DTU

Minute-Scale Wind Forecasting Using Lidar Inflow Measurements

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PhD Defence

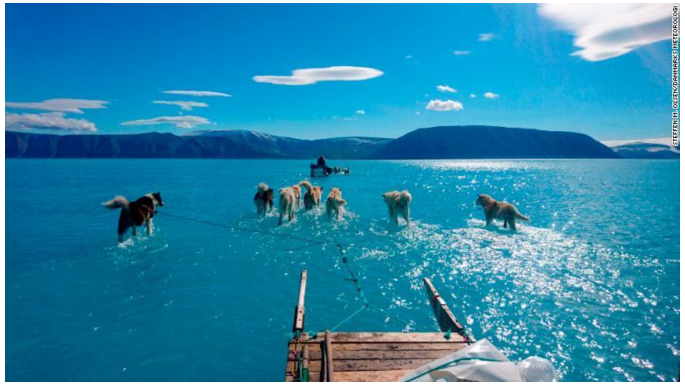
24 June, 2019

Outline

- Background and motivation
- Project objectives
- Experimental results
  1. WAFFLE
  2. Østerild Balconies
  3. LASCAR
- Outlook and conclusions

Our reality

- Energy is a critical resource
- Global transition towards clean and affordable energy systems
- Money to be made!



Environment

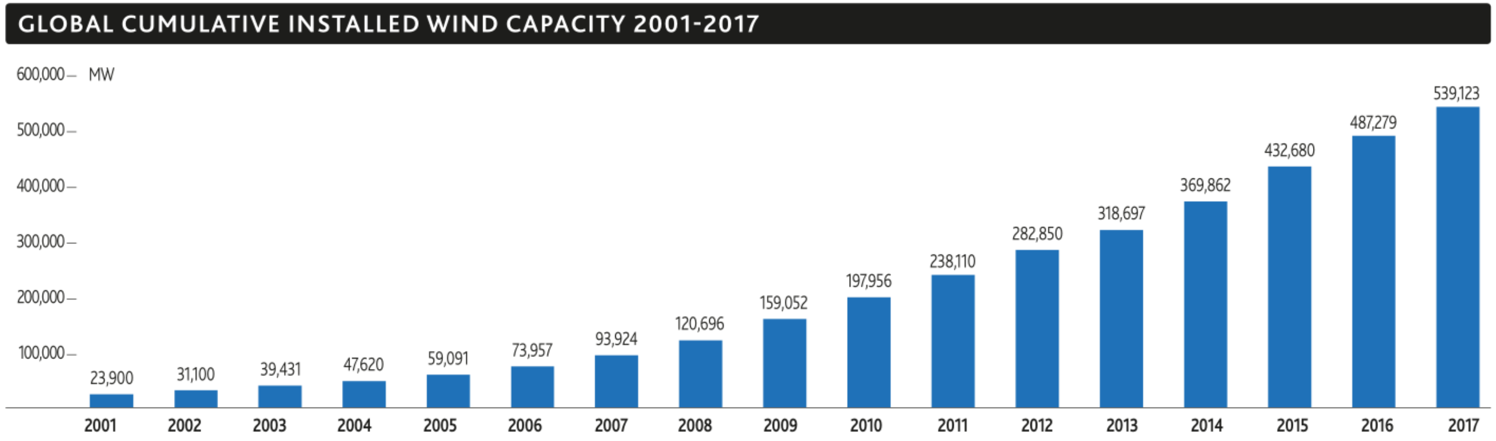
Wildlife

Health

Geopolitics

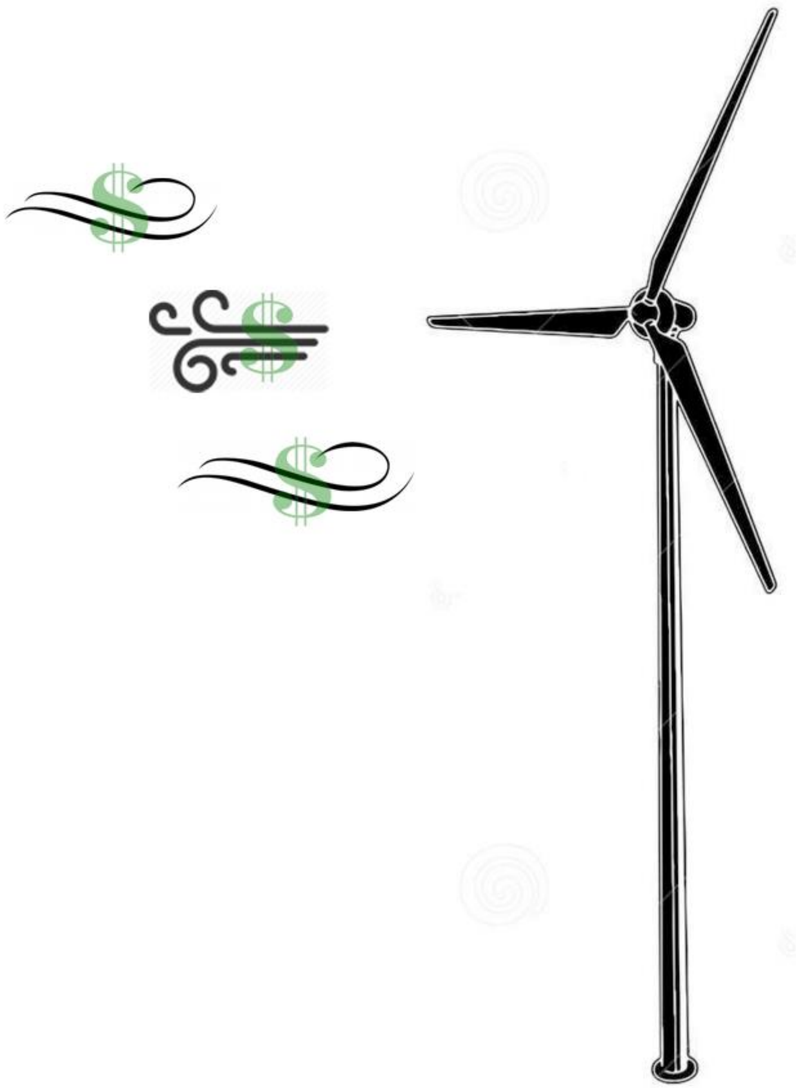
Wind power

- Industry is rapidly maturing to become competitive and efficient
- Wind supplies 4% (global) 14% (EU) and 44% (Denmark) of electricity demand
- Wind is leading renewable in new installed capacity



Important considerations (1)

- Atmospheric conditions dictate production (₼O₦£¥)
- Winds are highly variable
  (seasonal patterns, weather, turbulence, land effects)
- Variability of wind → variability in energy production
- Power grid requires constant balance
  (production = consumption)
- System level storage not feasible (at the moment)



Important considerations (2)

- Grid and markets not devised for high variability and uncertainty
- Grid failures are catastrophic
- Real-time power balancing is expensive!
  (Reserve capacity, ancillary services, demand response)
- Market designs are changing to accommodate renewables
  (e.g. 5/15/30-minute contracts in EPEX & AEMC)

2003 blackout: 55 million without power

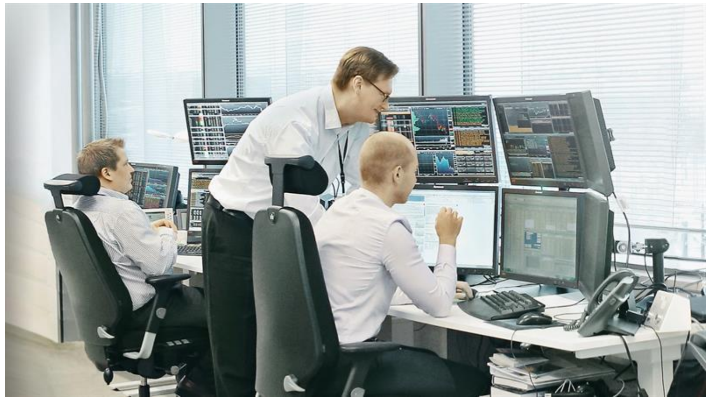
	NordPool		TSO
	Initial offers	Economic balancing	Physical balancing
Financial markets →	Day-ahead (Elspot) →	Intraday (Elbas) →	Regulating and reserves
Years, months, quarters	Days before delivery	Hour/minutes before	Real-time

Why do we need minute-scale wind forecasts?

- Predicting energy production
  - Support schemes being phased out
  - Financial risk from forecast errors
  - Grid planning and operation

- Large-scale and extreme event detection/response

- Collective wind farm control

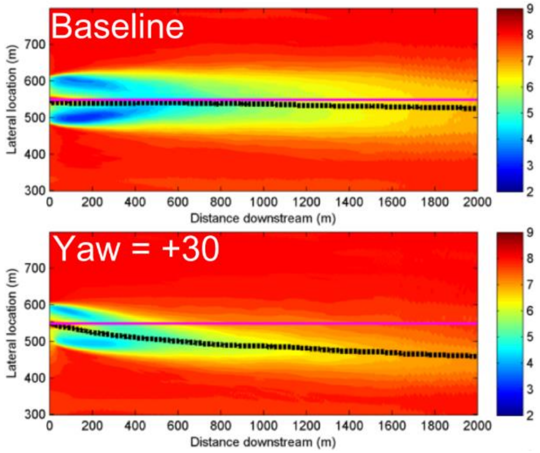


Wind farm control

- Production gains and fatigue load reductions
  - Wake steering
    ~5% AEP increase (Fleming et al, 2017)
  - Dynamic induction control
    ~1.5% AEP increase (Gebraad and Wingerden, 2015)

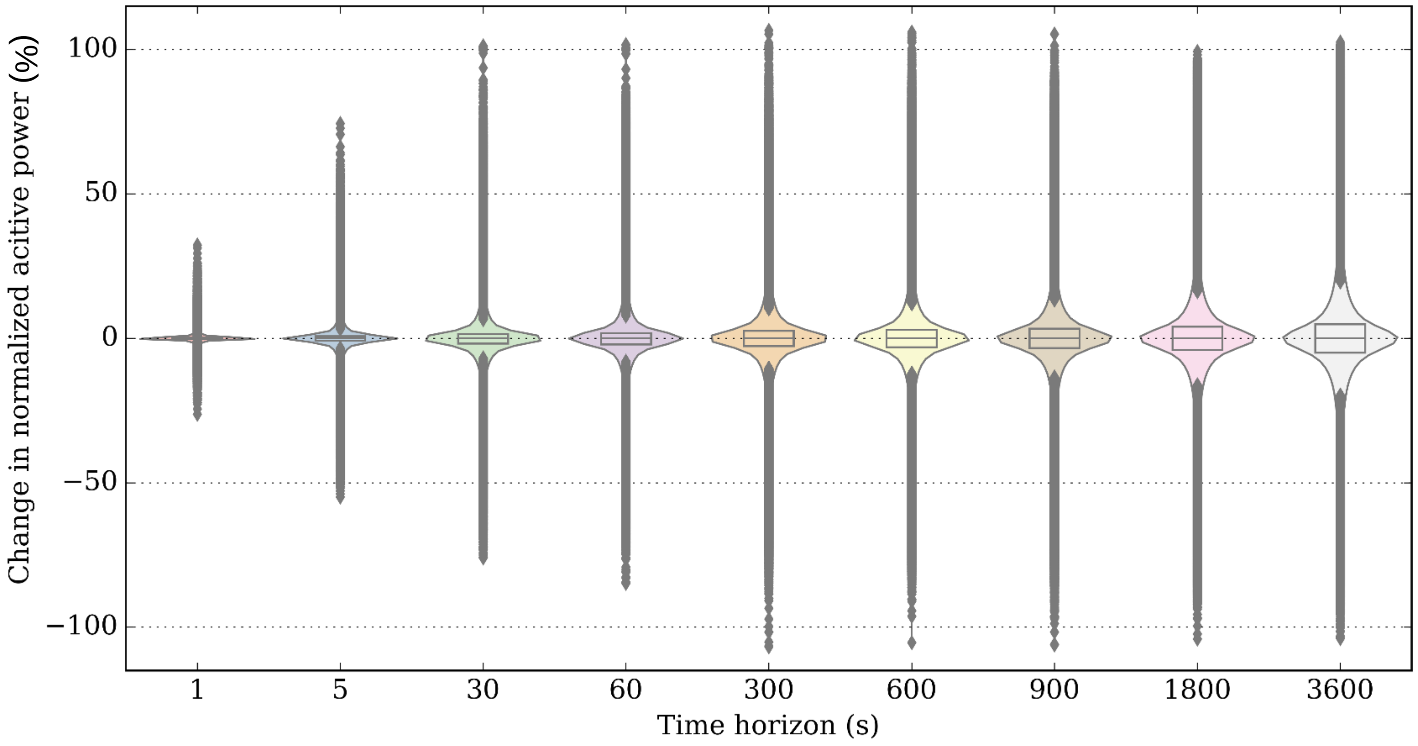
- Flow models and controllers require knowledge of conditions
  - Sensitive to wind direction input!

