Detection of Wind Turbine Contamination with a Convolution Neural Network

Nawal Husnoo[a], Timothy Darlington[a], Sebastiàn Torres[b], David Warde[b]

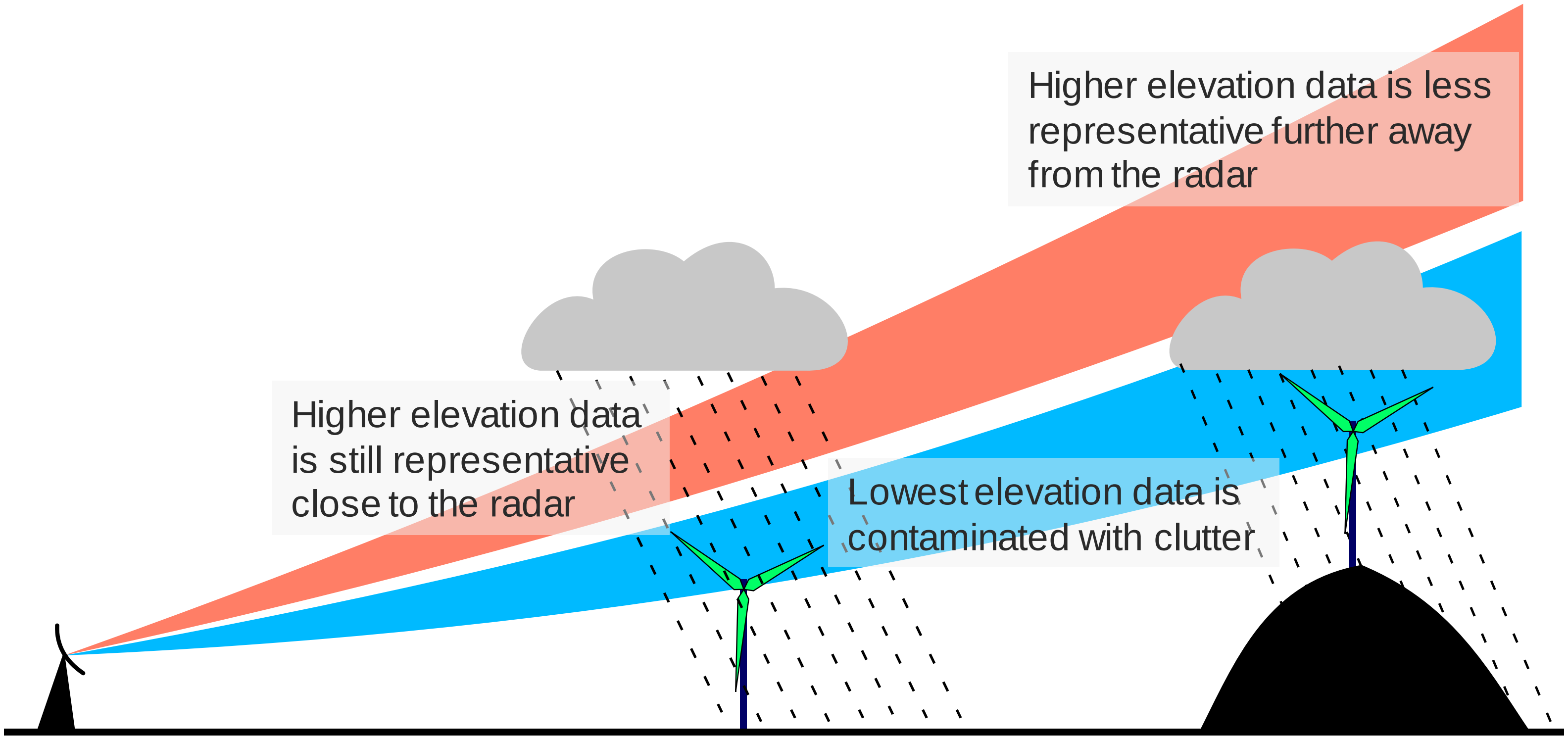
[a]Met Office

[b] Cooperative Institute for Severe and High-Impact Weather Research and Operations (CIWRO), The University of Oklahoma and NOAA/OAR National Severe Storms Laboratory

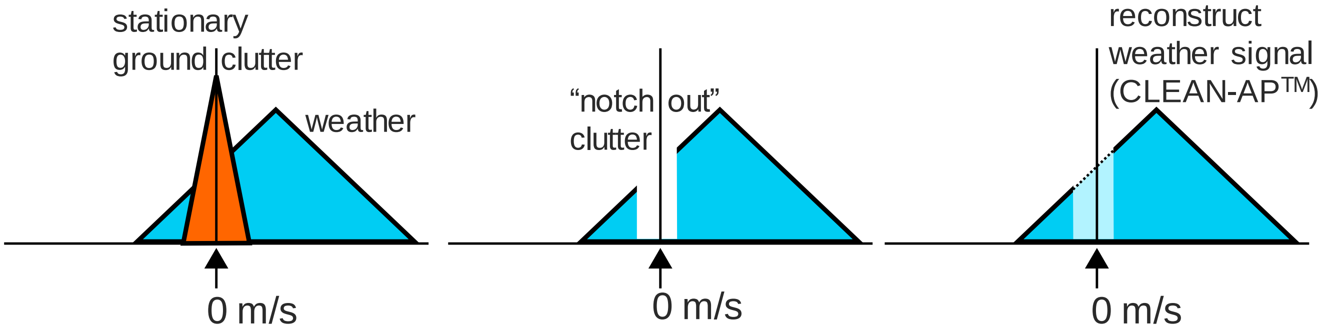
Introduction

- Wind turbines – part of the solution for renewable energy
- Growing threat to weather radar data quality
- Typical dual-pol quality control approach struggles with WT
- Doppler filters work for stationary clutter but often fail with WT
- I will describe our ***previous work on switching the Doppler filter on/off dynamically*** for stationary ground clutter
- I will then discuss our ***current work*** on using spectral dual-polarisation parameters to ***detect and flag wind turbines dynamically***

