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Very short term wind power forecasting using shore-based scanning lidar observations over the Danish North Sea

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Very short term wind power forecasting using shore-based scanning lidar observations over the Danish North Sea

EMS 2016 – Trieste, Italy

15 September, 2016 (11AM @ Saturnia)

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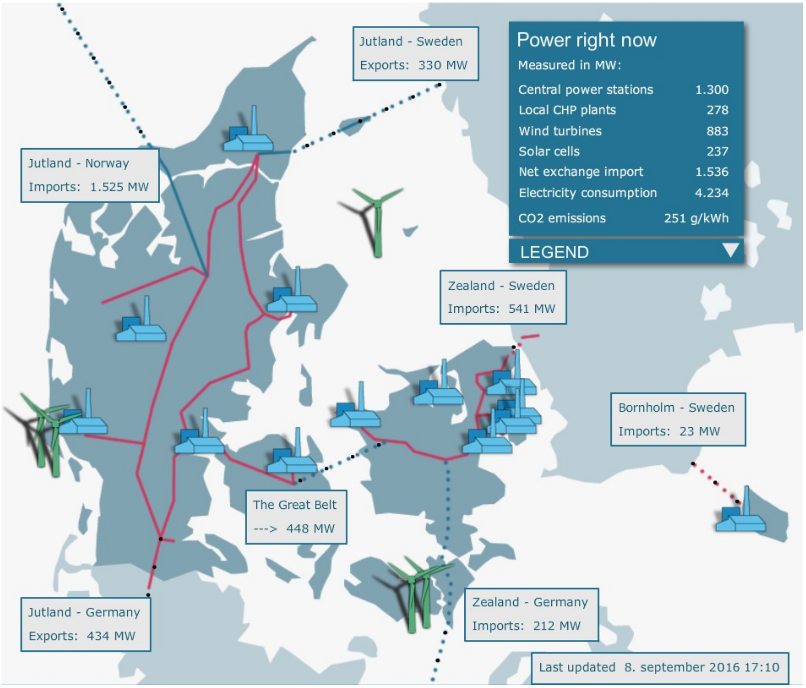
Motivation

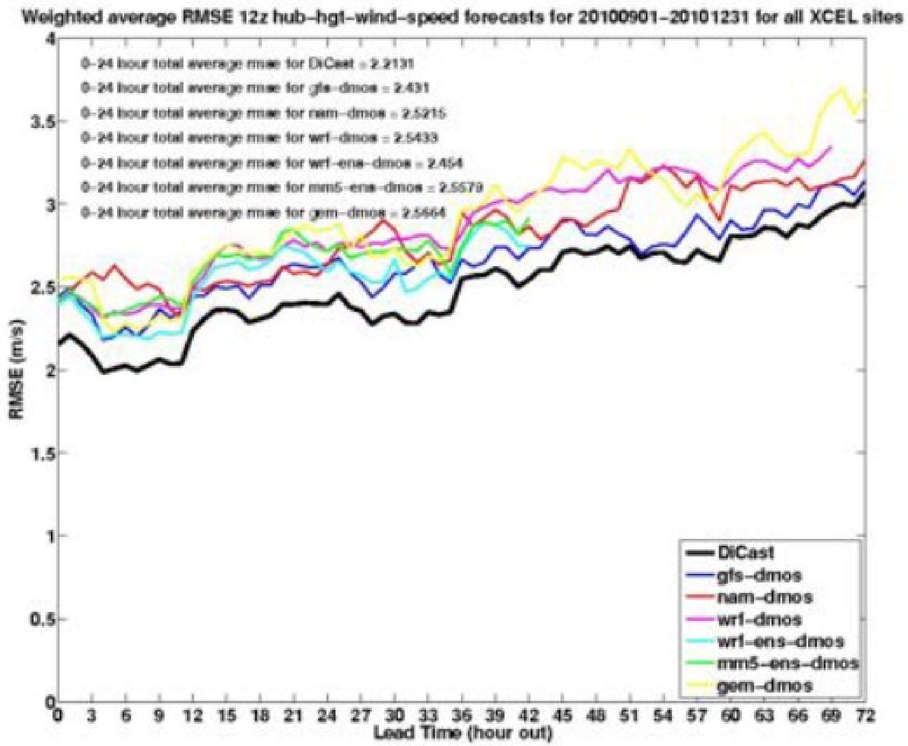
- Why are very short term wind power forecasts necessary?
  - Grid balancing, regulating market operation (e.g. EPEX 15 minute contracts for intermittent renewables)
  - Windfarm control applications (curtailment, active control)
  - Predicting gusts and ramp events (ex. load control)
  - Improve scheduling/dispatching of power plants for large scale integration

- Balancing costs amount to 8.3 EUR/MWh of generated wind! (Bruninx, 2014)



Standard techniques

- Current approach for this timescale is mainly statistical (from SCADA) and the persistence method
- NWP tools are using for longer forecast horizons, then finally climatology is used



(Haupt, 2016)

Lidar

- Lidar technology can provide us with inflow wind field measurements
  - Not only give us measurement data, but also temporal and spatial characteristics about how the wind field is behaving
  - Scanning lidar such as the long range WindScanner can scan up to 7km along complex trajectories