Wake steering



Wind variability on very-short timescales

- 35 days of 1 Hz active power measurements from 850 kW V52 wind turbine
- Change in active power (% capacity) over selected time frames



Forecasting approaches on minute-scale

- Numerical weather prediction (physical modelling e.g. WRF) not applicable
  - Lack knowledge of boundary conditions
  - Computationally not feasible

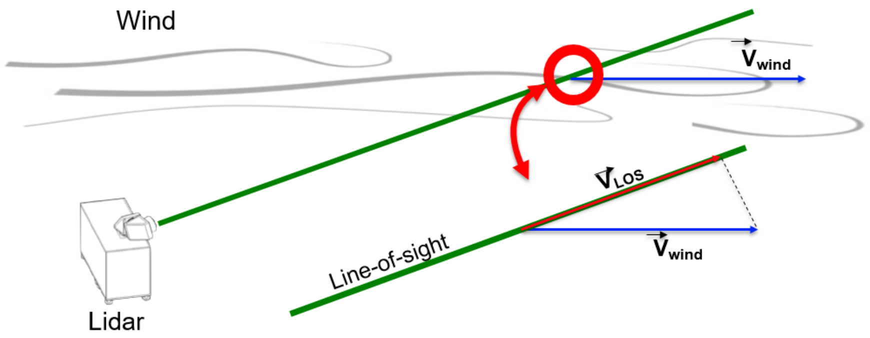
→ - Persistence – everything stays the same, next value = previous value
→ - Statistical time series modelling – inferring patterns from past observations

- Maybe we can do better?
- Use remote sensing to look ahead and anticipate what's coming

Remote sensing

- Measurement technique using radio/light/sound waves to observe phenomena at a distance
- Common examples: ranging radar, mapping lidar

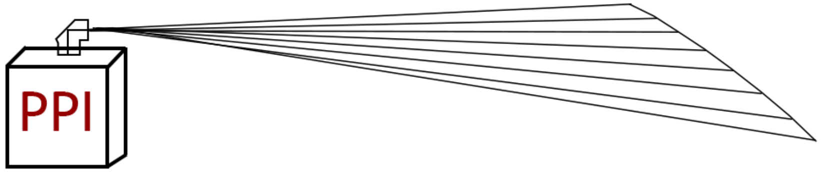
- Doppler remote sensing adds velocity information
- Doppler wind lidars are compact, commercially available, well established, and scatter off atmospheric aerosols
- Scan head allows great flexibility in measurement setup
- Measurements are radial! (velocity component along line-of-sight)

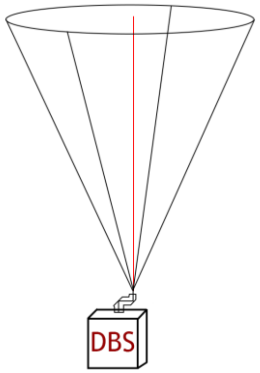


Source: [Vasiljevic (2014)]

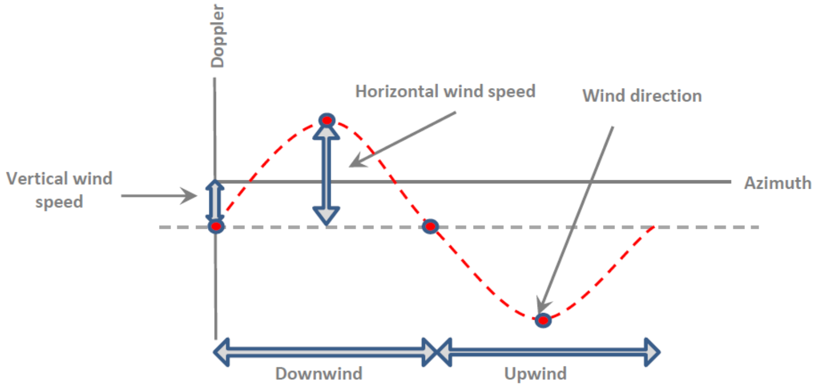
Scanning lidar measurement techniques

- Takes time to scan. Everything is a tradeoff!
- Plan position indicator (PPI)
  - Fixed elevation angle, azimuth sweep (full/partial)





- Doppler beam swing (DBS)
  - Fixed points (4 orthogonal and optional vertical beam)
  - Opposing pairs used to reconstruct horizontal winds



PhD project objectives

- Explore and document potential applications of minute-scale forecasts for wind energy
- Interface with forecast users and providers to survey existing practices and encourage community dialogue
- Perform field experiments to obtain observational data needed to build and evaluate remote sensing based forecast models
- Implement and test novel forecast methods using lidar observations which adhere to the constraints of real-time usage
- Benchmark the lidar forecast method’s skill to other commonly used methods
- Reflect on the potential benefits and drawbacks of a real-world fulfillment of such a system

Experiments introduction

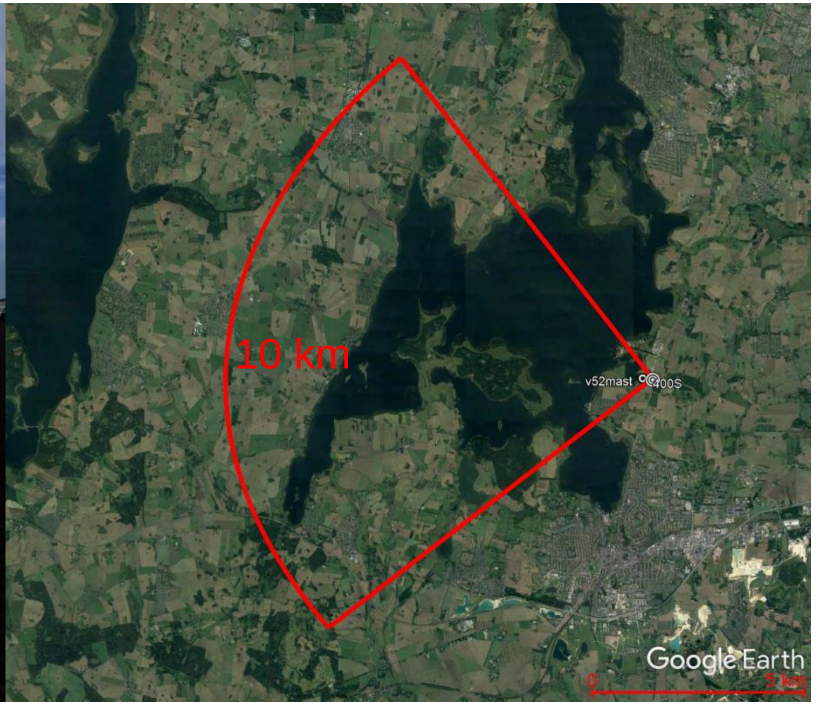
- Three field experiments performed using pulsed scanning lidars (DTU Long-Range WindScanners)
- All campaign data is released for public access (CC BY 4.0)
- Not a solo effort! Big thank you to everyone who contributed ☺

Experiment 1: WAFFLE

(Wind Analysis oF Fronts and Large Events)

WAFFLE experiment (Risø)

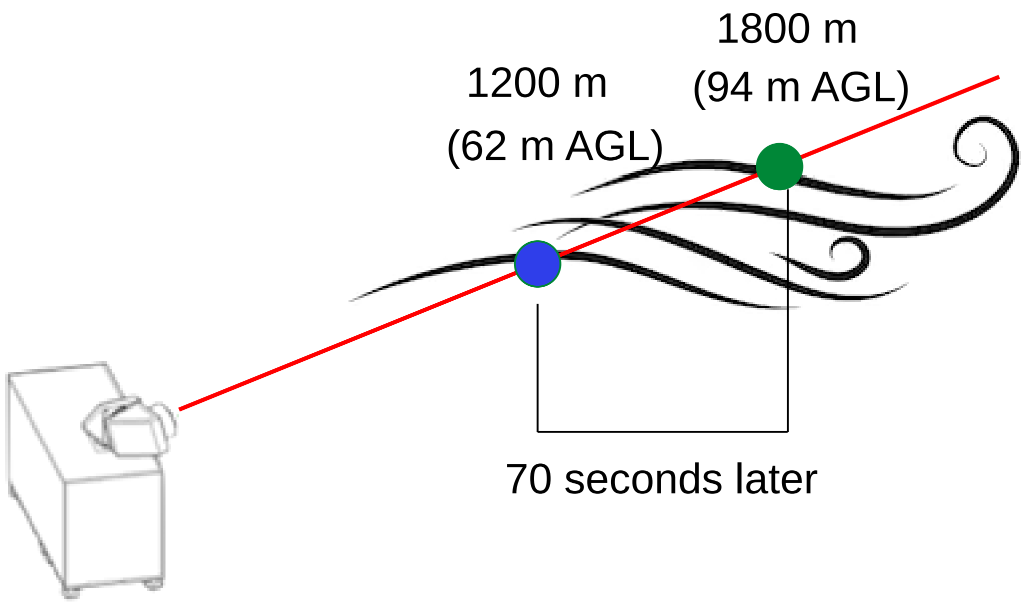
- Short feasibility study (3 weeks) for exploratory analysis and investigating advection based flow transport
- Single ground-based scanning lidar deployed, scanning upwind (west)
- Beam elevated at 3° to clear vegetation and intersect met-mast sensors



Data access: [Simon and Lea, 2019a]

WAFFLE methodology (1)

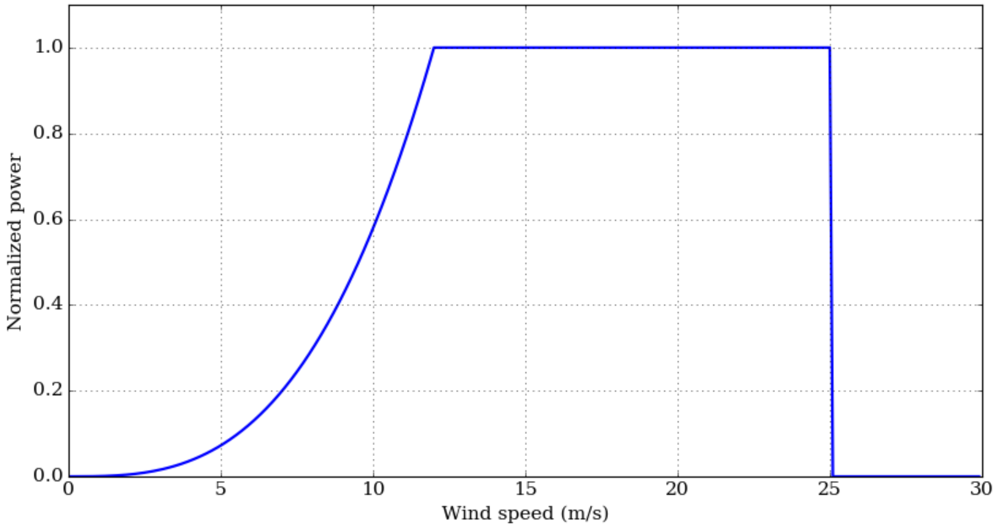
- Far point used to forecast wind speed at close point