Lowest elevation data is better

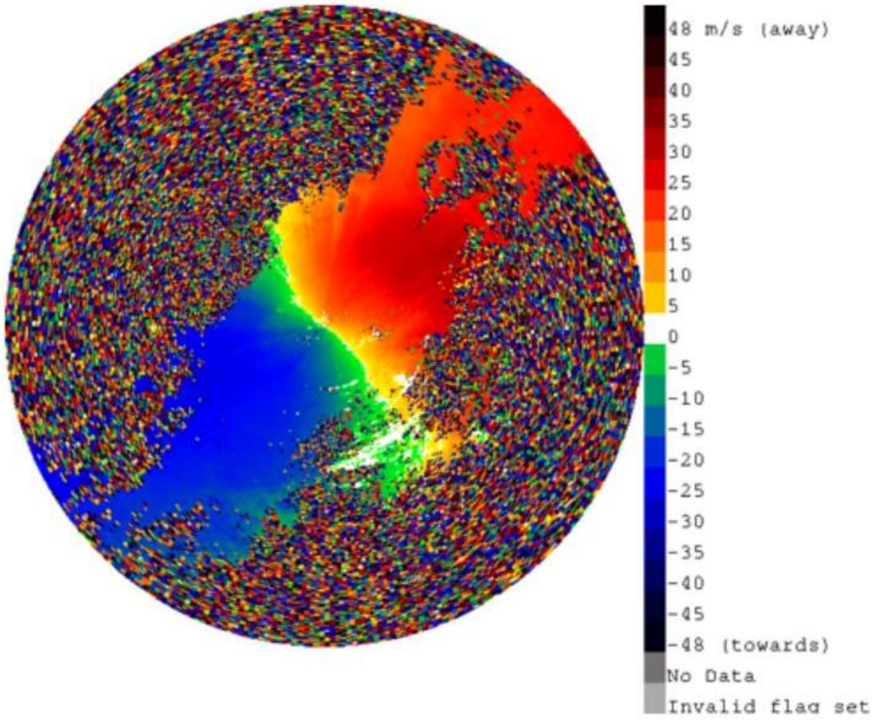


Doppler filtering of stationary ground clutter



Automatic detection and removal of ground clutter contamination on weather radars, Warde & Torres (2009)
http://cimms.ou.edu/~torres/Documents/Radar%20Conference%202009.pdf

Doppler filtering doesn't always work

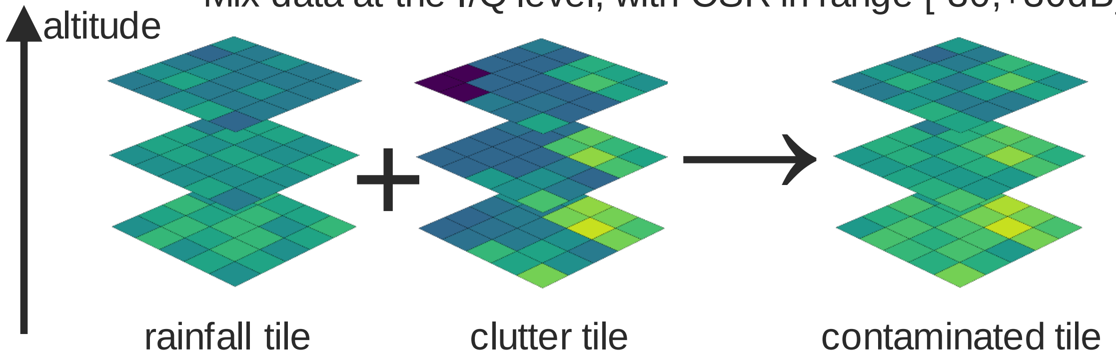


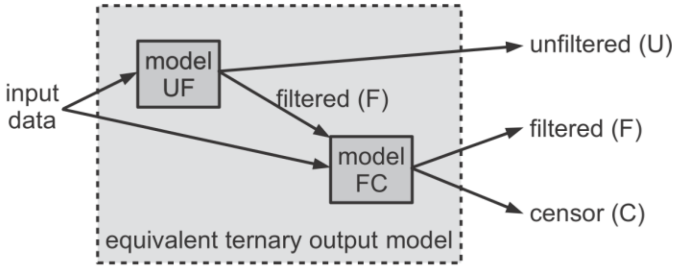
Previous work

Dynamic switching of CLEAN-AP(TM)

Previous work – unfiltered/filtered/censor

Mix data at the I/Q level, with CSR in range [-30,+30dB]



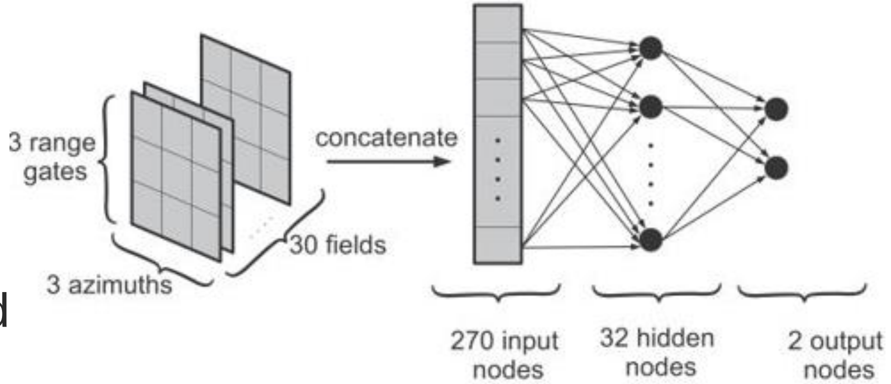


Dataset	# tiles
Training	30,658
Validation	30,933
Testing	31,074

Husnoo et al. (2021) - A Neural Network Quality-Control Scheme for Improved Quantitative Precipitation Estimation Accuracy on the U.K. Weather Radar Network, Jtech, Vol 38, issue 6, pp1157–1172

Previous work: Inputs to the neural network

- 30 gate-averaged parameters (see paper for details)
- noise-scaled uncalibrated abs autocorrelations (lag0, lag1)x(H,V)x(unfiltered,filtered)
- Notch width as estimated by CLEAN-AP(TM)
- RhoHV
- PhiDP and angles of lag1 autocorrelations included as (sin,cos)
- Circular variance of autocorrelations (lag0,lag1,cross lag0)
- Small spatial window – used fully connected dense neural networks,,,,,,,,,,,l;'