Example of PPI scan from RUNE

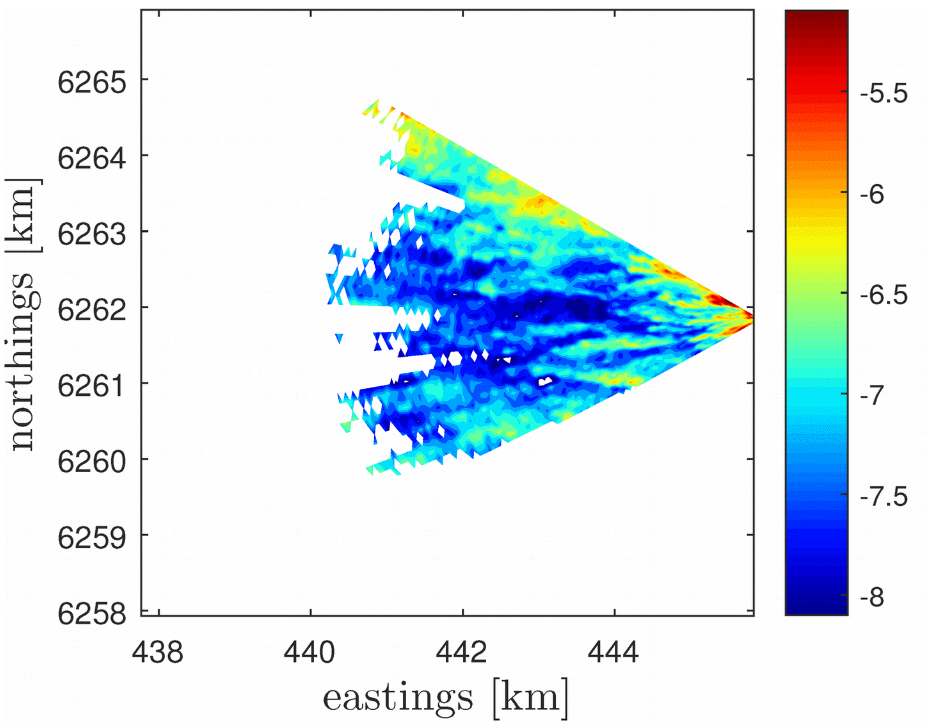


Illustration of concept 1