- Forecast horizon of 70 s derived from mean advection time between positions

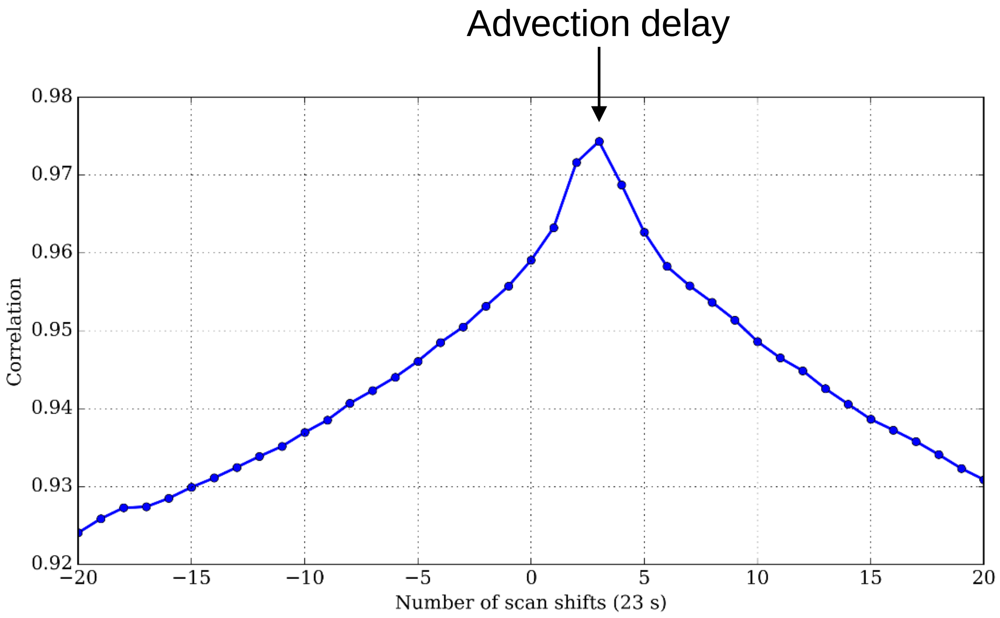
WAFFLE methodology (2)

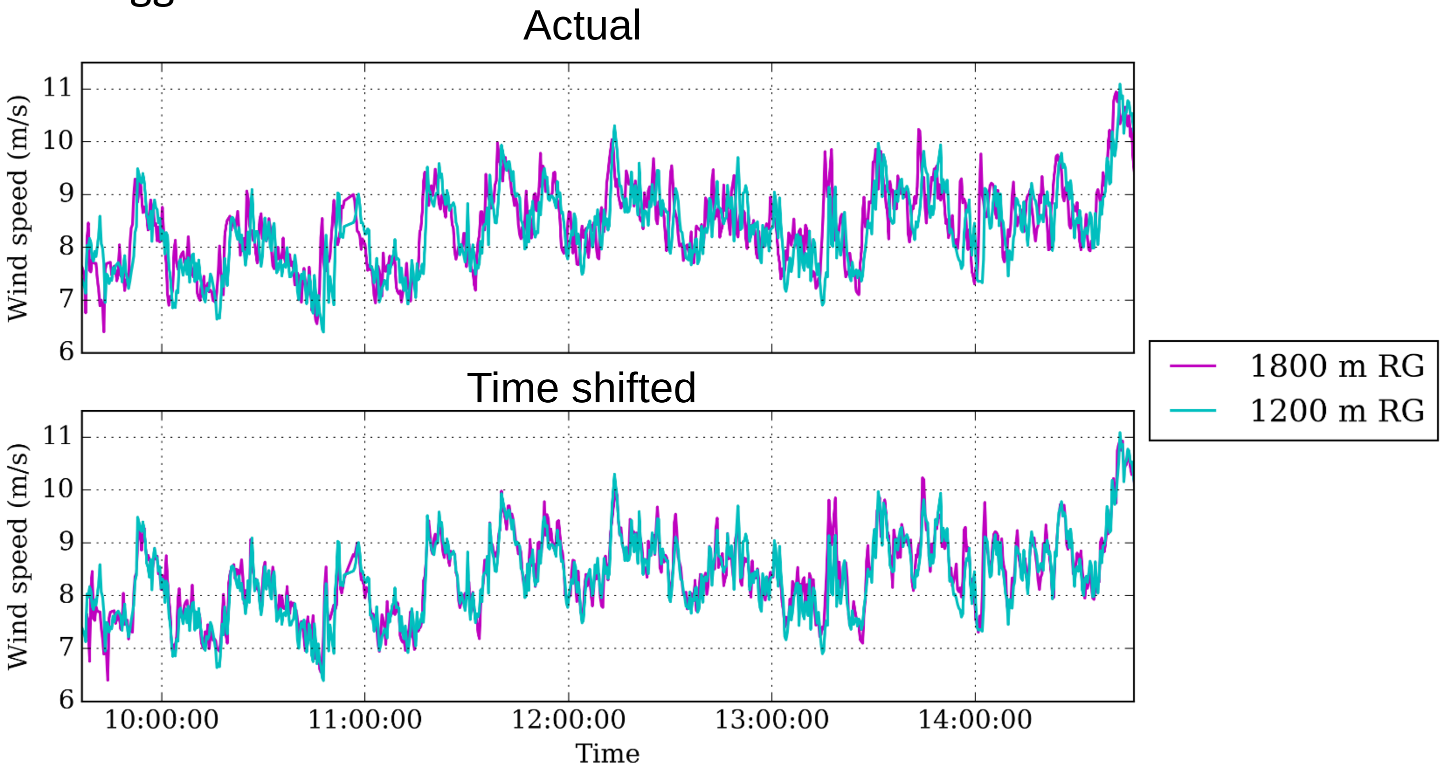
- Wind reconstruction performed using IVAP cosine fitting method (Liang, 2007)
- Measurements height-normalized using empirical wind profile power law (α=0.14)
  - (No inputs required beyond wind speed and height)
- 2-day period with neutral/near-neutral stability and westerly winds chosen
- Wind power transformation using generic power curve model



WAFFLE scan-shift method

- Upwind position at present time used to predict delayed downwind signal using time-of-flight
- Phase error apparent in time series and lagged cross-correlation





Performance evaluation metrics

- MAE (mean absolute error)

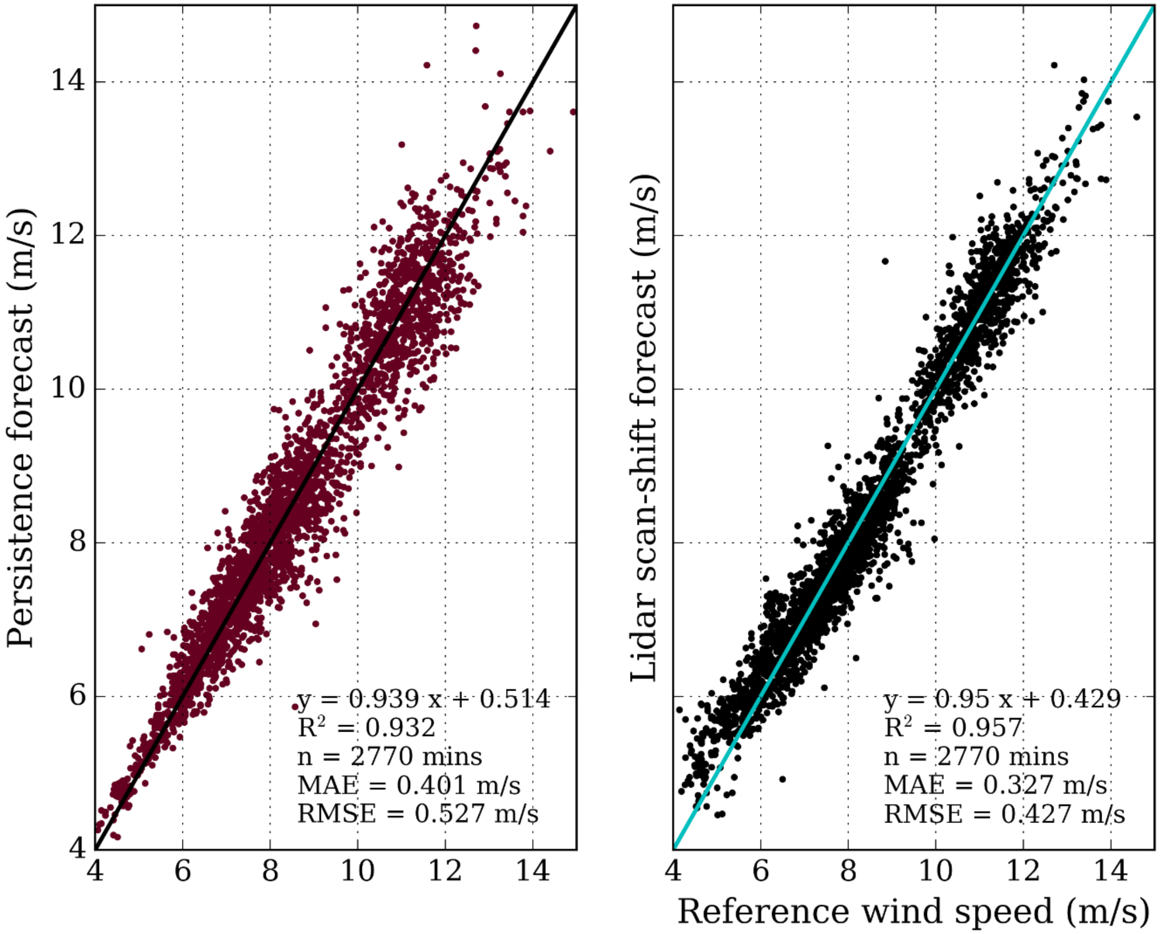
$$MAE(y,\hat{y}) = \frac{1}{n}\sum_{i=0}^{n-1}|y_i - \hat{y}_i|$$

- RMSE (root mean squared error)
  (larger errors are penalized disproportionately to smaller ones)