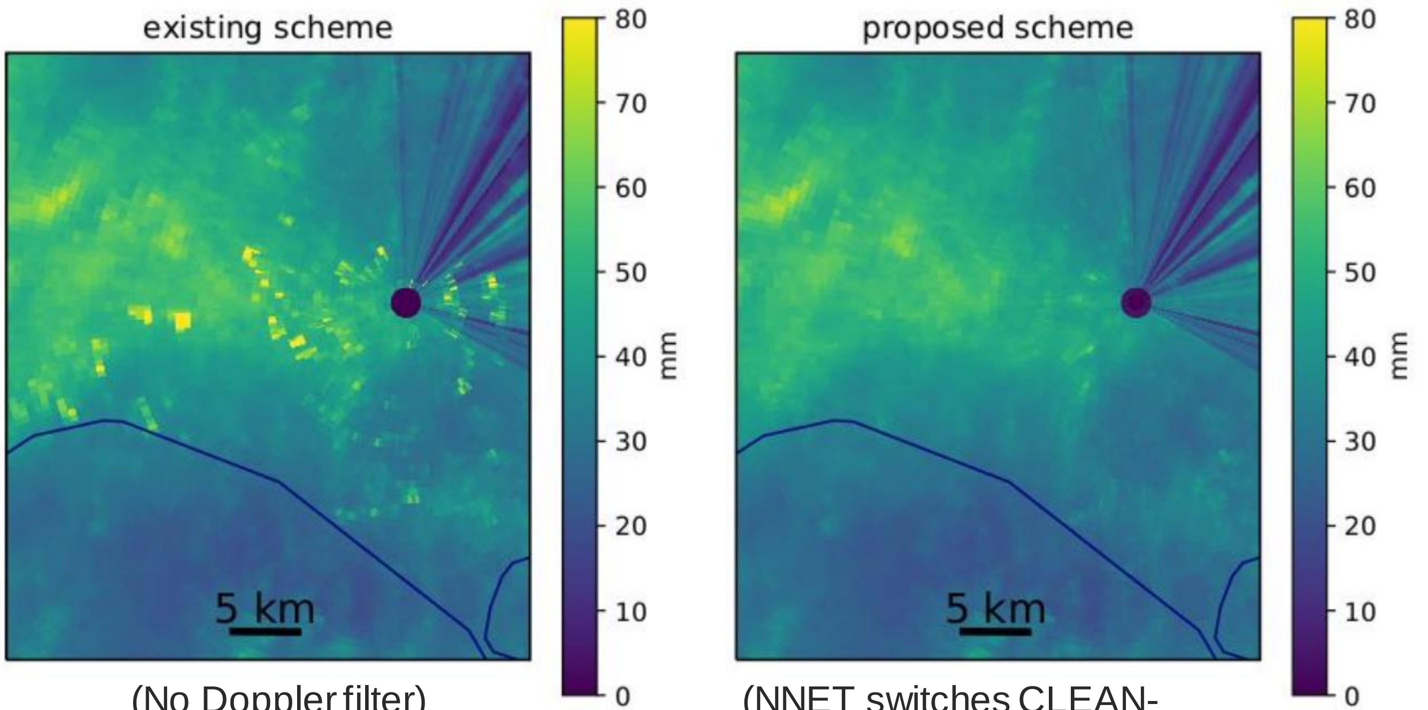
$$\boxed{\begin{array}{c} 10\log_{10}[R^f_{\mathrm{H}}(0)/N_{\mathrm{H}}] \\ 10\log_{10}[R^f_{\mathrm{V}}(0)/N_{\mathrm{V}}] \\ 10\log_{10}[|R^f_{\mathrm{H}}(1)|/N_{\mathrm{H}}] \\ 10\log_{10}[|R^f_{\mathrm{V}}(1)|/N_{\mathrm{V}}] \end{array}}$$
$$\boxed{\begin{array}{c} 10\log_{10}[R^u_{\mathrm{H}}(0)/N_{\mathrm{H}}] \\ 10\log_{10}[R^u_{\mathrm{V}}(0)/N_{\mathrm{V}}] \\ 10\log_{10}[|R^u_{\mathrm{H}}(1)|/N_{\mathrm{H}}] \\ 10\log_{10}[|R^u_{\mathrm{V}}(1)|/N_{\mathrm{V}}] \end{array}}$$
$$Q/n$$
$$10\log_{10}[R^u_{\mathrm{H}}(0)/R^f_{\mathrm{H}}(0)]$$
$$10\log_{10}[R^u_{\mathrm{V}}(0)/R^f_{\mathrm{V}}(0)]$$
$$-\log_{10}(1-\rho^u_{\mathrm{HV}})$$
$$-\log_{10}(1-\rho^f_{\mathrm{HV}})$$

$$\cos\phi^u_{\mathrm{dp}}$$
$$\sin\phi^u_{\mathrm{dp}}$$
$$\cos\phi^f_{\mathrm{dp}}$$
$$\sin\phi^f_{\mathrm{dp}}$$
$$\boxed{\begin{array}{c} \cos\{\arg[R^u_{\mathrm{H}}(1)]\} \\ \sin\{\arg[R^u_{\mathrm{H}}(1)]\} \\ \cos\{\arg[R^u_{\mathrm{V}}(1)]\} \\ \sin\{\arg[R^u_{\mathrm{V}}(1)]\} \end{array}}$$
$$\boxed{\begin{array}{c} \cos\{\arg[R^f_{\mathrm{H}}(1)]\} \\ \sin\{\arg[R^f_{\mathrm{H}}(1)]\} \\ \cos\{\arg[R^f_{\mathrm{V}}(1)]\} \\ \sin\{\arg[R^f_{\mathrm{V}}(1)]\} \end{array}}$$

$$1-1/n\sqrt{\left\{\textstyle\sum_{i=0}^{n-1}\cos[\arg(H_i)]\right\}^2+\left\{\textstyle\sum_{i=0}^{n-1}\sin[\arg(H_i)]\right\}^2}$$
$$1-1/n\sqrt{\left\{\textstyle\sum_{i=0}^{n-1}\cos[\arg(V_i)]\right\}^2+\left\{\textstyle\sum_{i=0}^{n-1}\sin[\arg(V_i)]\right\}^2}$$
$$1-1/n\sqrt{\left\{\textstyle\sum_{i=0}^{n-2}\cos[\arg(H_iH^*_{i+1})]\right\}^2+\left\{\textstyle\sum_{i=0}^{n-2}\sin[\arg(H_iH^*_{i+1})]\right\}^2}$$
$$1-1/n\sqrt{\left\{\textstyle\sum_{i=0}^{n-2}\cos[\arg(V_iV^*_{i+1})]\right\}^2+\left\{\textstyle\sum_{i=0}^{n-2}\sin[\arg(V_iV^*_{i+1})]\right\}^2}$$
$$1-1/n\sqrt{\left\{\textstyle\sum_{i=0}^{n-1}\cos[\arg(H_iV^*_i)]\right\}^2+\left\{\textstyle\sum_{i=0}^{n-1}\sin[\arg(H_iV^*_i)]\right\}^2}$$

