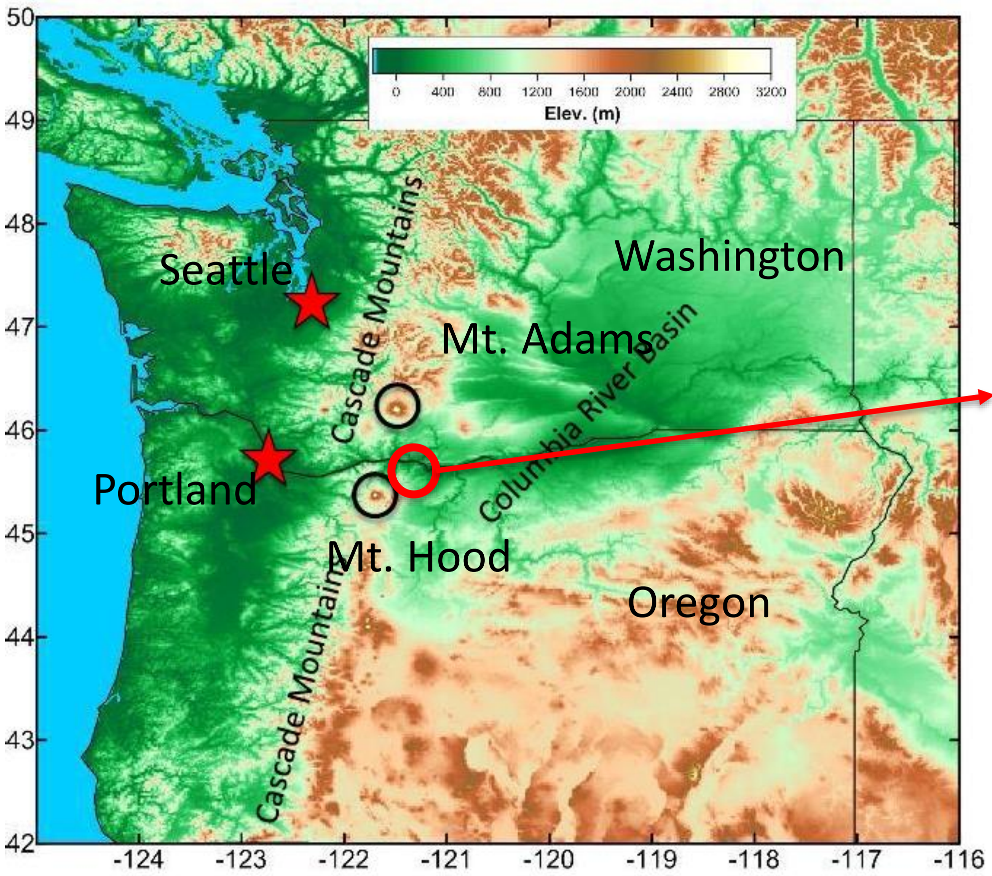



Churchfield et. al (2012). Journal of Turbulence, **13**

# Goal and Experiment Setup

**Can the use of turbulence and stability inputs improve ML predictions?**

**What is uncertainty associated with different model choices?**




| | |
|---|---|
| **Atmospheric Data** | WFIP2 Physics Site |
| **Wind power data** | Nearby wind farm |
| **Time period** | 2016-07 to 2017-03 |
| **Time resolution** | Hourly |