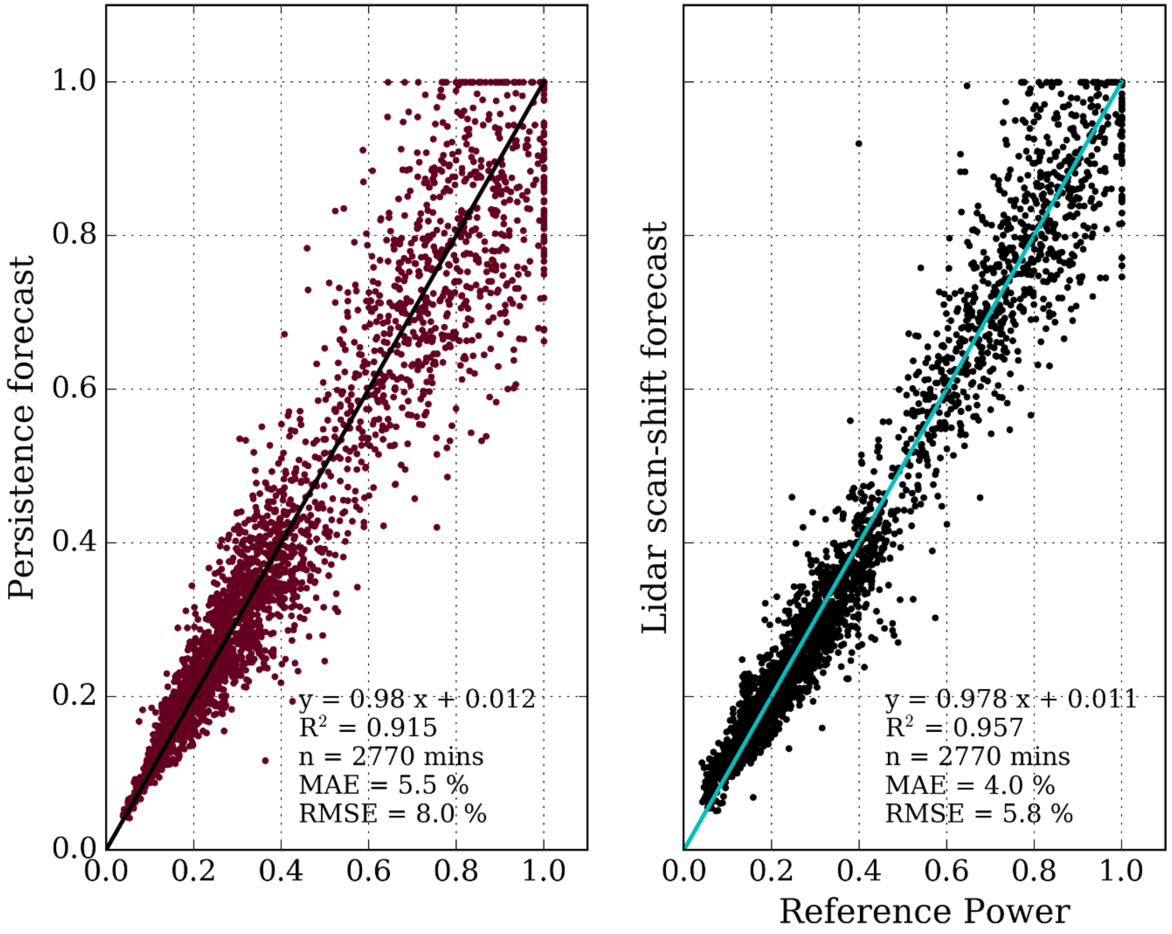
$$RMSE(y,\hat{y}) = \sqrt{\frac{1}{n}\sum_{i=0}^{n-1}(y_i - \hat{y}_i)^2}$$

- General linear model fit
  - Slope
  - Intercept
  - R^2 coefficient of determination

WAFFLE forecast evaluation (wind speed)



WAFFLE forecast evaluation (wind power)



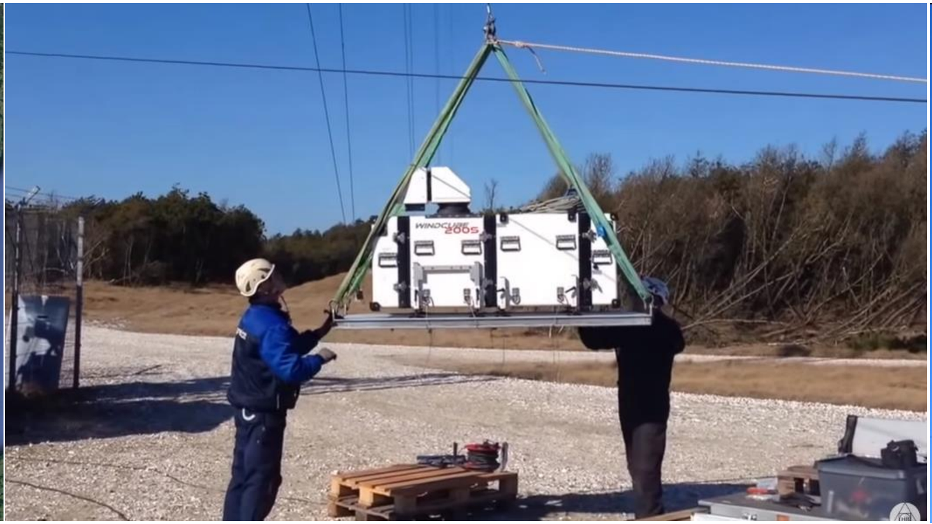
WAFFLE key results

- Scan-shift significantly outperforms persistence benchmark
- 20% (30%) improvement in RMSE for wind speed (power) forecast
- Persistence skill decreases as wind speed increases
- Inclined measurement plane is not ideal for correlating far distances and height normalization has limitations
  - Valldecabres (2018) would sympathize

Experiment 2: Østerild Balconies

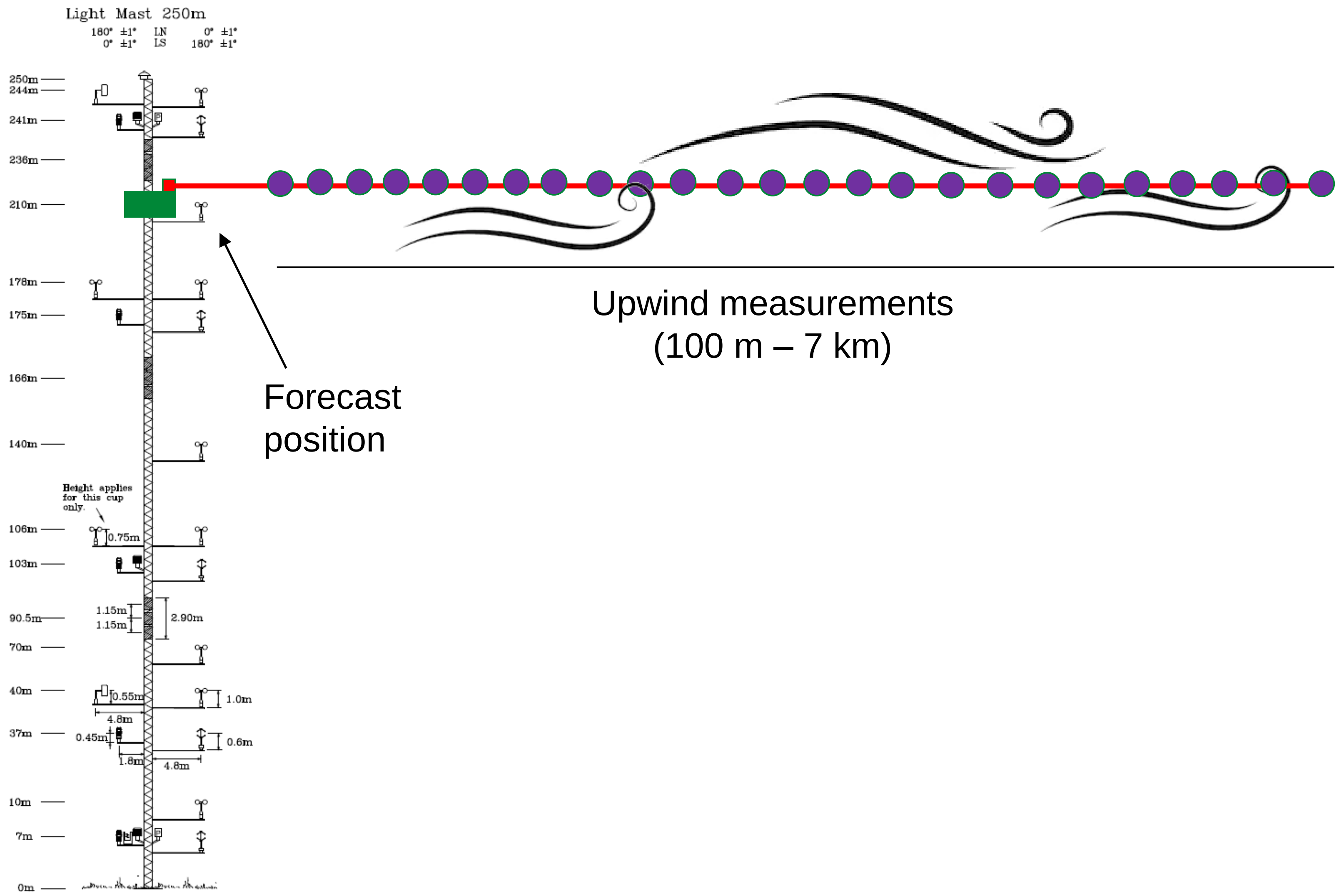
Balconies experiment (Østerild)

- Full scale (4 month) measurement campaign in coastal western Denmark
- Scanning lidars mounted at height to met-towers (50 m and **200 m** AGL)
- PPI scans provide 2D cross-sections of the horizontal wind field with no height change over distance




Data access: Simon and Vasiljevic, 2018

Balconies methodology

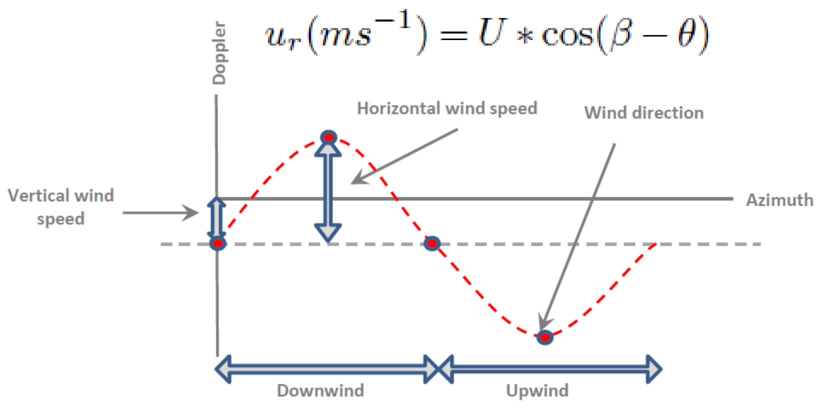


Upwind measurements
(100 m – 7 km)

Forecast
position

Balconies data processing

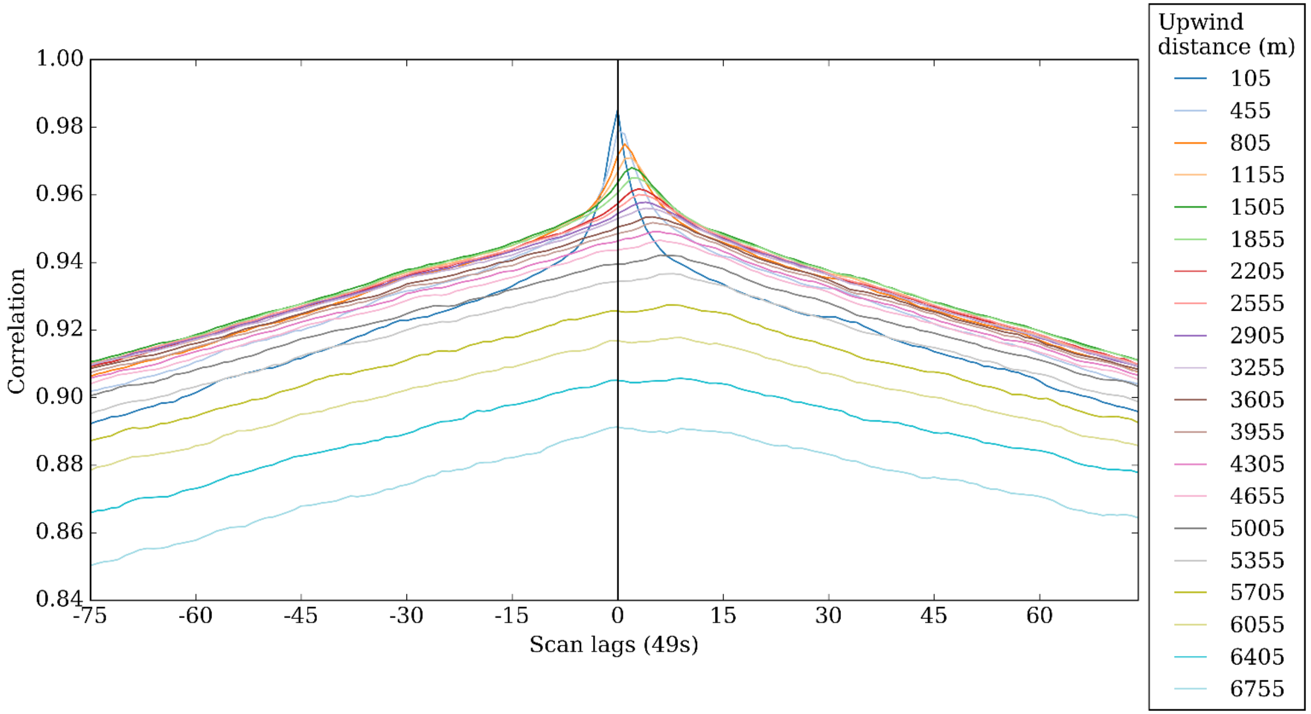
- Simple and quick wind retrieval method introduced