Previous work: accumulations (9–15 June 2019)

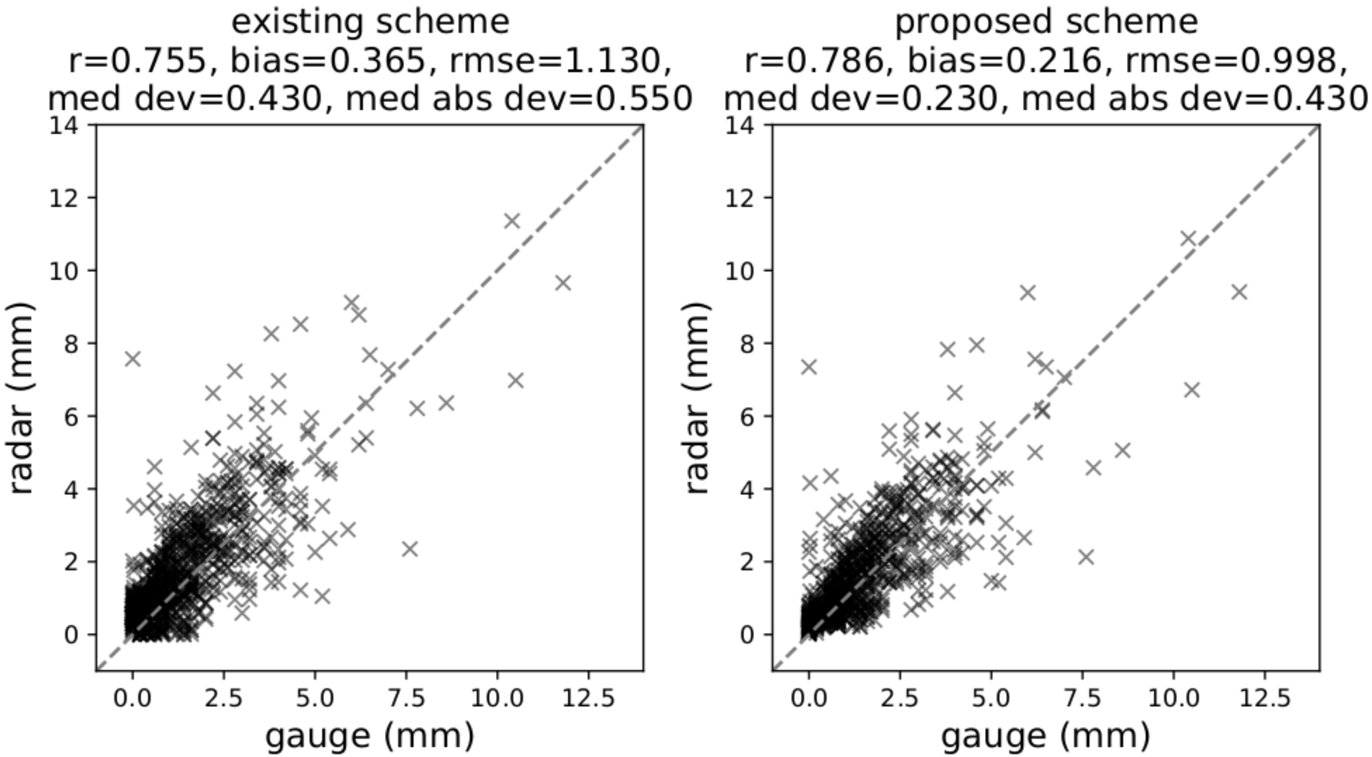
- Note: in-filling of censored lower elevation data using higher elevation data



(No Doppler filter)

(NNET switches CLEAN-AP(TM))