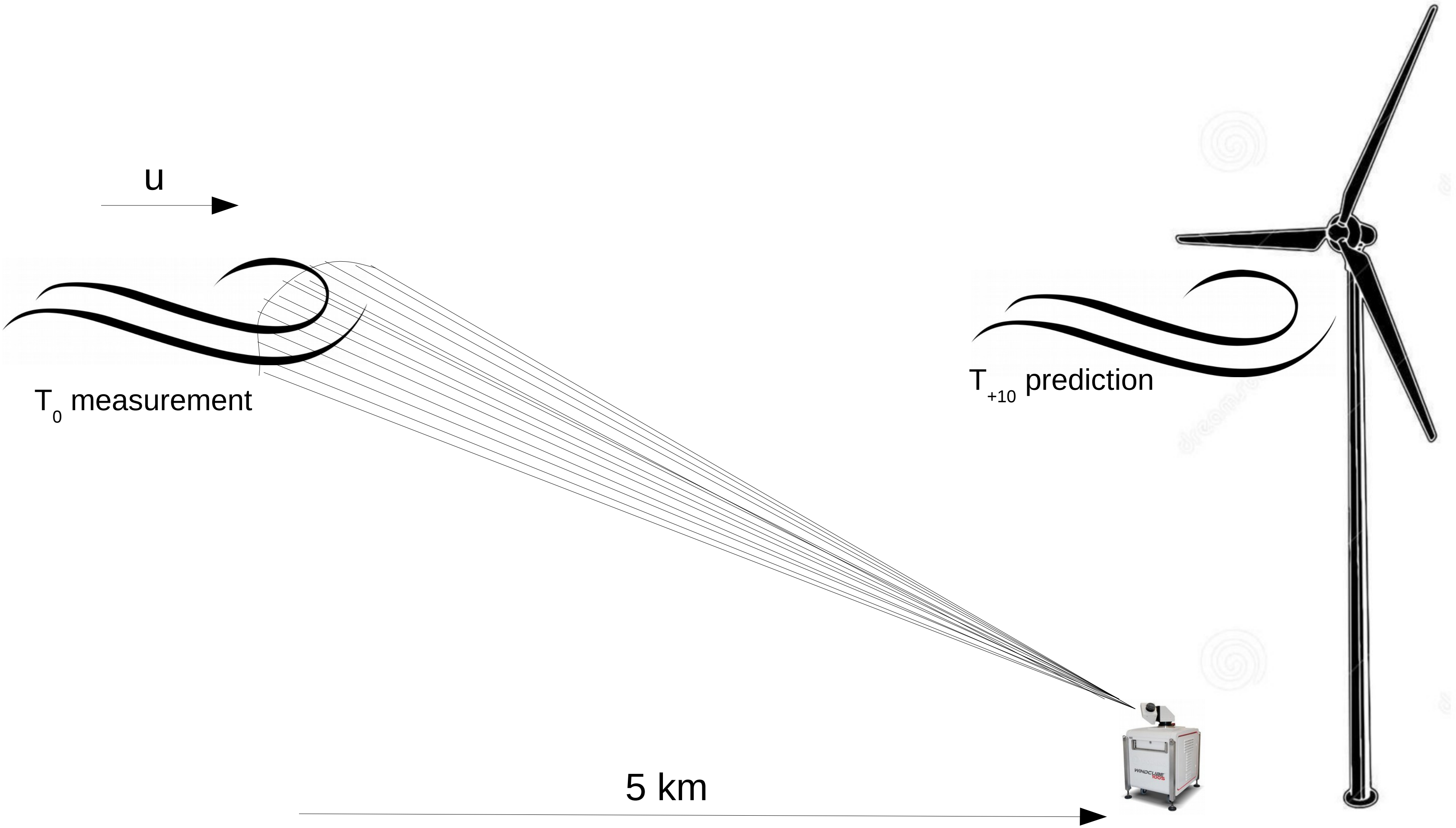
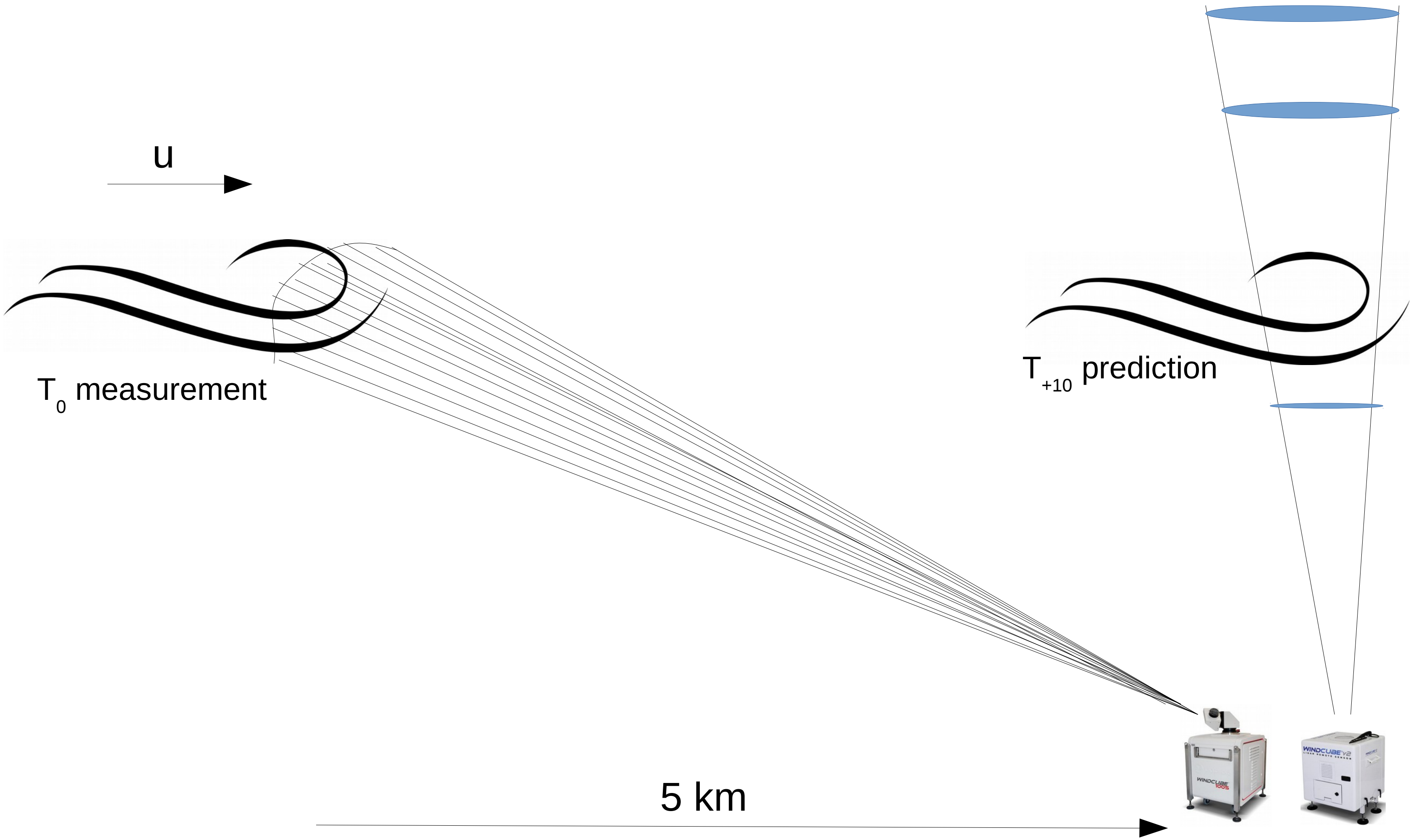