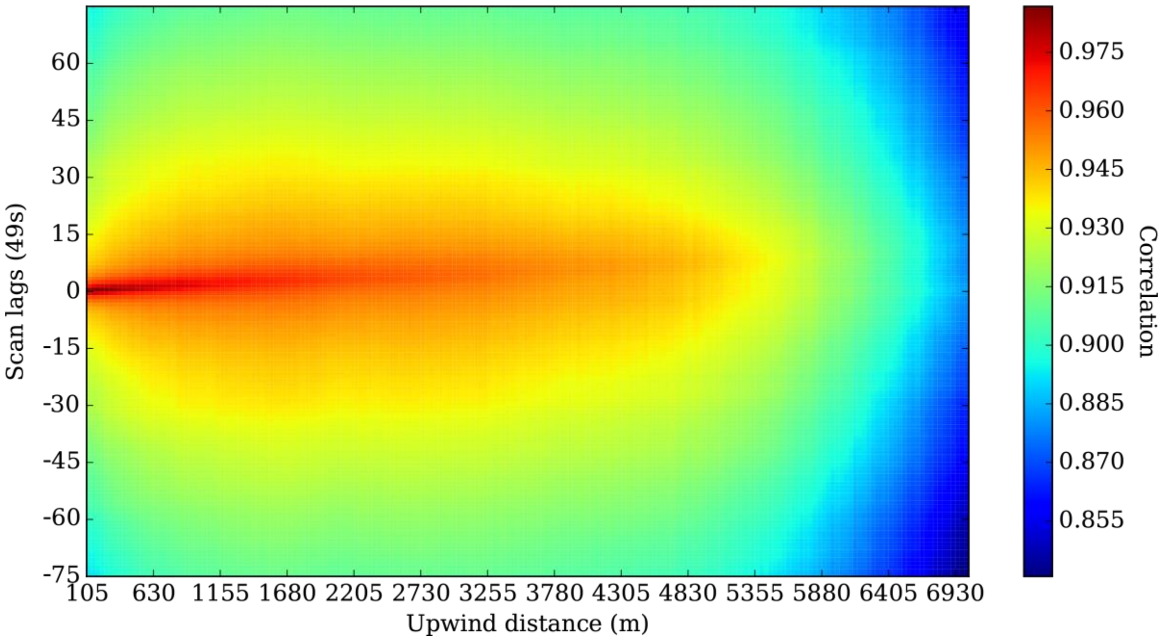


- Cup anemometer measurements from same height used as reference signal
- Sampling rate of both instruments matched using moving average
- Data sources synchronized to align timestamps

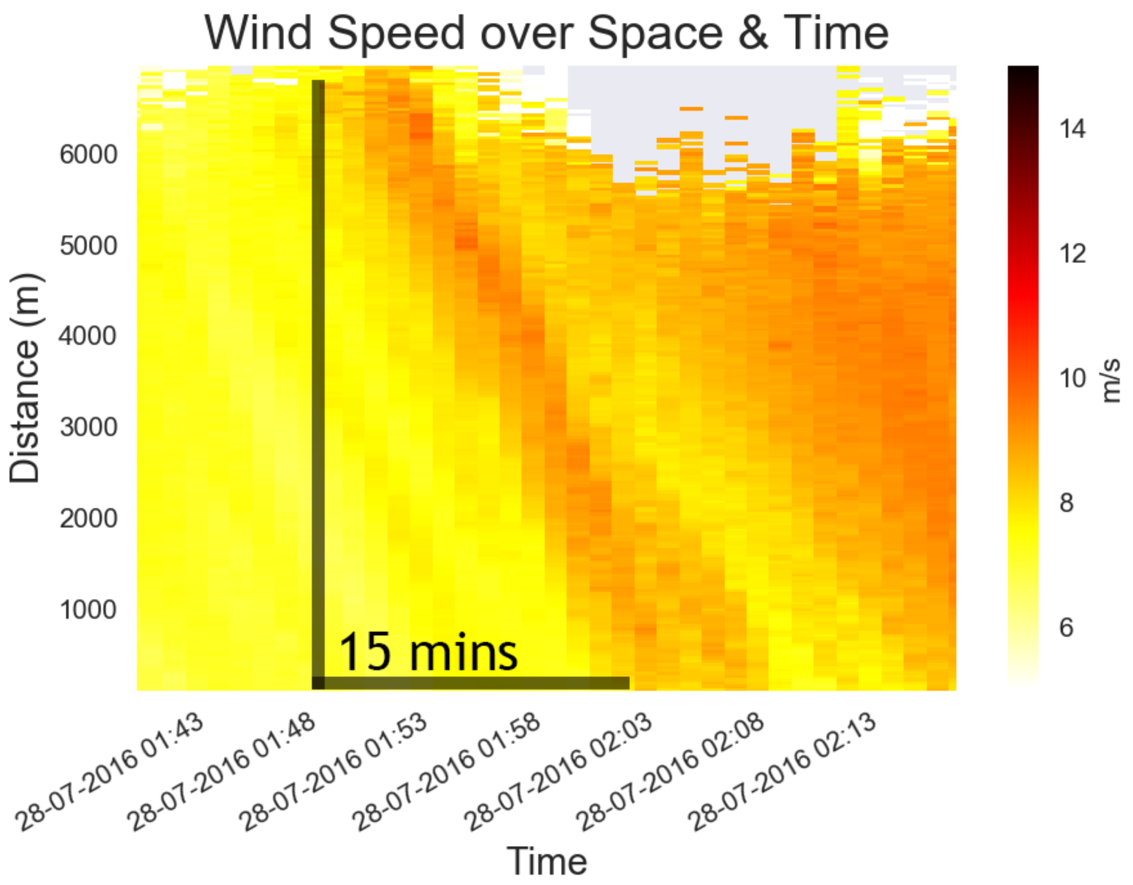
Balconies upwind space-time correlations (1)

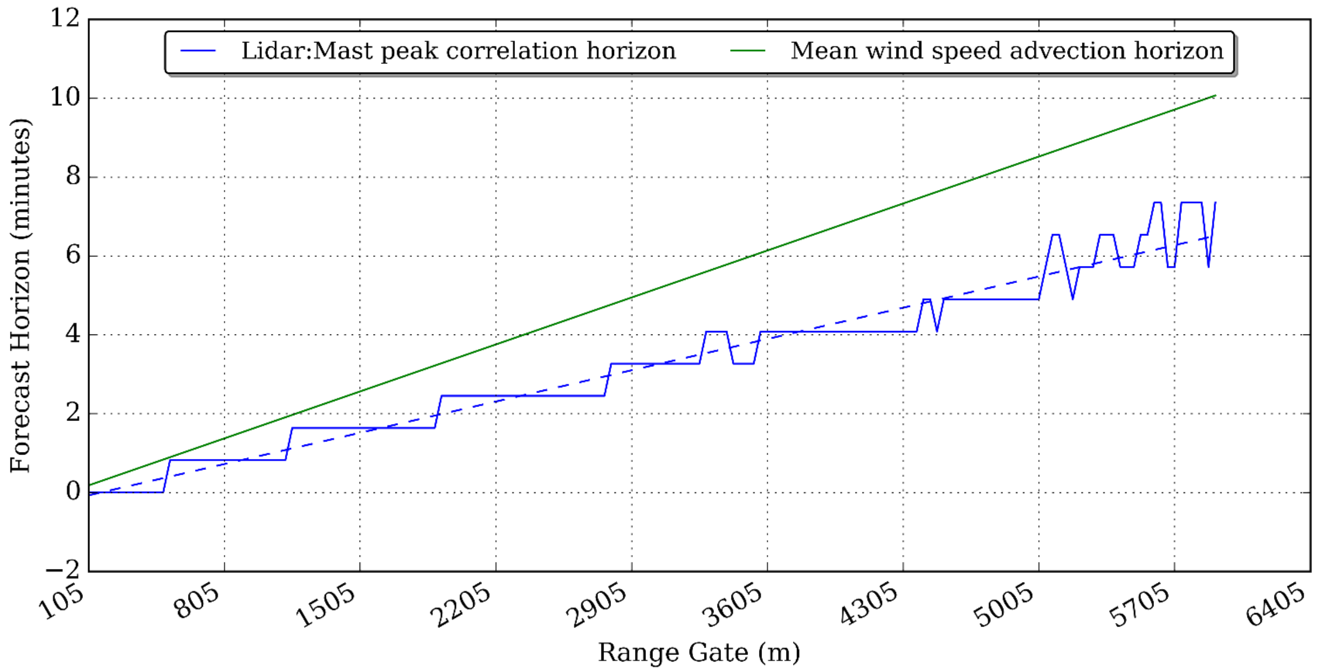
Upwind lidar measurements shifted and cross-correlated to reference signal





Balconies upwind space-time correlations (2)