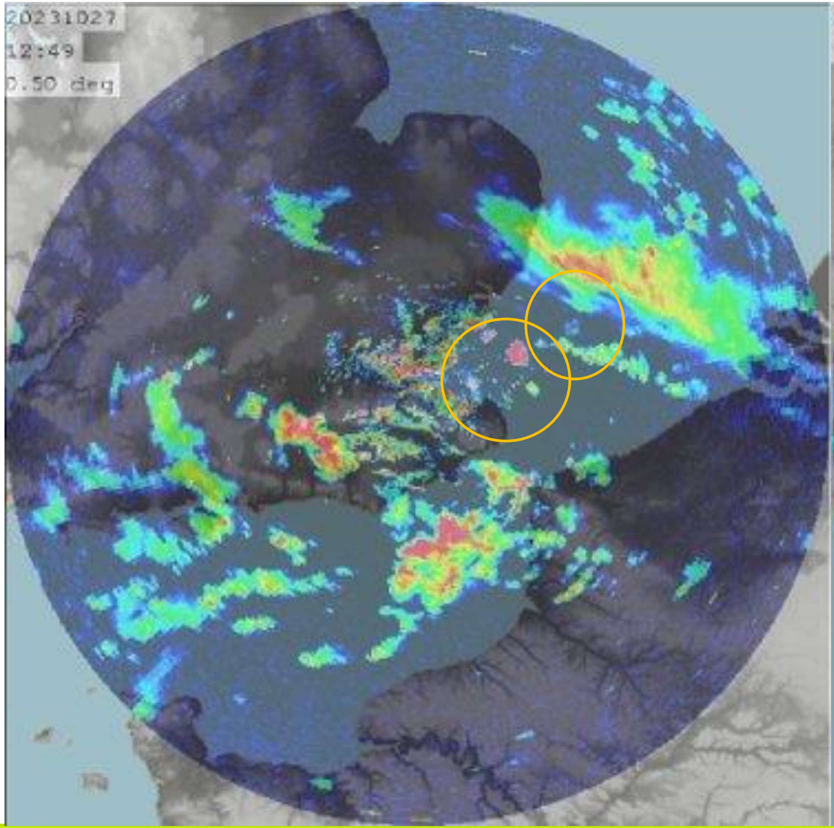
Previous work: gauge comparisons

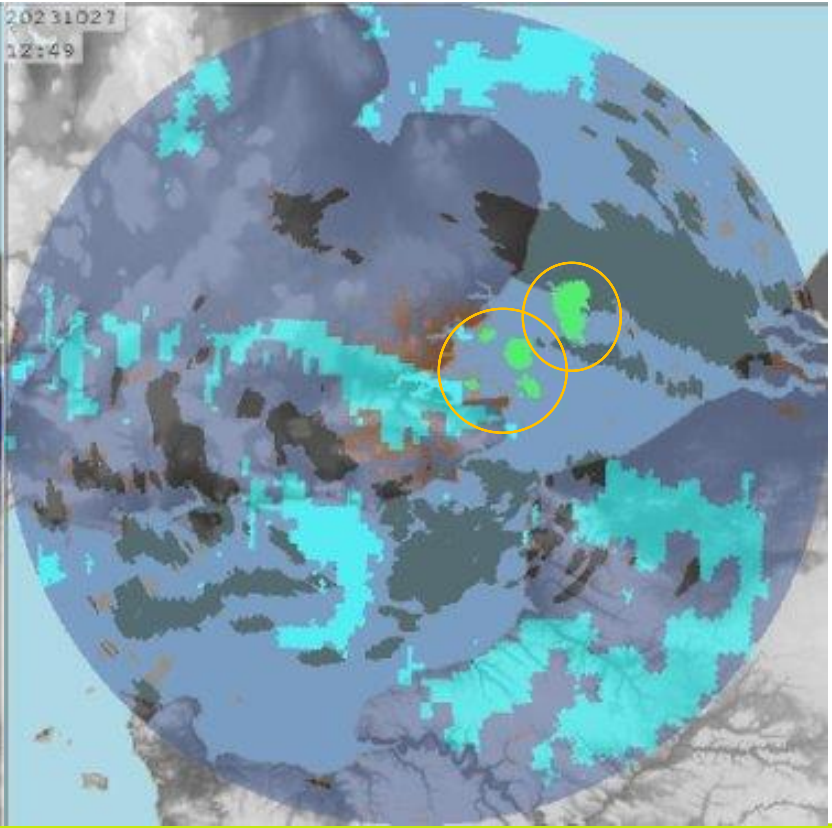


Present work

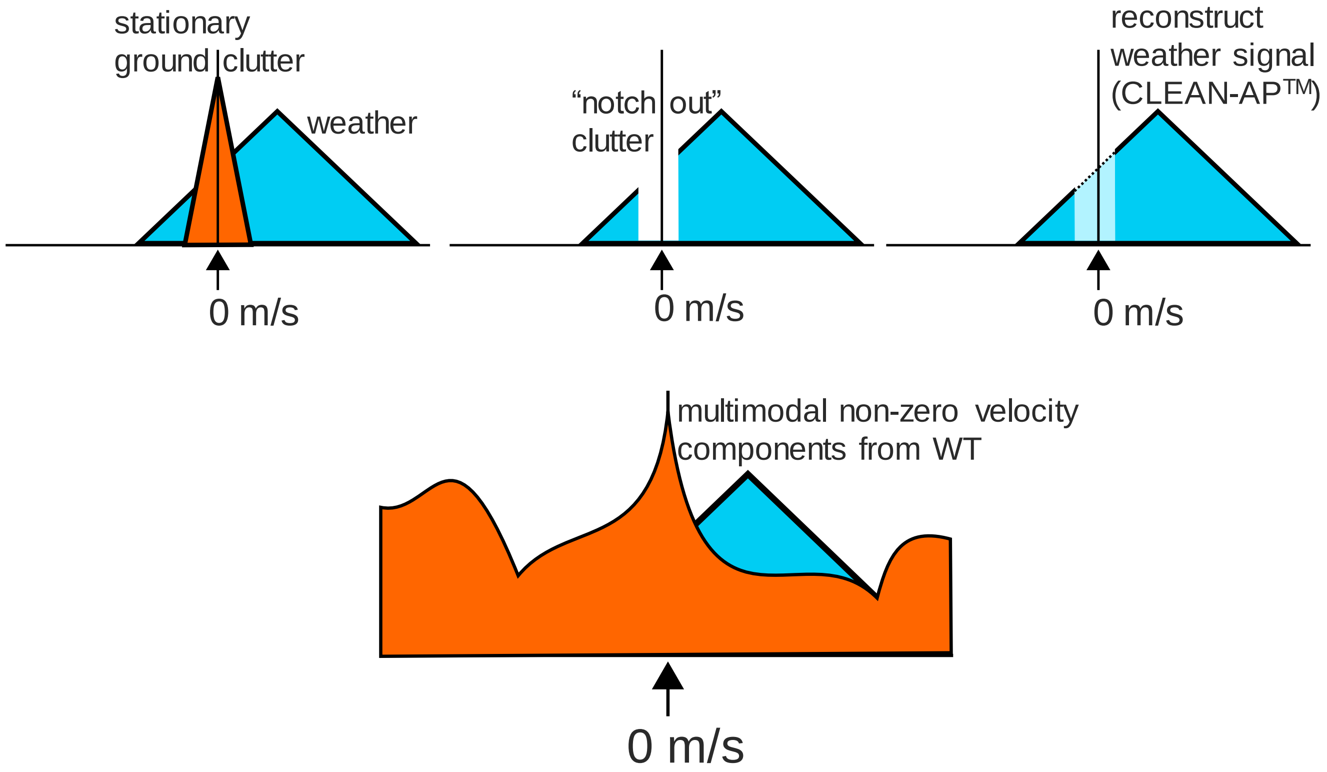
Dynamic identification of wind turbines

Masking - some WT only present during anaprop

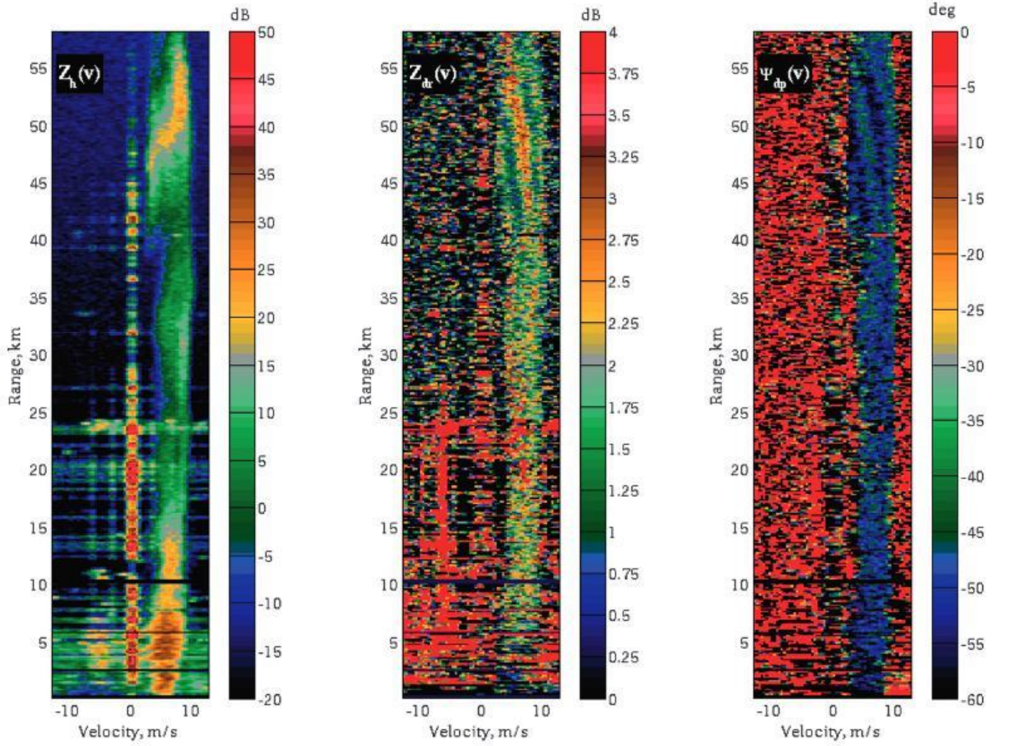




Doppler filtering doesn't always work

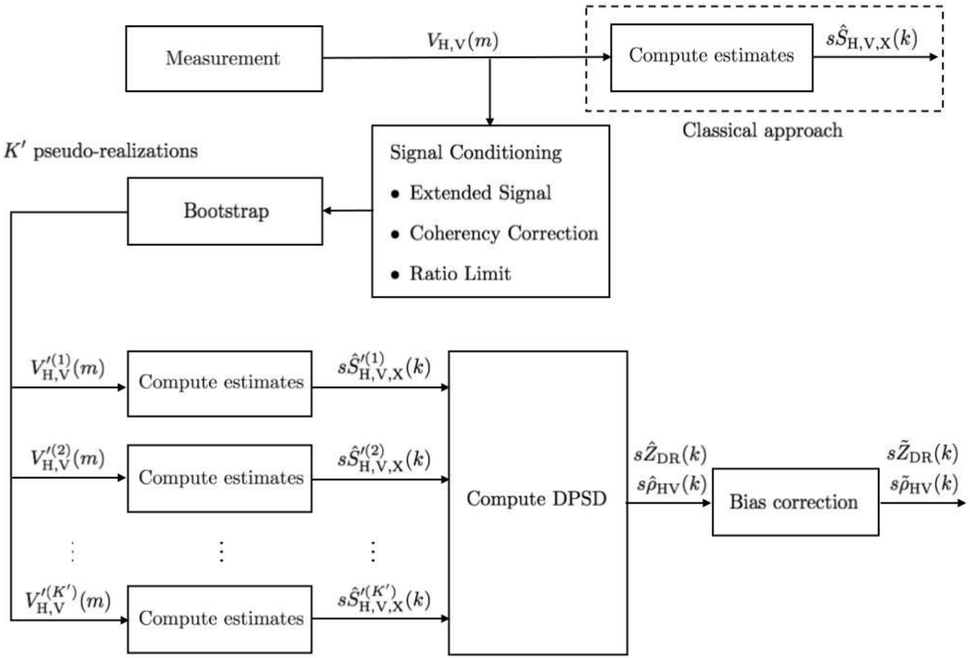