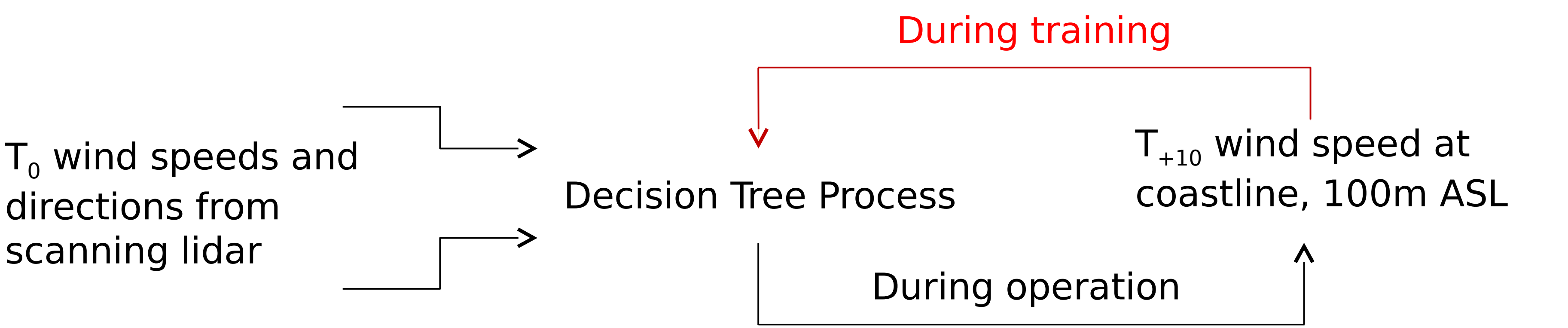
Illustration of concept 2



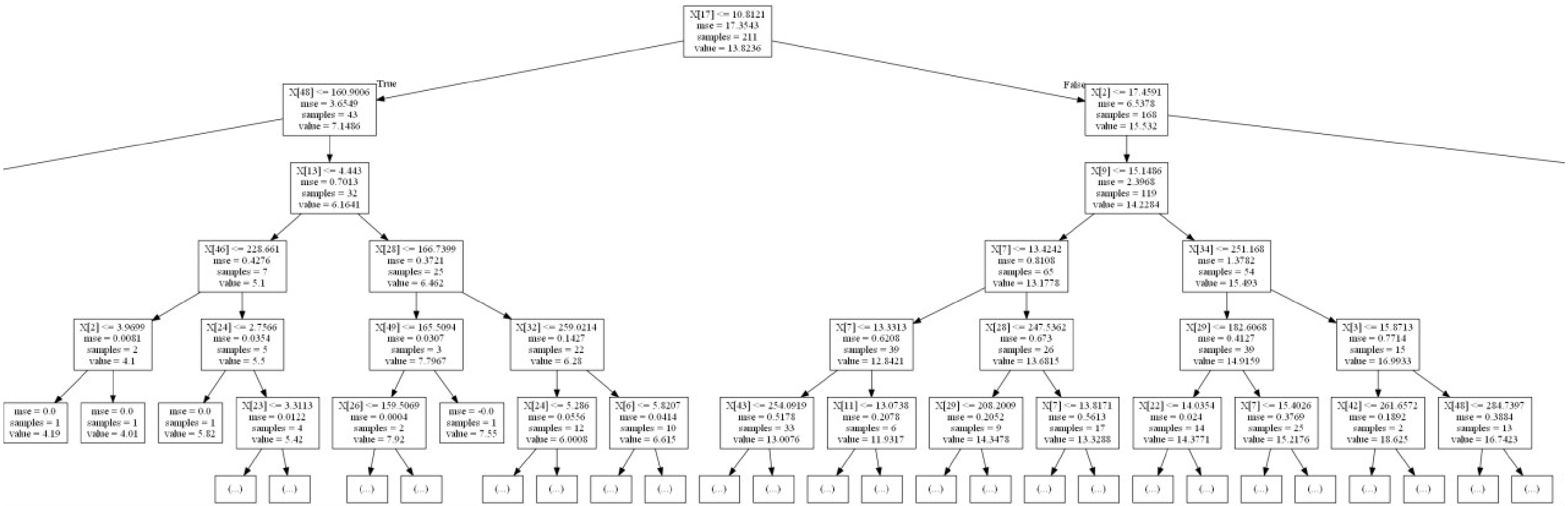
Machine learning

- Uses training data to build predictive model (e.g. decision tree, classifier)
- Inputs (features) are then fed into model, and a best fit result (label) is given

- Here we implement the DecisionTreeRegressor class from scikit-learn
- Our model does NOT learn during validation (persistence not incorporated)



Decision tree example



RUNE experiment

- **R**educing **U**ncertainty of **N**ear-shore wind resource **E**stimates using onshore scanning lidar technology combined with ocean and satellite information
  - Perform near-shore WRA using onshore instruments
  - Compare & improve mesoscale model performance in coastal areas

RUNE experimental setup

SS: 3 heights (50,100,150m ASL @ 5km)

DD: 3 heights

(50,100,150m ASL)