# Algorithms and Inputs

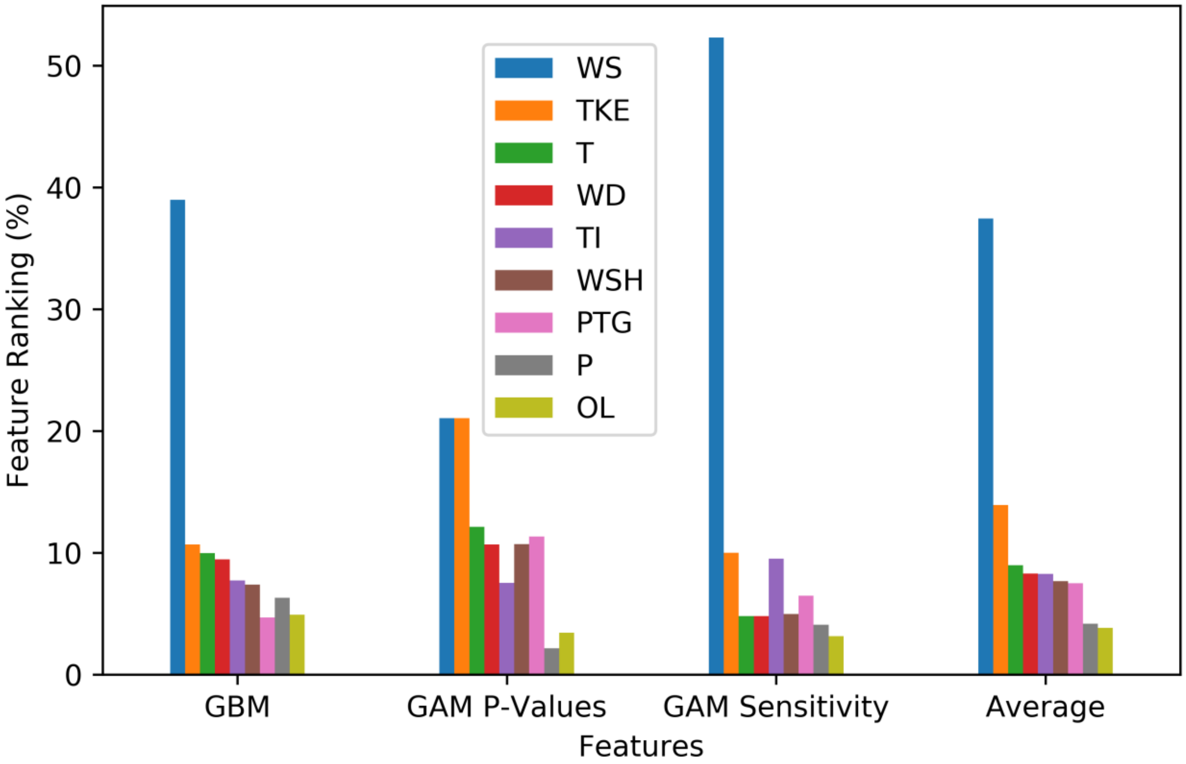
| Learning Algorithms | Atmospheric Features |
| --- | --- |
| Neural network (ANN)*<br>Generalized additive model (GAM)<br>Gradient boosting model (GBM)<br>Extra trees regression (ERT)<br>Support vector machine (SVM) | Wind speed (80m)<br>Wind direction (80m)<br>Air density (80m)<br>Temperature (80m)<br>Turbulence Intensity (80m)<br>Wind speed shear (80-50m)<br>Potential temperature gradient (80-17m)<br>Turbulent kinetic energy (80m)<br>Obukhov length (80m) |

- Hyperparameters for each algorithm optimized through cross-validated grid search over parameter space
- K-fold cross-validation (95% train, 5% test)
  - ~1 week test periods
  - Common time interval for curtailment loss estimation