Spectral dualpol – range-velocity plots



Polarimetric Spectral Filter for Adaptive Clutter and Noise Suppression
Moisseev & Chandrasekar (2009), JTECH, Vol 26, Issue 2, pp215-228

WT – inputs – spectral dualpol and power (H/V), filt/unfilt

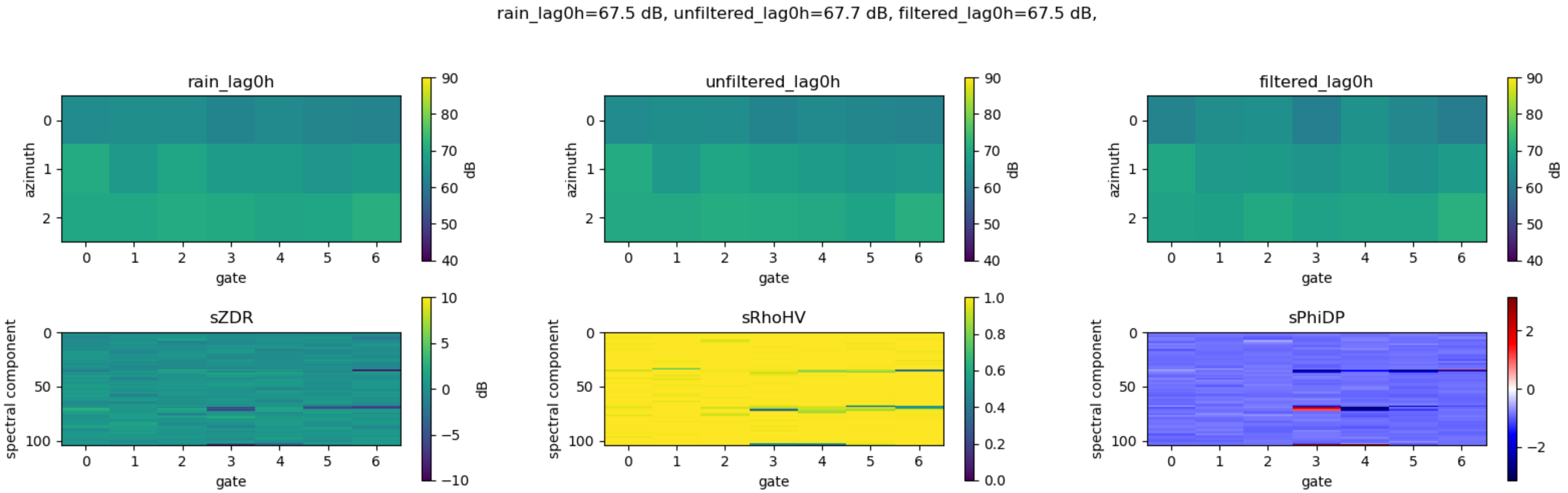


Spectral dualpol inputs: (?, 3*35,7,4)
[sZDR, sRhoHV, cos(sPhiDP), sin(sPhiDP)]