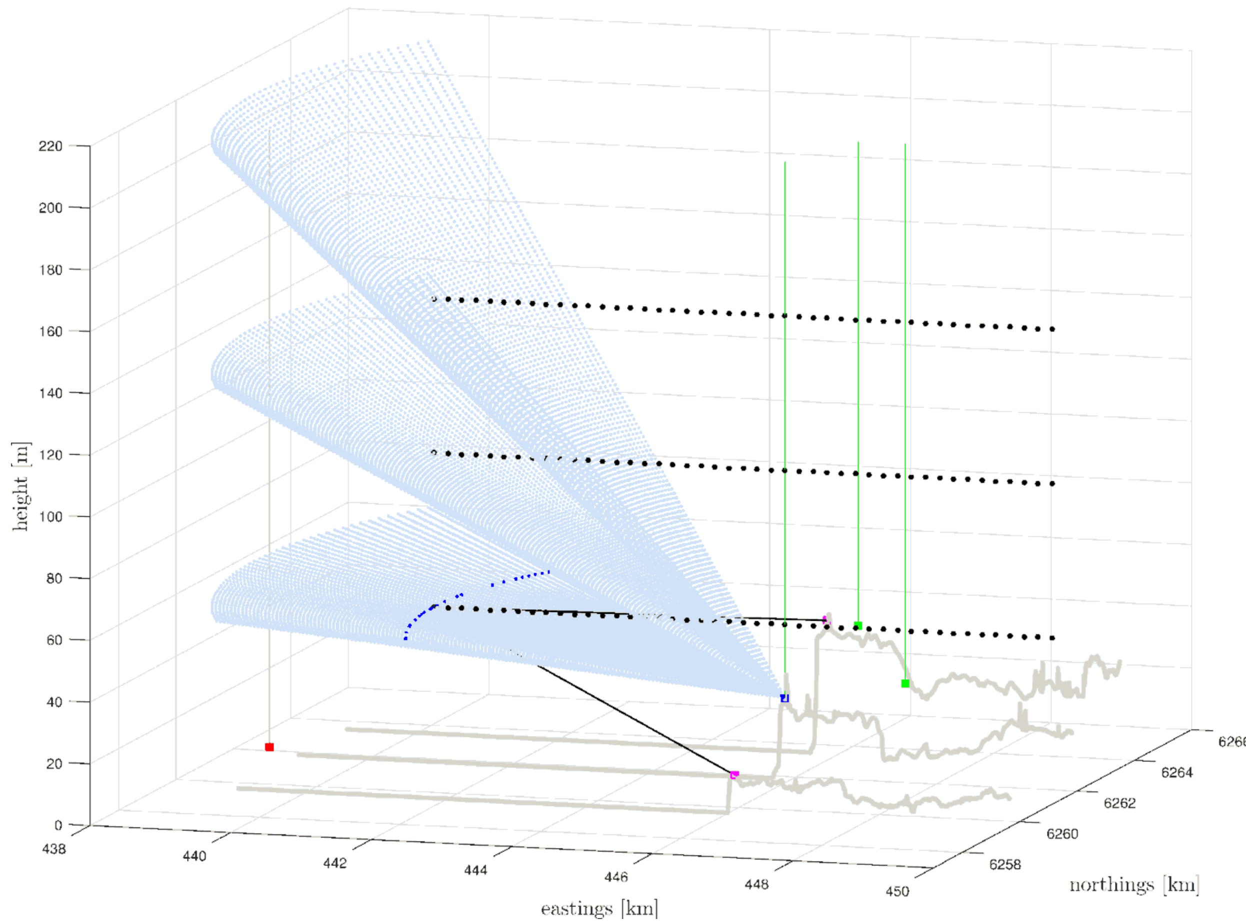
3 scanning lidars

4 profiling lidars

1 floating lidar buoy

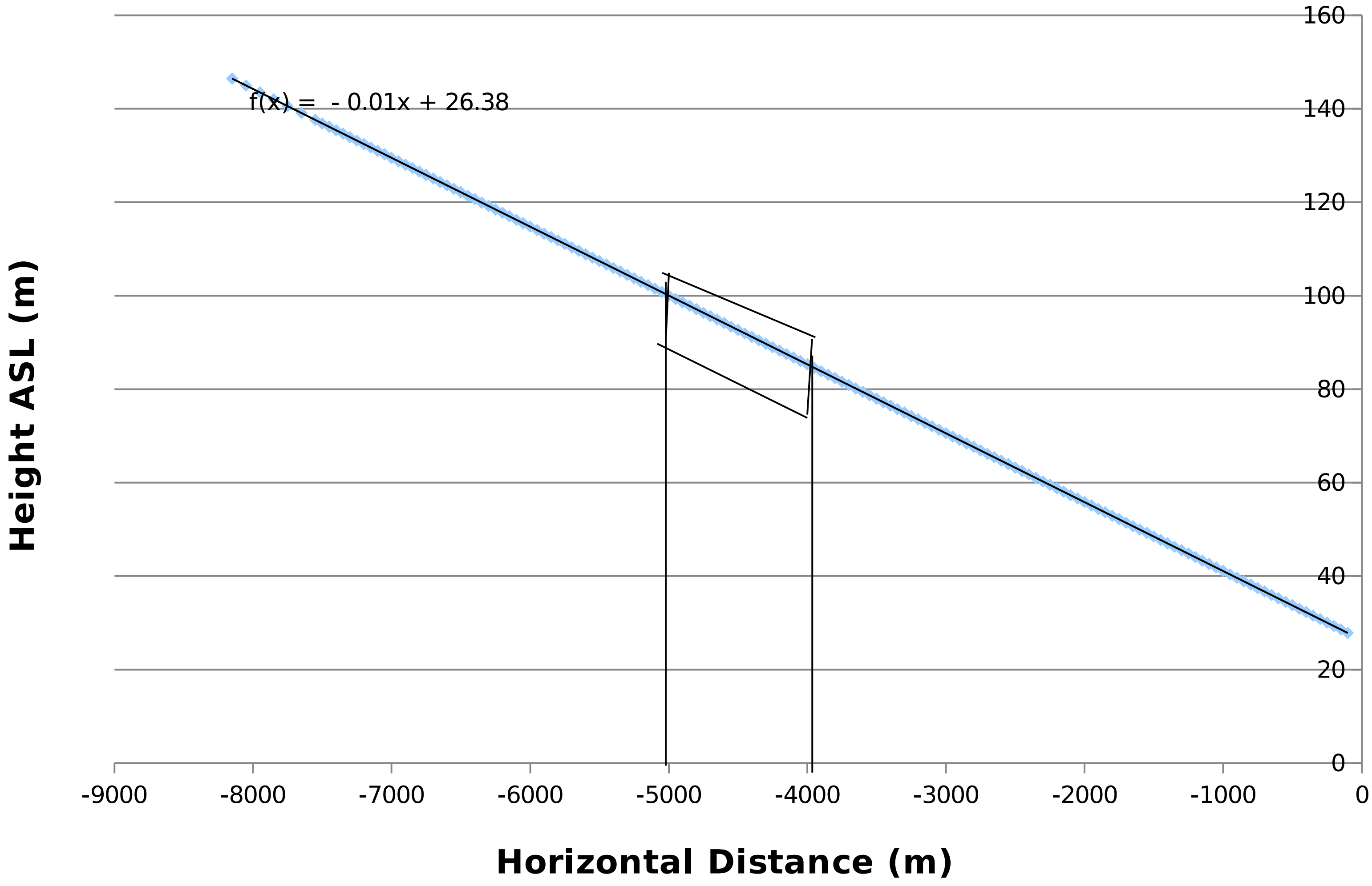
1 wave buoy

TerraSAR-X, Sentinel-1 satellite images



Floors et.al: Report on RUNE's coastal experiment and first inter-comparisons between measurements systems