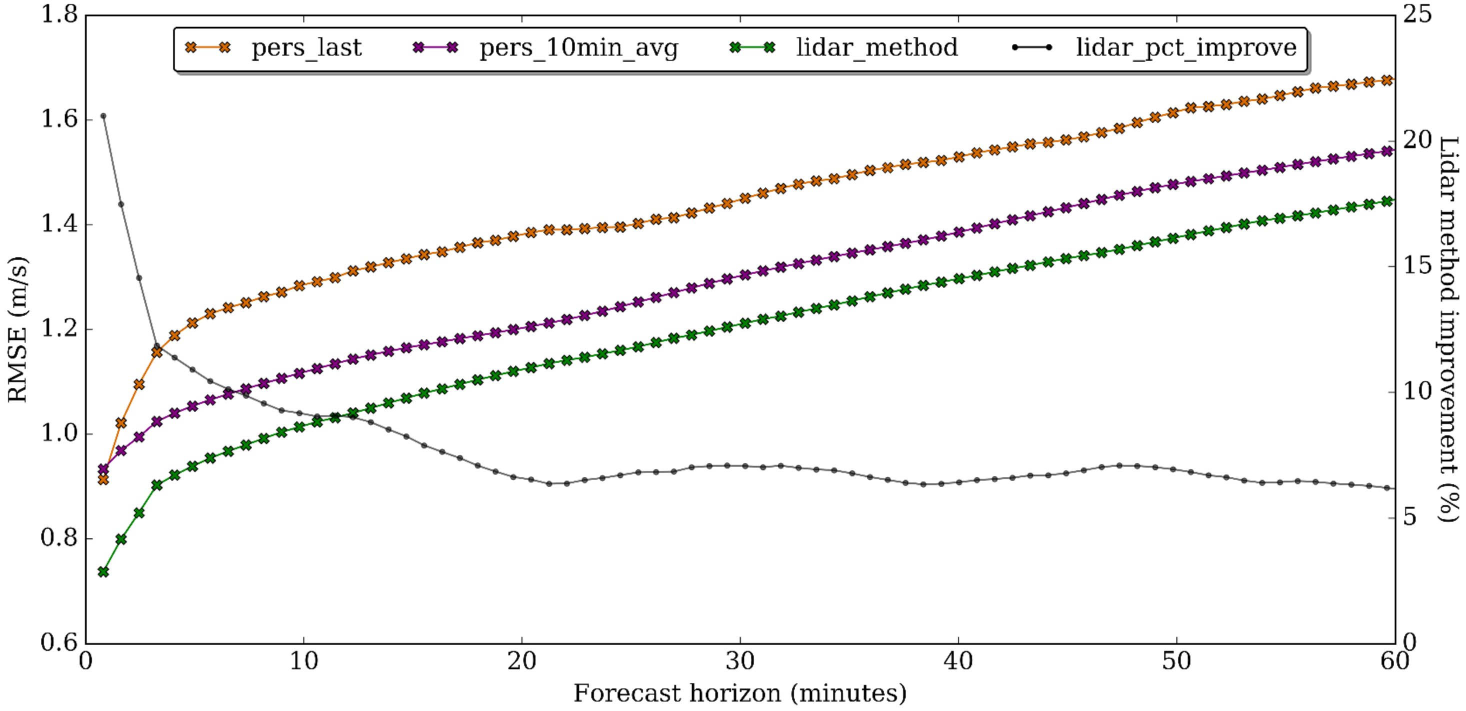


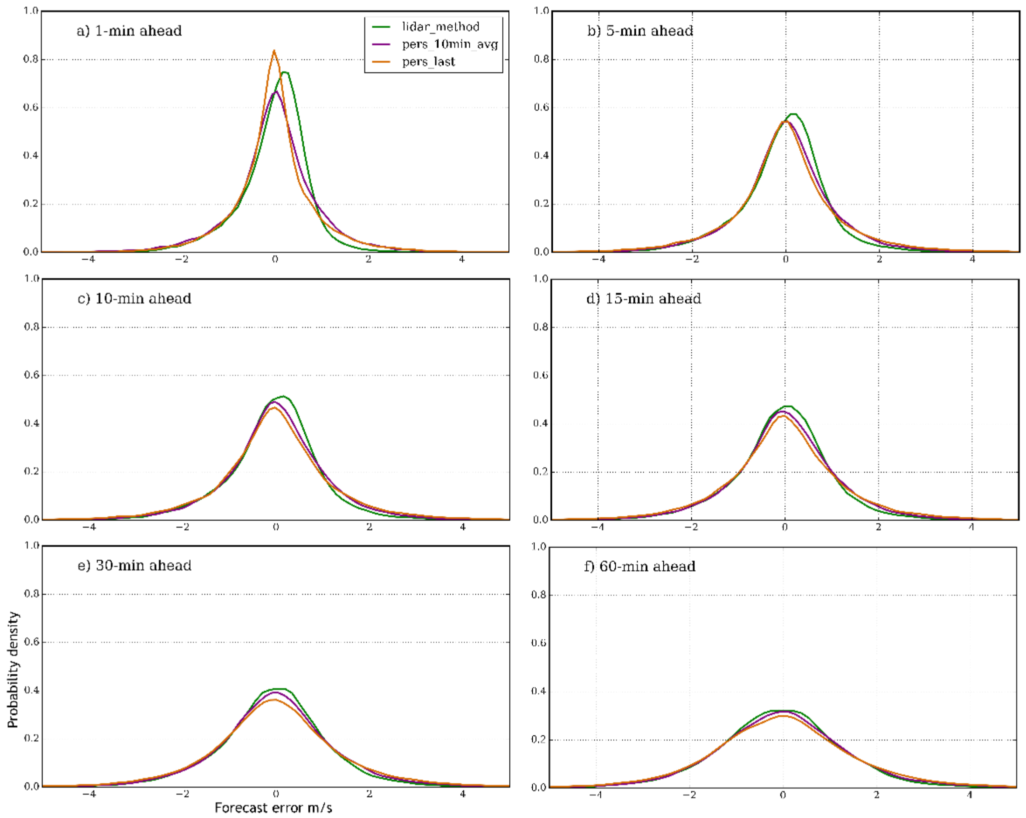
Balconies forecasting model

- Available lidar measurements (100 m - 7 km upwind scalar wind speeds) used to predict 1-60 min ahead wind speeds at met-mast
- Direct multi-step forecast model (separate models for each time step)
- Rolling walk-forward training and prediction architecture (assimilates latest observations to update model weights at each step)
- Optimization using Stochastic Gradient Descent Regression (SGDR)
  - Includes regularization penalty to perform feature selection and counter overfitting
  - Allows online learning (partial fitting to previously trained model)
  - Quick and suitable for very large datasets

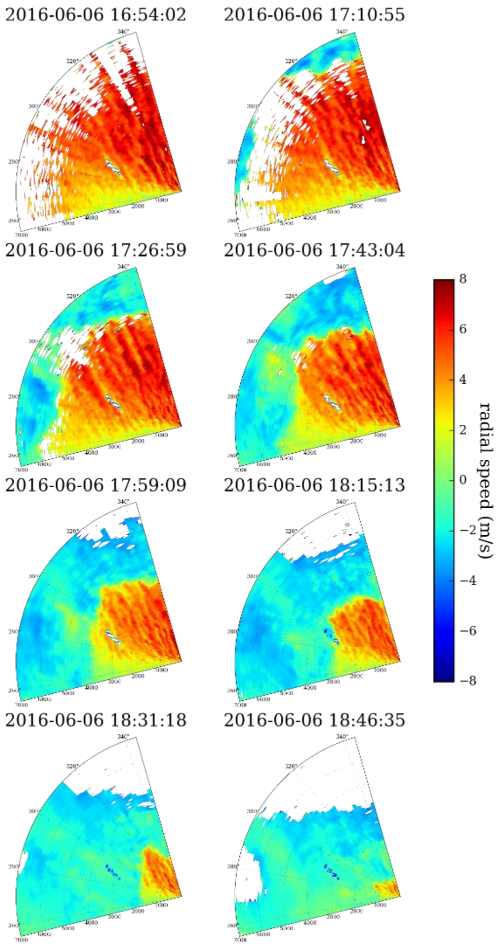
- All details and flowcharts in the thesis!

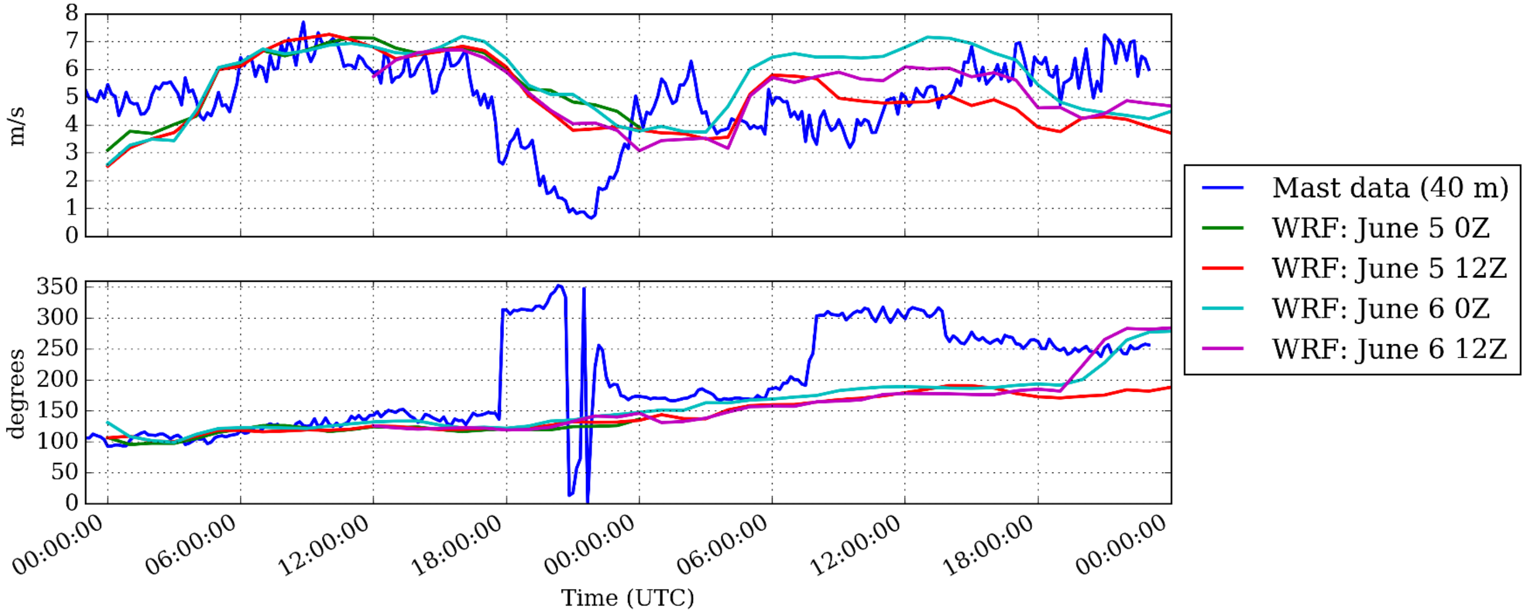
Balconies forecast evaluation





Balconies weather front event

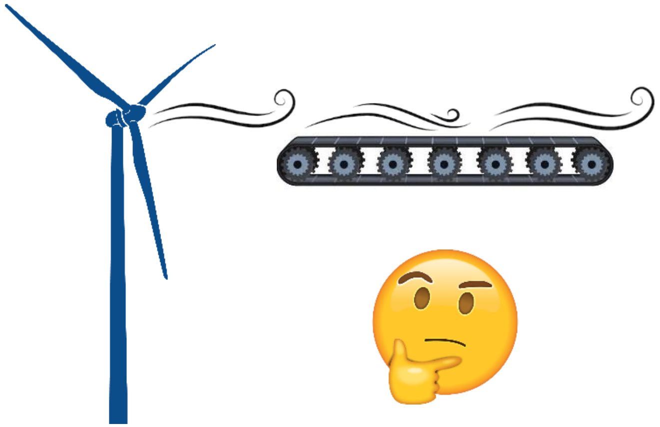




Balconies key results

- Horizontal scan configuration corrects prior measurement concerns
- Space-time correlations demonstrate sharp discernable peak up to 2-3 km upstream
- Theoretical and empirical wind field advection shows good agreement within this range
- RMSE reduction of 21% (1-min ahead), 11% (5-min), 9% (10-min), 7% (30-min), 6% (60-min) over (10-min average) persistence
- At least some coherent structures able to be seen and their propagation tracked

- But the atmosphere isn’t a 1-Dimensional conveyor belt!