* Simple multi-layer perceptron model with back propagation

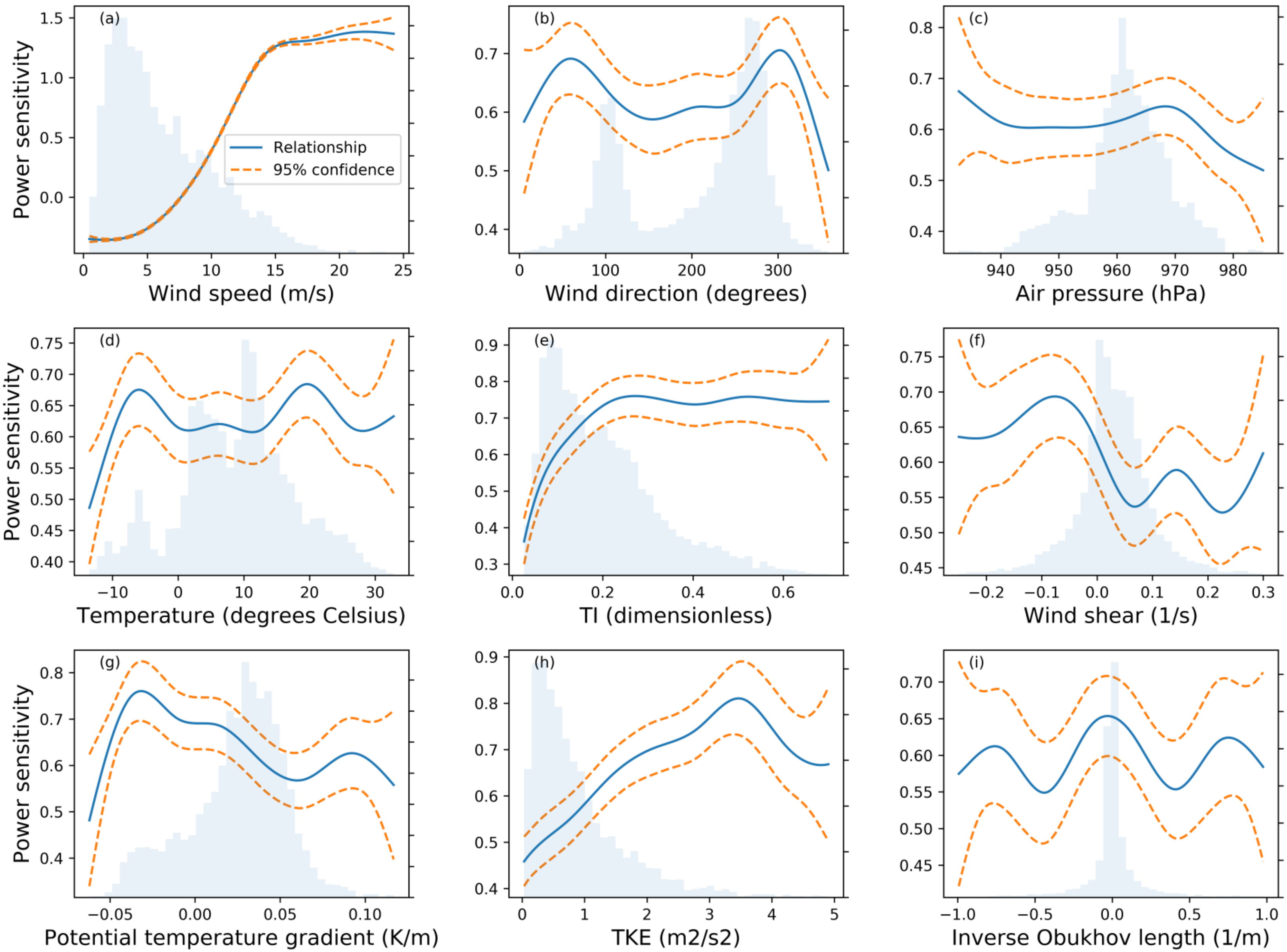
# Feature Importance

- 3 methods to assess feature importance
- Turbulence and stability all statistically relevant
- **TKE is second most significant after wind speed**