Vertical Slice of Scan (0.844 deg elevation)



Data filtering

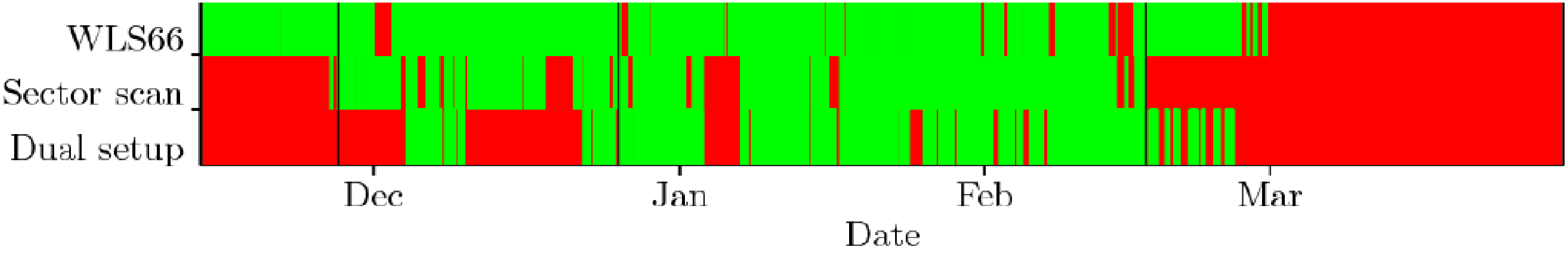
- Scanning lidar
  - CNR < -26.5 dB (remove)
  - Missing measurements along LOS (remove entire line)
  - Low availability in 10 minute average (only 1 point, remove)

- Profiling lidar
  - Availability < 90% (remove)
  - Maximum CNR > 10 dB (remove)
  - Low CNR filter already implemented during operation

- Results
  - Wind direction outside range 225-315 degrees (remove)

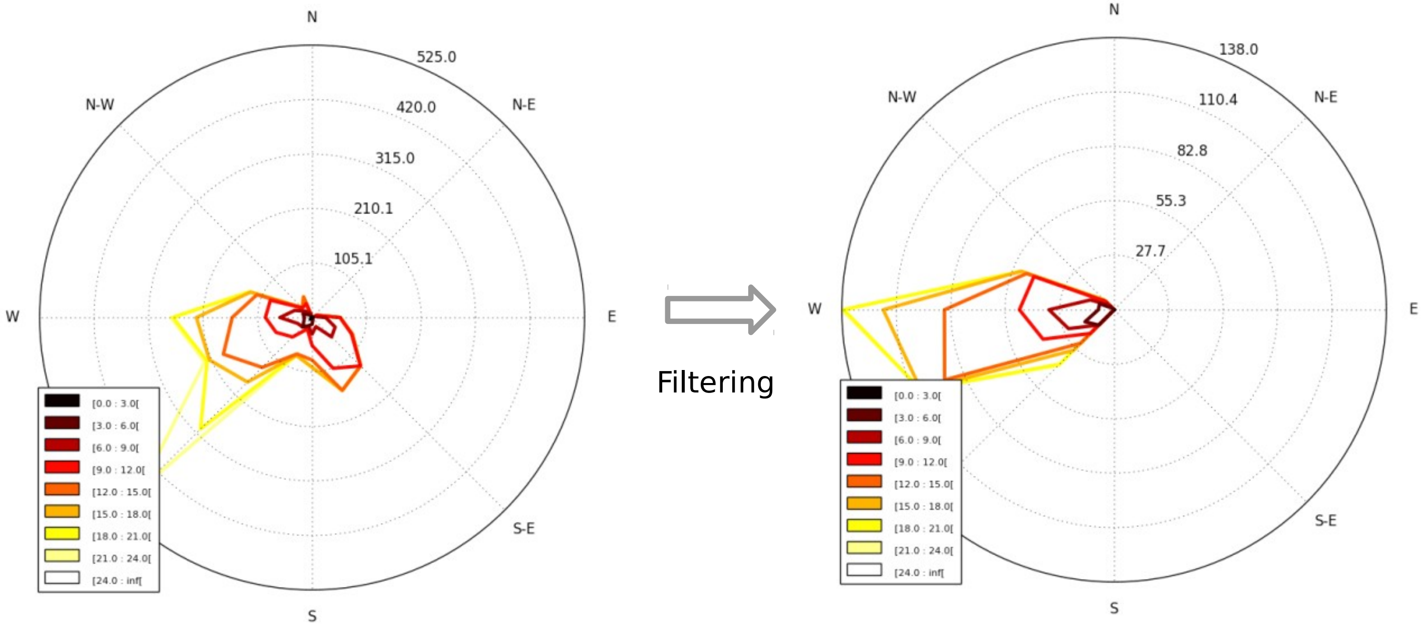
Sector scan dataset

- Overview:
  - 2015-11-26-1530 to 2016-02-17-0750
  - 4203 10 minute periods with 5km range and >1 sample per 10min
    - 700 hours, or 29 days of data
  - 156 range gates per elevation height
    - 0.271, **0.844** and 1.417 degrees
    - 100-8150m horizontal distance
    - Middle elevation = 100m height @ 5km