Power inputs: (?, 3, 7, 4)
[Lag0H_unfilt, Lag0V_unfilt, Lag0H_filt, Lag0V_filt]
(scaled by noise floor estimates)

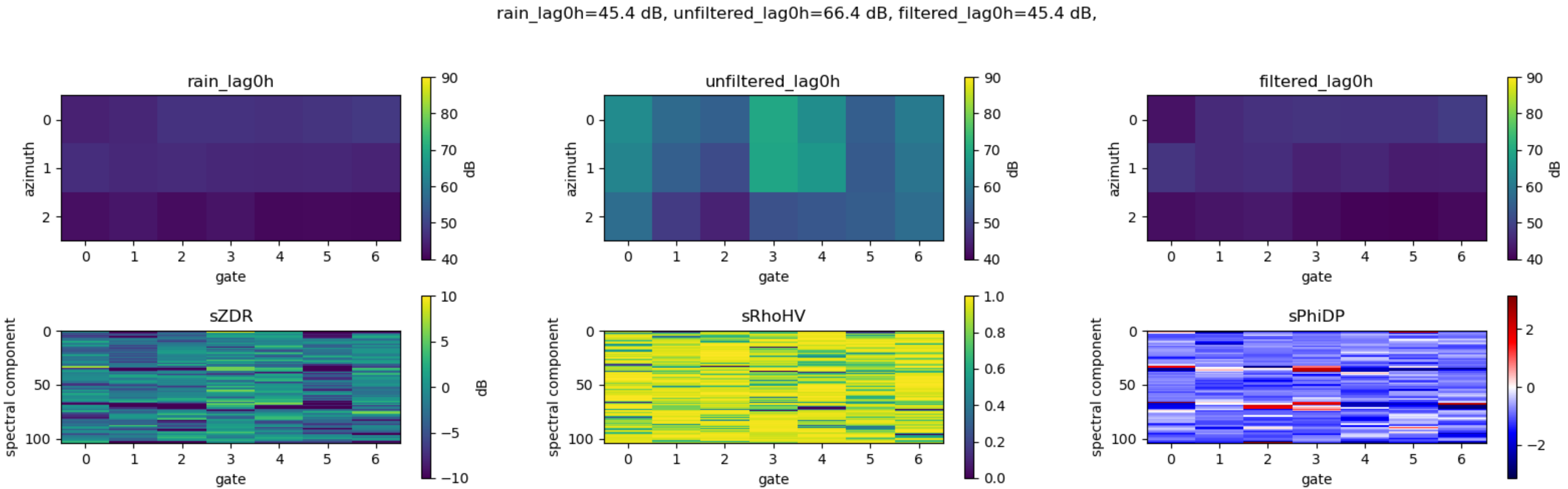
Bootstrap Dual-Polarimetric Spectral Density Estimator,
Umeyama, Torres and Cheong (2007), IEEE Transactions On Geoscience and Remote Sensing, vol. 55, no. 4, April 2017.

Met Office Synthetic tiles – rain (unfiltered)



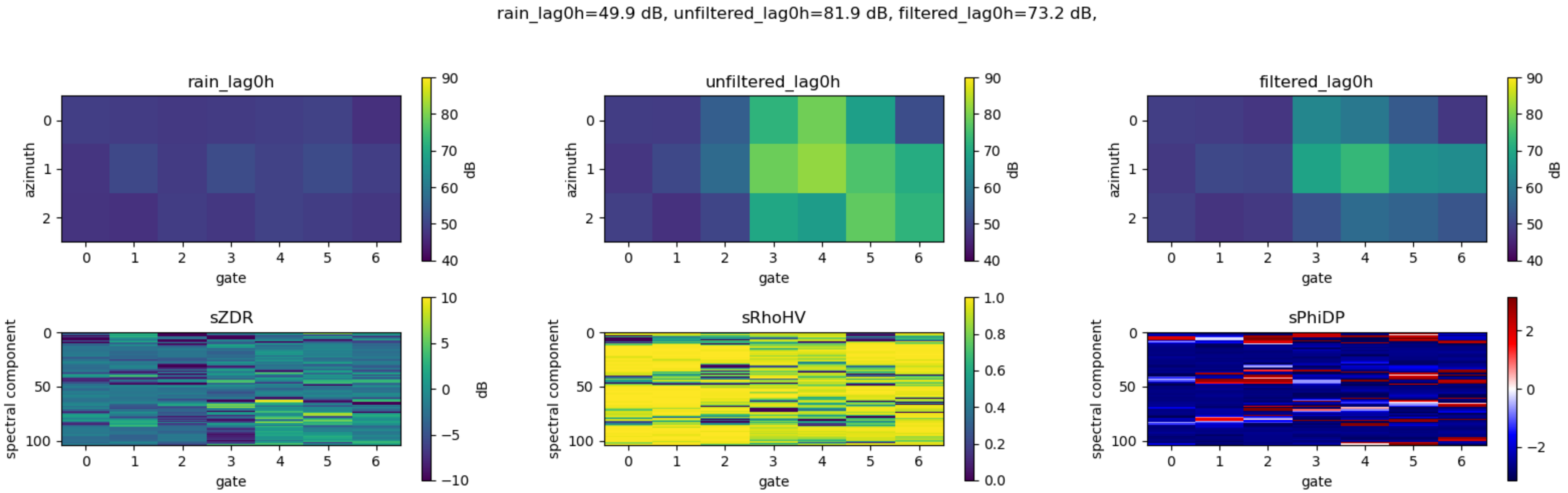
Spectral components: concatenated 3 rays worth of Doppler velocities.