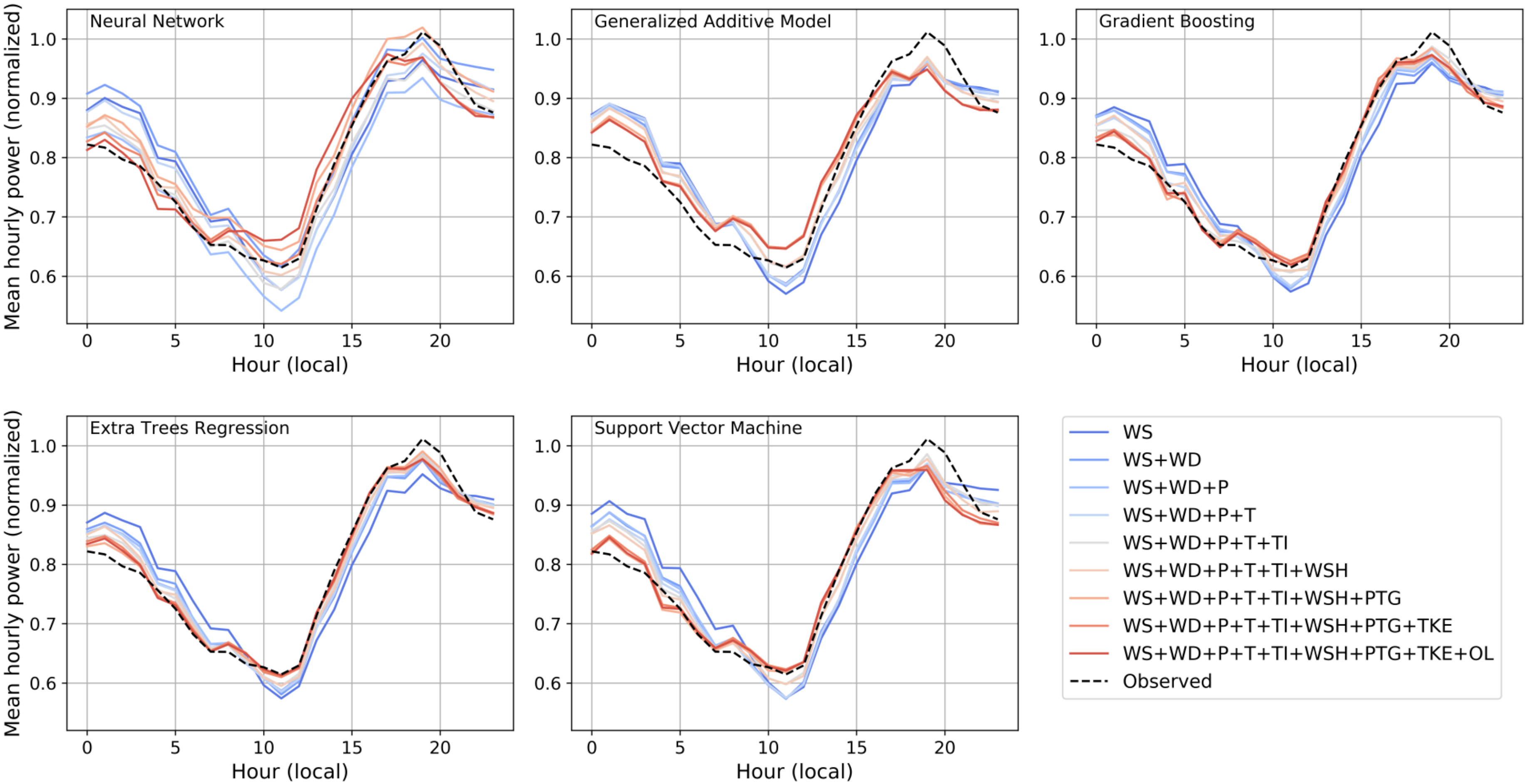



WS - wind speed
TKE - turbulent kinetic energy
T - temperature
WD - wind direction
TI - turbulence intensity
WSH - wind shear
PTG - potential temperature gradient
P - pressure
OL - Obukhov length