Case study:

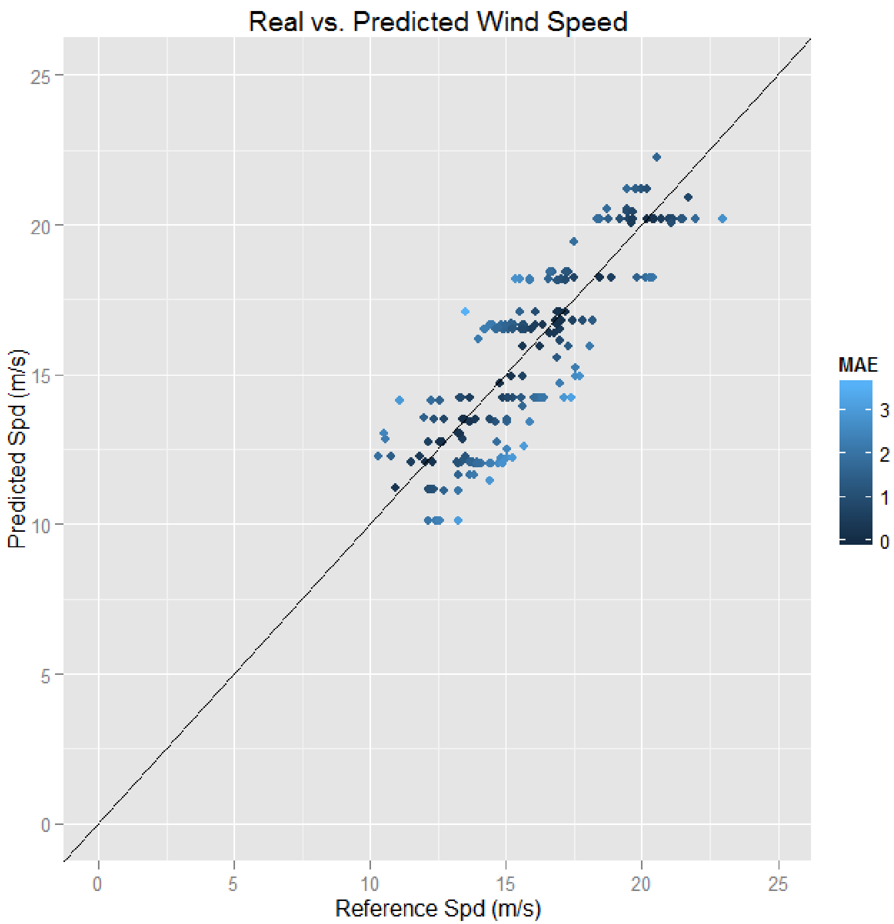
- Input: SS wind speeds and directions along 4km-5km horizontal distance
- Training data: 2015-12-04-0940 to 2015-12-18-0510 (14 days)



- Validation period: 2015-12-21-0950 to 2015-12-24-1620 (3.6 days)

Case 1 Results:

- n=194 x 10 min (32h)
- 27% of points filtered/missing



Regression coefficient = 1.005

$R^2 = 0.9896$

Standard error = 0.007 m/s

RMSE = 1.628 m/s

RMCE = 1.790 m/s

MAE = 1.406 m/s

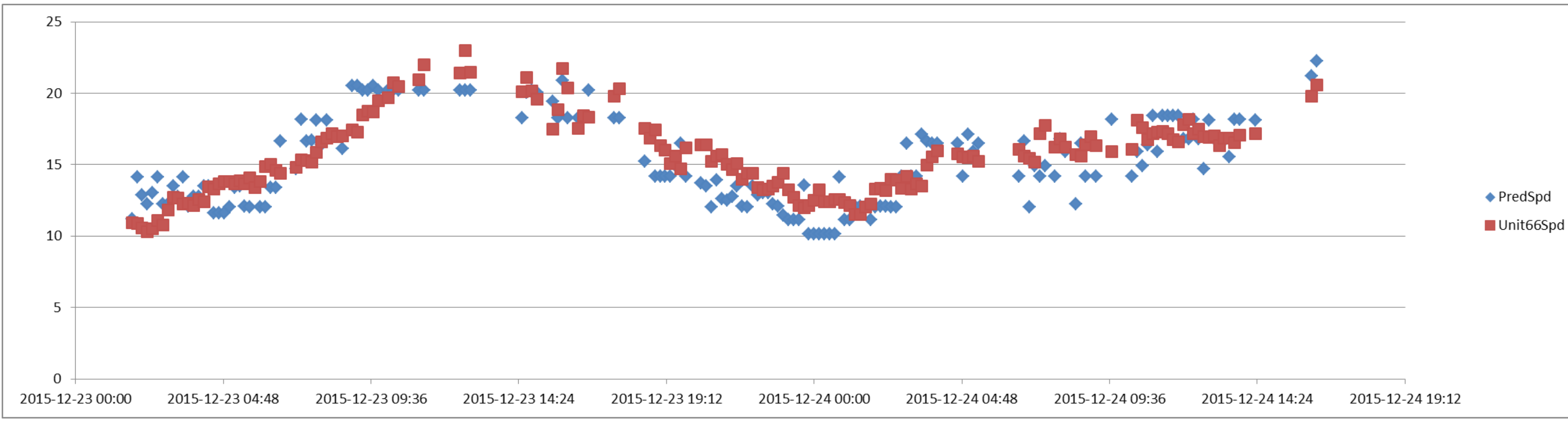
Train Data

```
     Spd66
 Min.   : 1.08
 1st Qu.: 8.85
 Median :11.76
 Mean   :12.18
 3rd Qu.:14.91
 Max.   :24.03
```