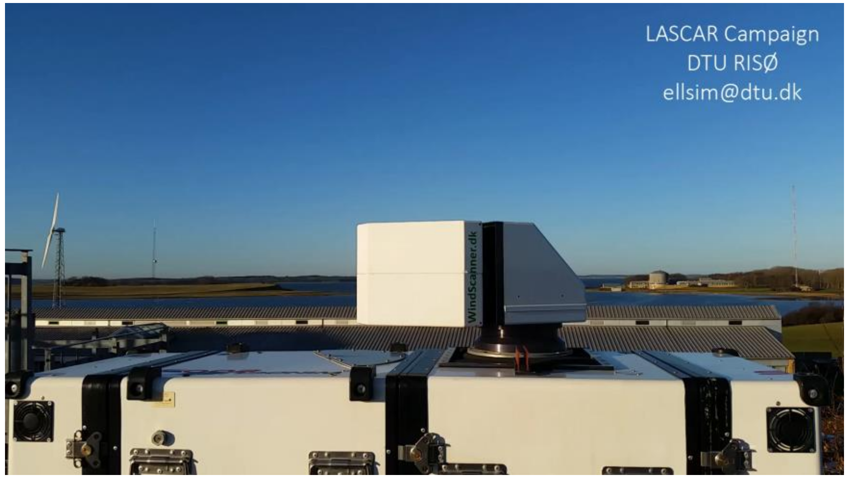


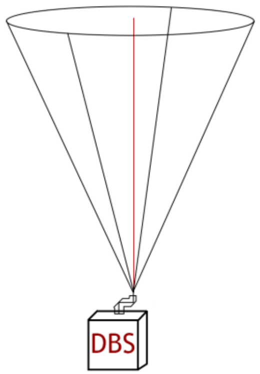
Experiment 3: LASCAR

(LASt Campaign At Risø)

LASCAR experiment (Risø)

- Full scale (4 month) measurement campaign along inland fjord
- Rooftop lidar performed rapid PPI scans up to 4 km
- Ground based lidar performed DBS profiling

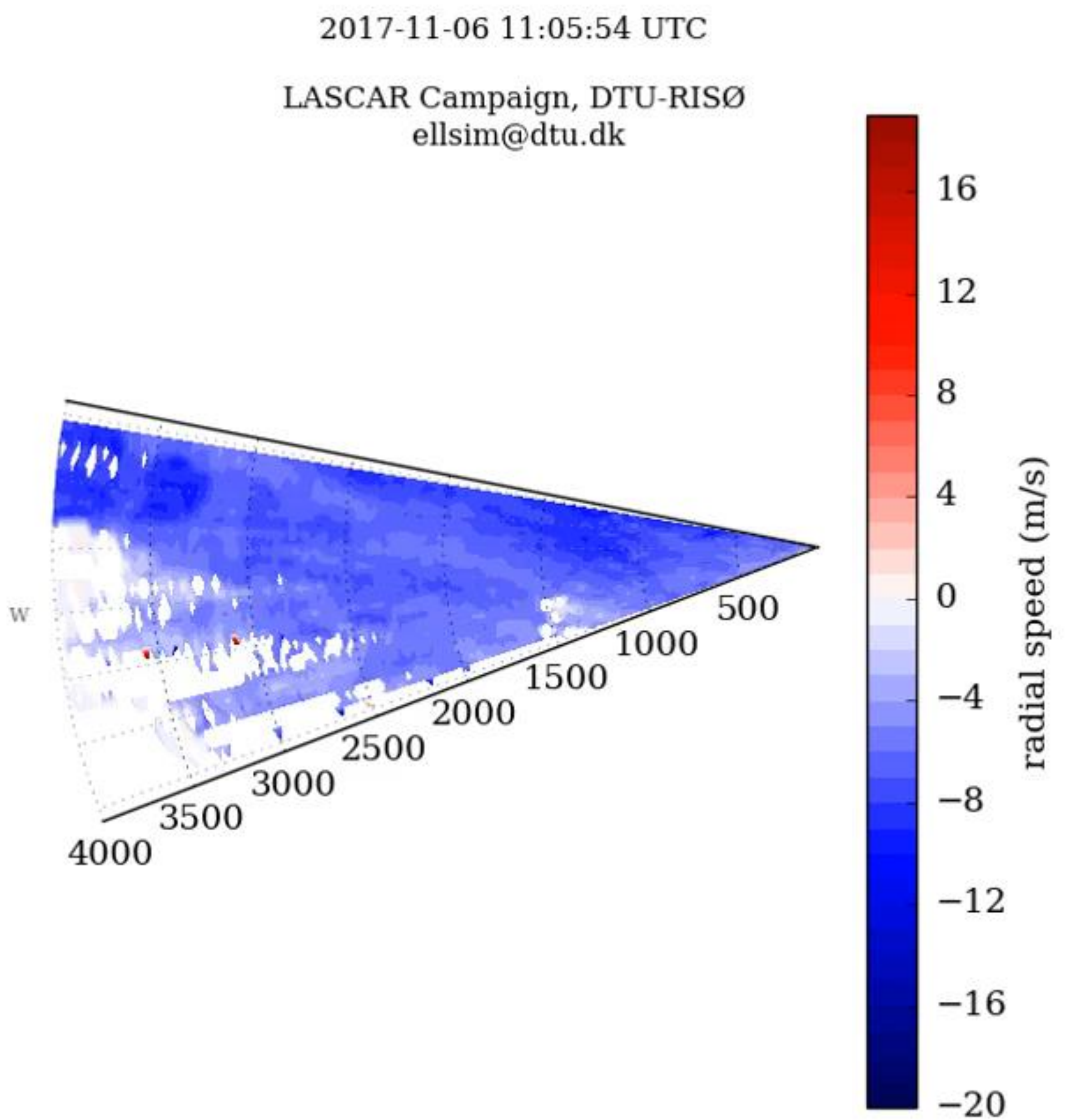




Data access: Simon and Lea, 2019b

LASCAR forecast approach

- Most spatial information is lost through wind reconstruction/retrieval
  - Can we preserve this?
- Investigate 2D space-time forecasting methods from computer vision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LASCAR Campaign, DTU-RISØ
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radial speed (m/s)

How can we apply this?

- Convolutional recurrent neural networks used for image sequence prediction (spatial features and time are key attributes)

- What does this look like in a real product?

Inspiration from computer vision

LASCAR forecast model (1)

- 2-D convolutional LSTM neural network
- Same online learning approach as before
- Trained on Google Cloud Compute instance (1x Tesla P100 GPU) using tensorflow

- Sequence of last 5-mins of upwind PPI scans used to forecast following 5-mins conditions at downstream position (DBS lidar profiles)
- Multiple output strategy (one model for all time steps)
- Wind vectors (u and v) are output to give both speed and direction predictions
- Benchmarked against persistence, ARI(5,1) and ARIMA(5,1,1) models

LASCAR forecast model (2)

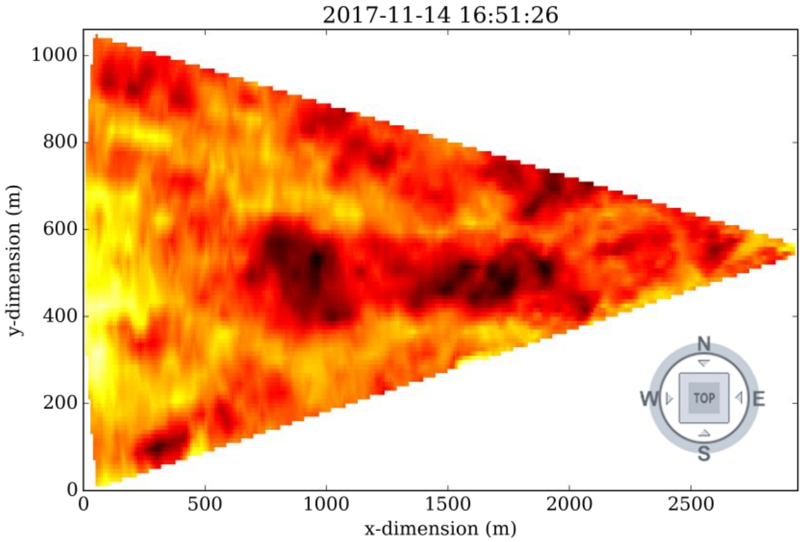
- 12 hour continuous period with inflow direction
- Re-projected polar to Cartesian coordinates
- Scaled values (0-1) according to:

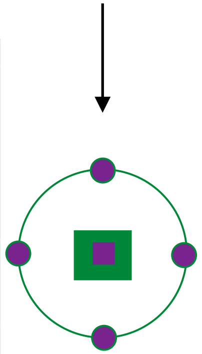
$$X_{\max} = \overline{X} + 4\sigma_X^2$$