# Power Sensitivity to Inputs

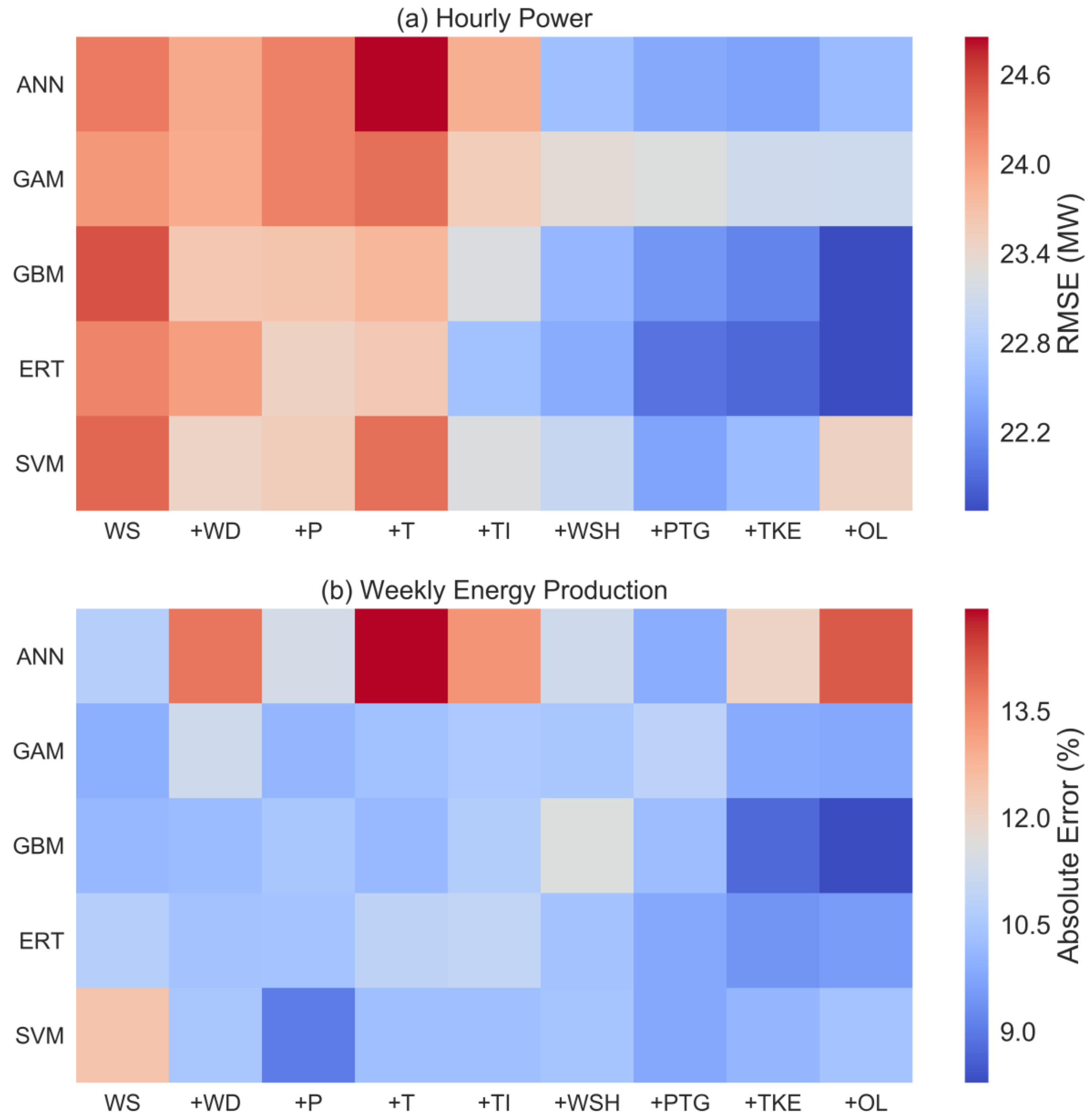


# Diurnal Cycle



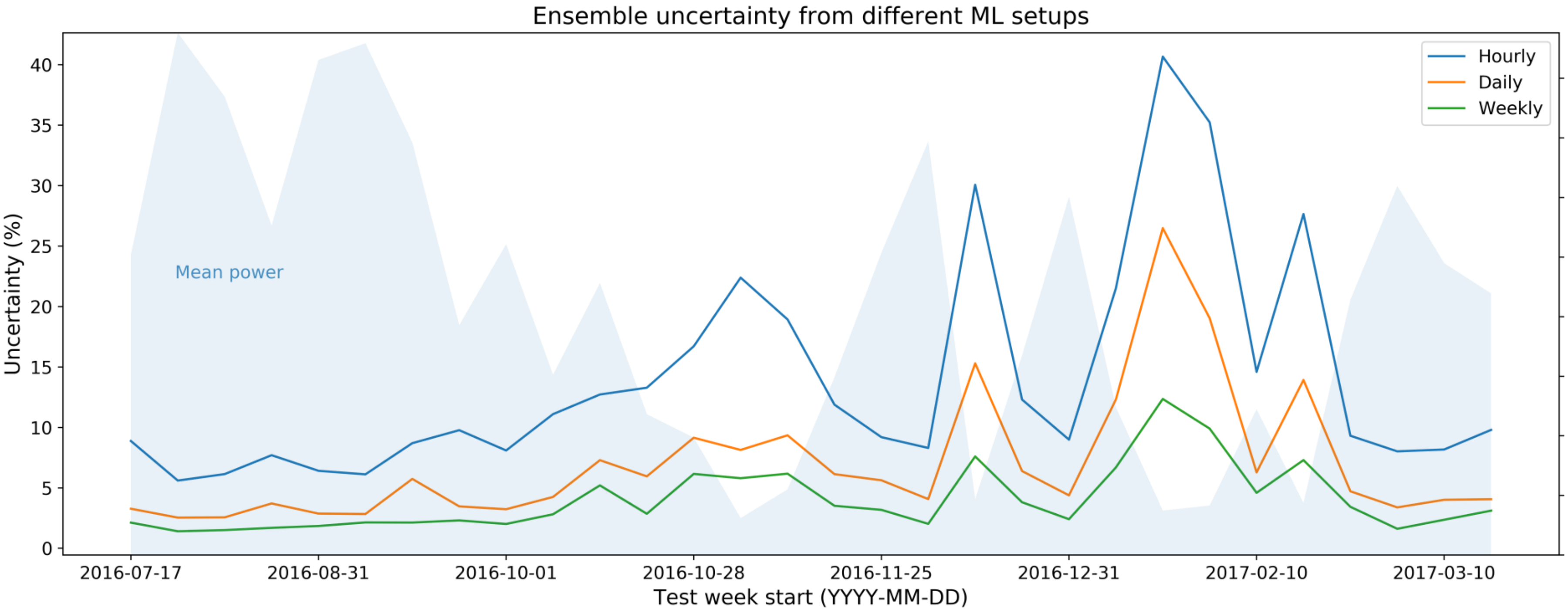

- Better diurnal modeling with more features
- Regression-tree approaches perform relatively well

# Model Accuracy on Different Timescales




- Improvement in hourly performance once turbulence/stratification is considered
- Not much improvement when predicting sum of energy over 1 week
- Model biases tend to average out over longer periods

# Uncertainty from ML Model Choice



# Remarks

- **Atmospheric turbulence and stability features should be considered**
- **Significant uncertainty** depending on inputs and algorithm selected
- No consensus on what model setup is best, although:
  - Regression tree-based approaches worked well here (and are simple)
  - More input variables the better
- Do we need complex neural networks for most wind energy problems?
- **Yet another non-standardized analysis…**

# Next Steps

**How can we standardize ML model assessment for wind power modelling?**

1. Standard datasets
    - Several wind farms in different wind regimes
    - Observed and NWP-modelled atmospheric variables
    - Pre-processed and ready for ingestion by ML frameworks