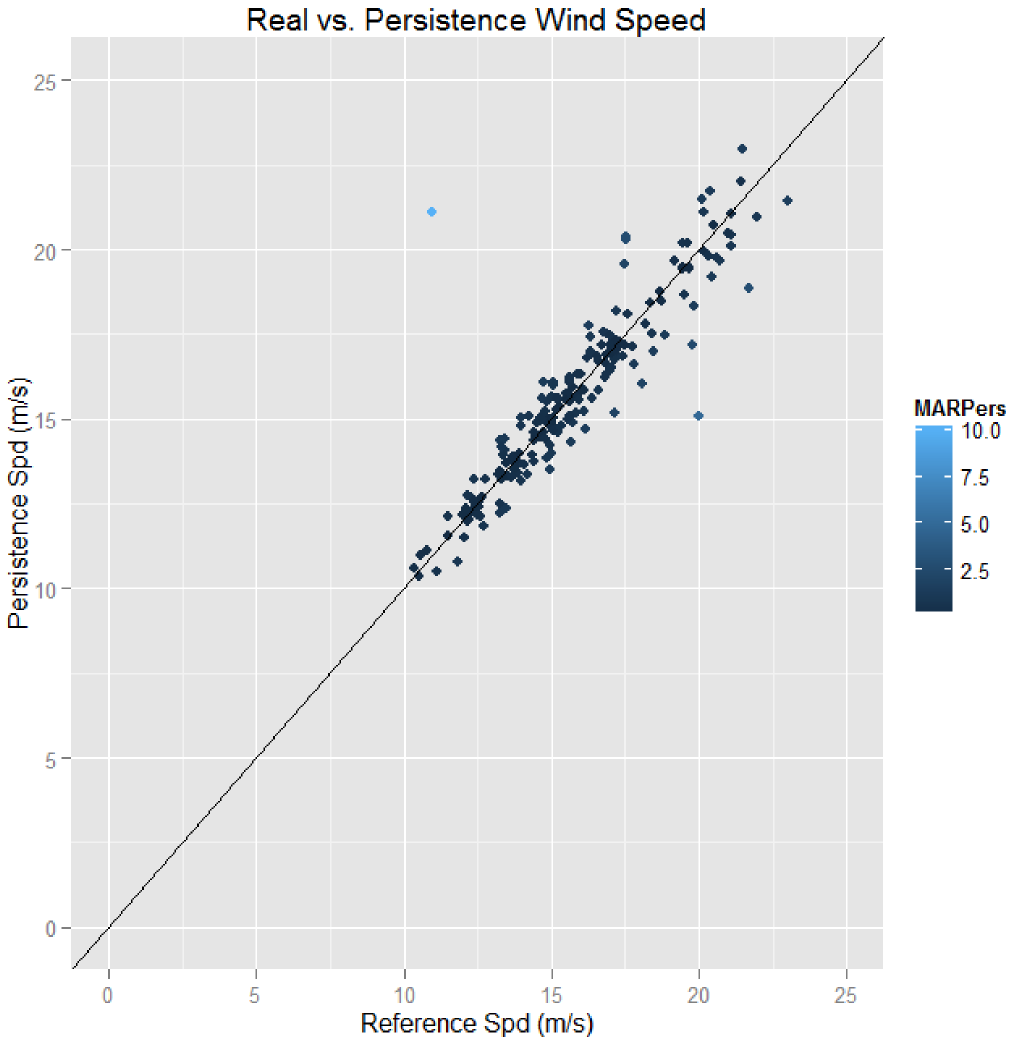
Prediction Data

```
    PredSpd            RealSpd
 Min.   :10.13    Min.   :10.33
 1st Qu.:12.63    1st Qu.:13.84
 Median :14.93    Median :15.51
 Mean   :15.42    Mean   :15.73
 3rd Qu.:18.13    3rd Qu.:17.18
 Max.   :22.23    Max.   :22.98
```

Time series result, wind speed:



Persistence comparison



- n = 194 x 10 min (32h)
- Regression coefficient = 1.004
- $R^2 = 0.9979$
- Standard error = 0.004 m/s
- RMSE = 1.126 m/s
- RMCE = 1.907 m/s
- MAE = 0.649 m/s

Conclusion

- Lessons learned
  - Persistence wins for now for normal operation (MAE & RMSE)
  - Added value may lie within the extremes (RMCE)
  - Sampling rate from RUNE is not fast enough (n=4 per 10 min)
  - Elevated scanning including height variation not ideal
  - There are other processes (e.g. air-sea interaction, orography, sea breeze) which modify advection near the coast

- Future work
  - Østerild balcony data remedies many of these issues
  - Incorporate ongoing measurements during validation
  - Recalibration of model in real time
  - Probabilistic output
  - Wind direction output

- Grazie :)
  - Also check out Tobias Ahsbahs Thursday @ 18:00 ASI4, Vulcania