$$X_{scaled} = \frac{X - X_{\min}}{X_{\max} - X_{\min}}$$

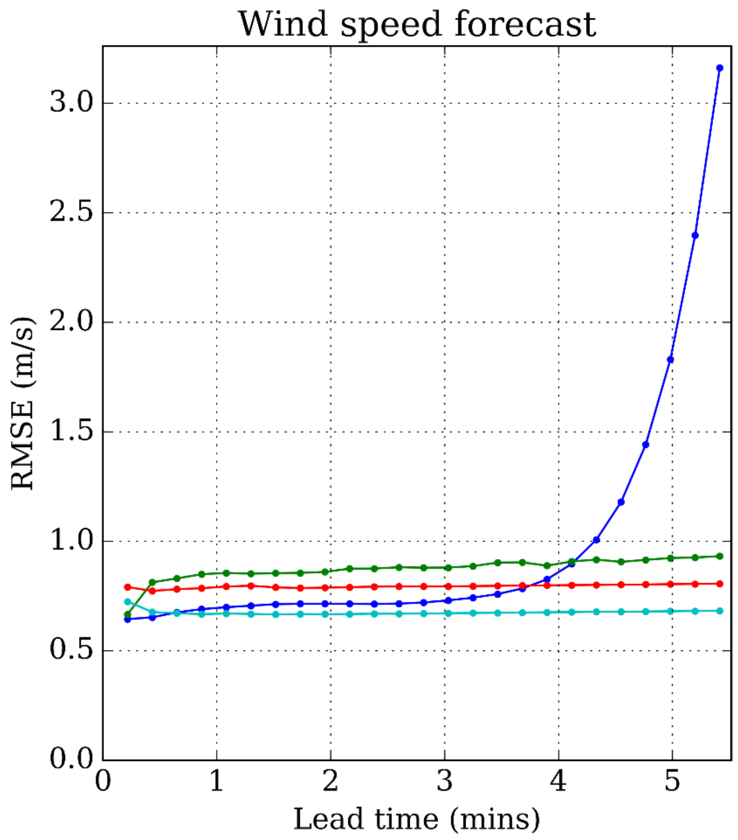
Upwind measurements (2-D)
80 m – 3 km

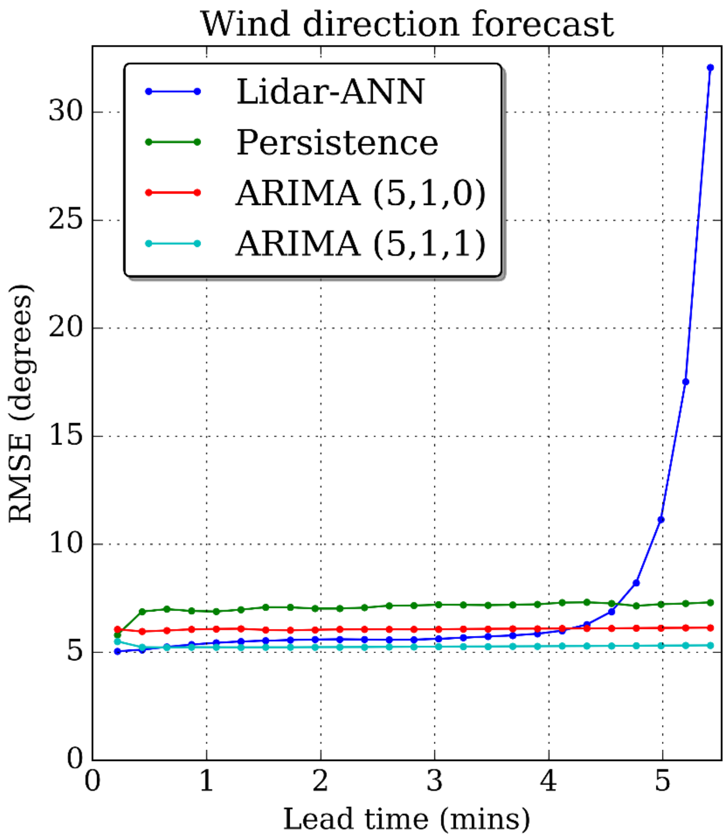
Forecast position





LASCAR forecast evaluation





Lead time (mins)	Relative improvement of Lidar-ANN model compared with:					
	Wind speed			Wind direction		
	Persistence (%)	ARIMA (5,1,0) (%)	ARIMA (5,1,1) (%)	Persistence (%)	ARIMA (5,1,0) (%)	ARIMA (5,1,1) (%)
0.22	3.30	18.53	11.10	13.09	16.89	8.41
0.43	19.68	15.60	3.57	25.65	14.15	2.22
0.65	18.71	13.58	-0.57	25.05	12.71	-0.44
0.87	18.77	12.16	-3.47	22.56	11.66	-2.29
1.08	18.35	11.94	-4.26	21.05	10.54	-3.97
1.30	17.17	11.45	-5.70	21.13	9.70	-5.15
1.52	16.62	9.71	-6.97	21.88	8.24	-5.86
1.73	16.50	9.15	-7.07	21.41	7.54	-6.43
1.95	16.96	9.37	-7.12	20.42	7.45	-6.75
2.17	18.37	9.61	-7.05	20.28	7.53	-6.90
2.38	18.51	10.00	-6.67	20.87	7.78	-6.64
2.60	18.86	9.92	-6.90	22.09	8.04	-6.26
2.82	18.09	9.26	-7.54	22.05	7.88	-6.29
3.03	17.04	8.08	-8.73	21.97	7.35	-6.91
3.25	16.26	6.64	-10.45	21.18	6.64	-7.77
3.47	15.91	4.70	-12.75	20.27	5.85	-8.75
3.68	13.21	1.67	-16.27	19.73	5.07	-9.61
3.90	7.00	-3.43	-22.32	18.89	3.91	-10.93
4.12	1.20	-12.17	-32.62	17.80	1.61	-13.53
4.33	-9.94	-25.84	-48.69	14.10	-2.89	-18.77
4.55	-30.19	-47.14	-73.88	5.25	-12.62	-29.98
4.77	-57.58	-79.64	-112.31	-14.97	-34.33	-55.07
4.98	-98.38	-127.87	-169.25	-54.31	-82.12	-110.15

LASCAR key results

- Space-time features from sequences of PPI scans applied in forecasting model
- Coherent patterns retain discernable features up to 3 km and up to 5-minutes ahead
- ANN-lidar method outperformed 2/3 benchmarks (persistence & ARI(5,1))
- ANN-lidar method performed best up to 30s ahead
- Similar performance gains over persistence to previous study (18% lower RMSE)
- ARIMA(5,1,1) model performs remarkably well!

Outlook and broad conclusions

- We **can** do better than persistence (at least in simple terrain)
  - Order of 20% to 5% RMSE improvement, depending on lead time
- Lidar regression models may not deliver broad overall value compared with time series models using ‘free’ existing data
  - Measure and save high-frequency data!
- Real value of lidar forecasting system lies in detecting large scale events where NWP misses entirely, or gets the scale and timing wrong
- Advection assumption likely only holds in simple terrain / offshore
  - WESC 2019: Ines Würth
    Experiences, Challenges and Opportunities of Lidar-Based Minute-Scale Forecasting in Complex Terrain

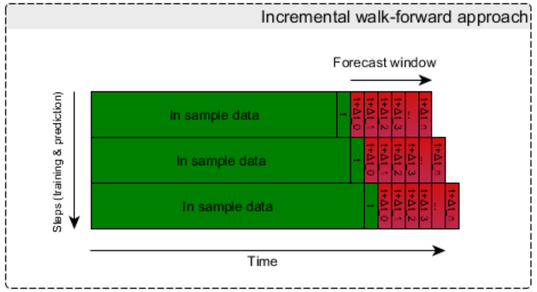
Thank you for joining!

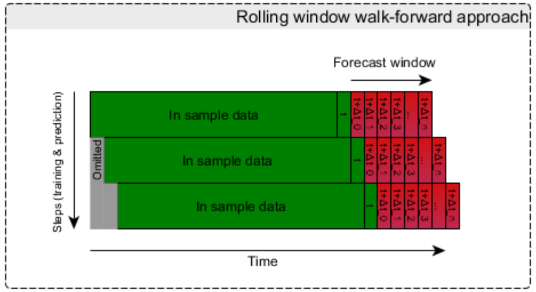
Please get in touch if you have anything to discuss:

Elliot Simon <ellsim@dtu.dk>

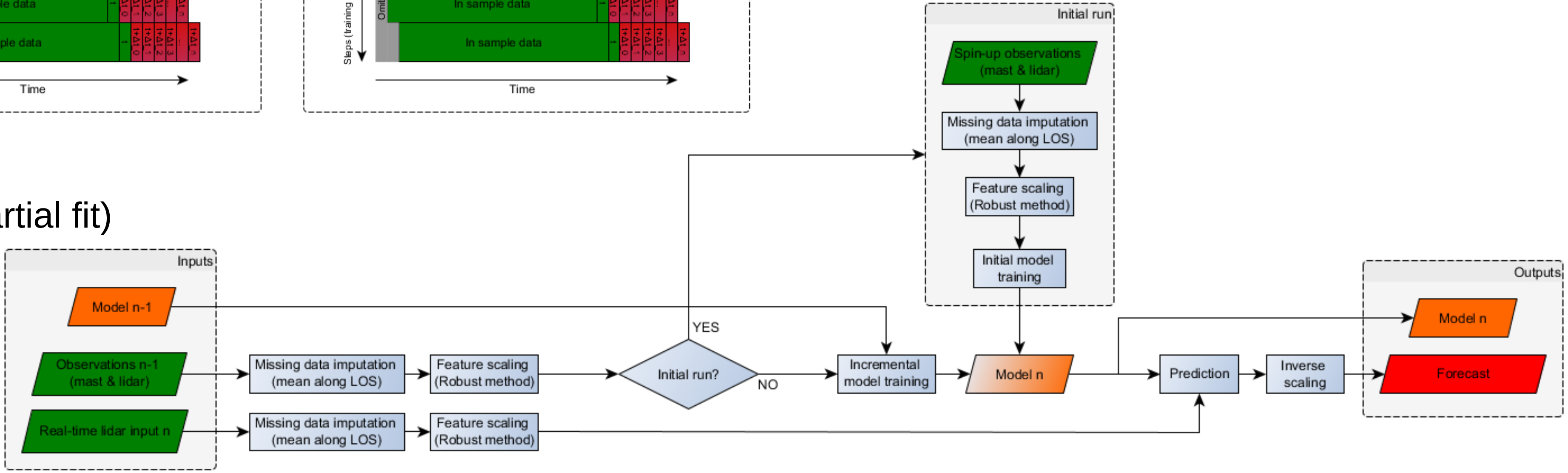
Balconies

Data flowchart

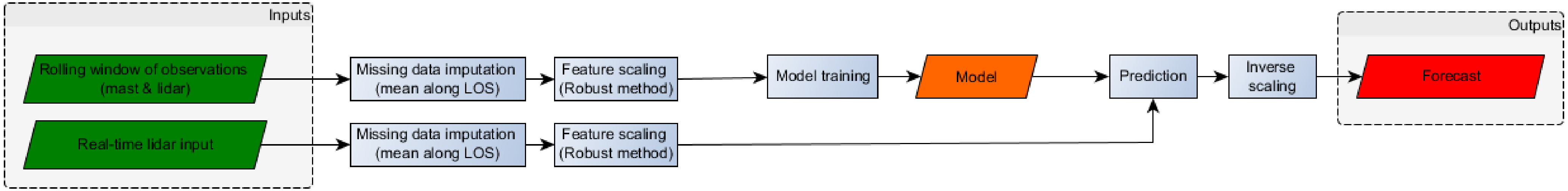




Forecast model (partial fit)

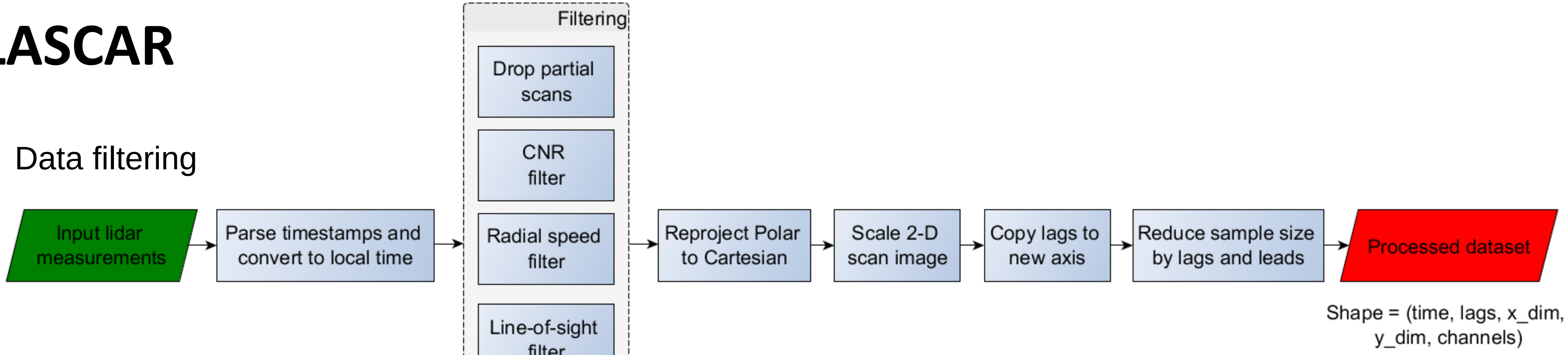


Forecast model (rolling re-training)

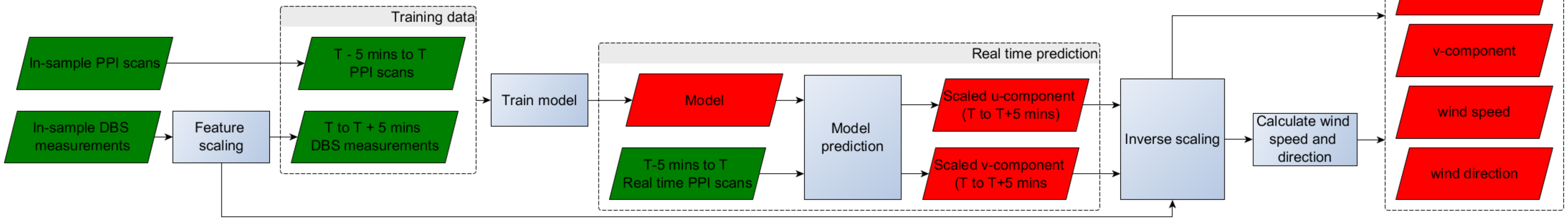


LASCAR

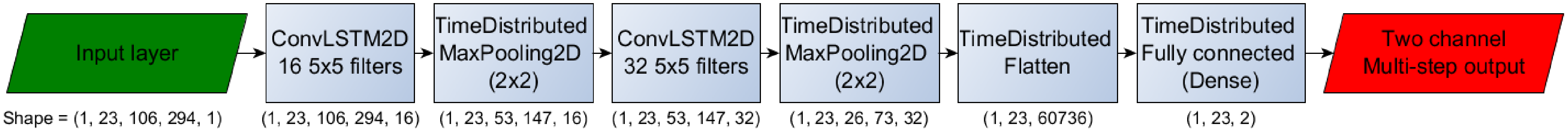
Data filtering



Model implementation



Neural network architecture



Practical recommendations

- Measure inflow with lowest elevation angle possible
- Simplified application specific instrument (e.g. long-range fixed beam adaptation)
- Use only 1 system (no dual/triple Doppler)
- Use radial speeds directly, or simple wind retrieval methods
- Faster sampling rate is more important than spatial resolution
- Use dynamic filtering to increase data availability

Extensions of this work

- Use real-time inflow measurements to correct pre-run NWP forecasts
- Develop classification system for identifying and tracking large-scale events
- Integrate upstream measurements into wind farm flow models
- Dynamically adapt scan pattern depending on conditions
- Include uncertainty estimates for probabilistic output
- Extend measurement range (e.g. up to 30 km with LMWT or SmartWind radar)