    - **Challenges with proprietary data**

2. Standard assessment methods
    - Hyperparameter optimization
    - Cross-validation
    - Error metrics

Optis, M. and Perr-Sauer, J. (2018). Renewable and Sustainable Energy Reviews, under review

# Thank You

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# Annex: Hyperparameter Ranges

| Algorithm | Optimized Hyperparameters | Possible Values |
|---|---|---|
| GAM | Number of splines | 5-40 |
| NN | Activation function | logistic, tanh, relu |
| | Hidden layer size | (100), (100, 100), (100, 50), (100, 100, 100), (100, 100, 50), (100, 100, 25), (100, 50, 25, 9) |
| GBM | Maximum depth | 2, 4, 8, 12, 16, 20 |
| | Maximum features | 1 to number of total features |
| | Minimum sample split | 2-11 |
| | Minimum samples per leaf | 1-11 |
| | Number of estimators | 10 to 400 in increments of 40 |
| ERT | Maximum depth | 4, 8, 12, 16, 20 |
| | Maximum features | 1 to number of total features |
| | Minimum sample split | 2-11 |
| | Minimum samples per leaf | 1-11 |
| | Number of estimators | 10 to 400 in increments of 40 |
| SVM | Penalty parameter of the error term | 0.1, 1, 10, 50, 100 |
| | Kernel coefficient | 0.01, 0.1, 1, 10 |
| | Kernel | Polynomial, RBF, sigmoid |