Synthetic tiles – rain (filtered)



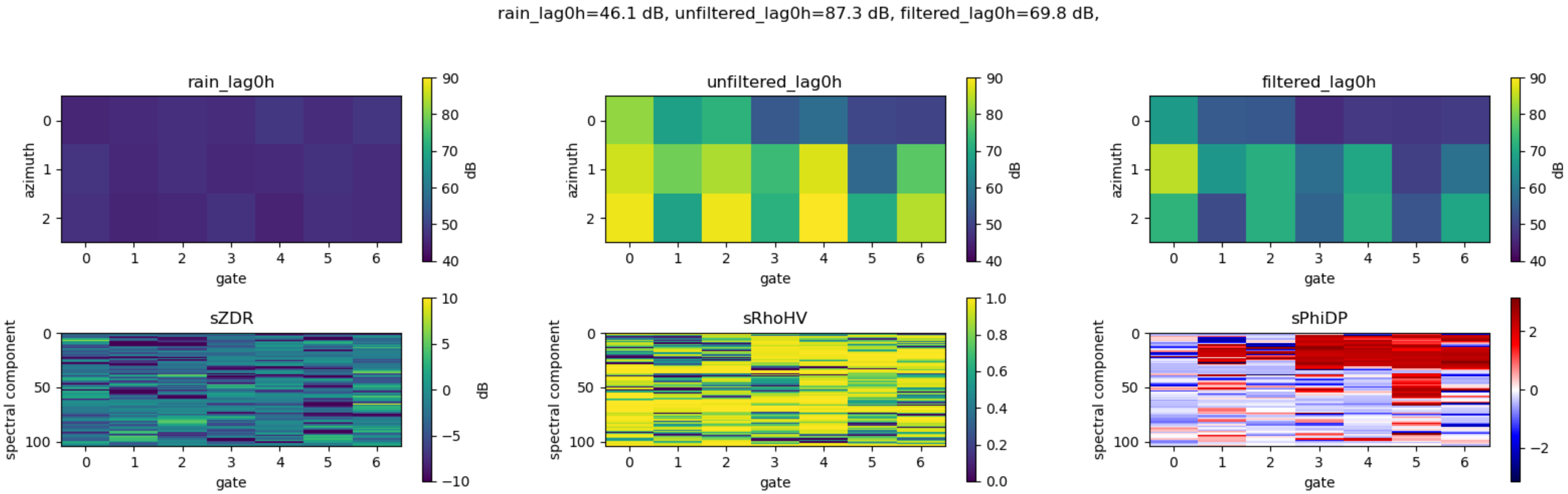
Spectral components: concatenated 3 rays worth of Doppler velocities.

Synthetic tiles – clutter-giveup



Spectral components: concatenated 3 rays worth of Doppler velocities.

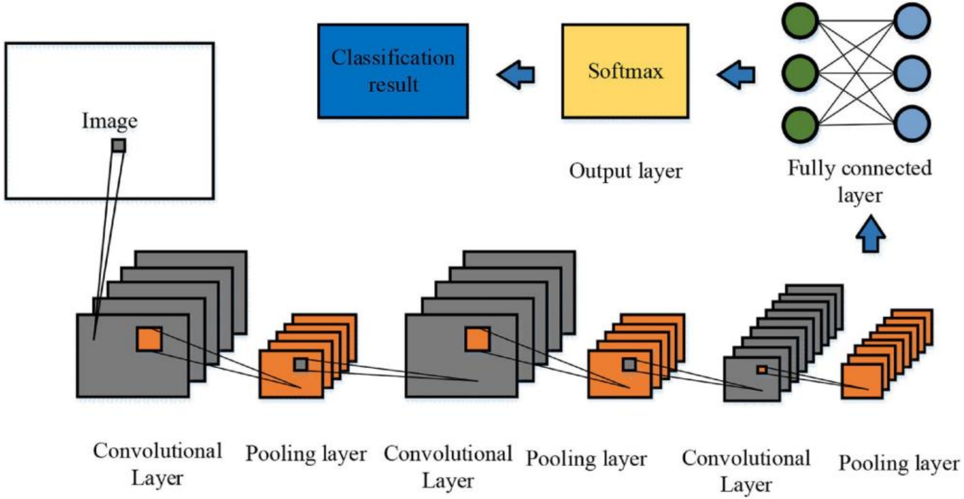
Synthetic tiles – wind turbine-giveup



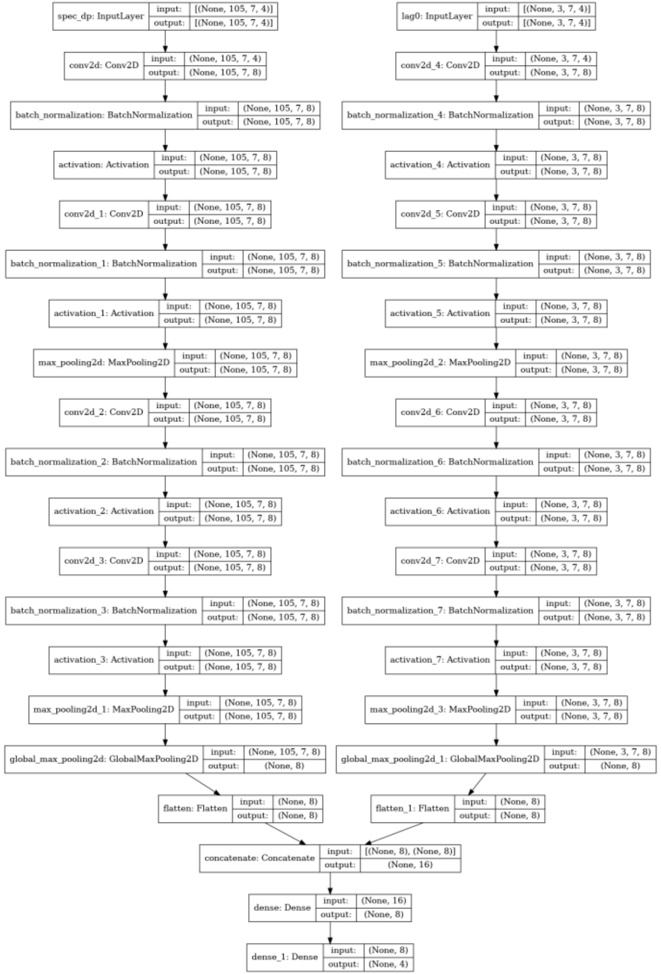
Spectral components: concatenated 3 rays worth of Doppler velocities.

Met Office Model and training details

- 2 columns (spectral dualpol and power)
- 4 output neurons with SoftMax: [**unfiltered**/**filtered**/**clutter**/**WT**]
- Total number of parameters: 4,524

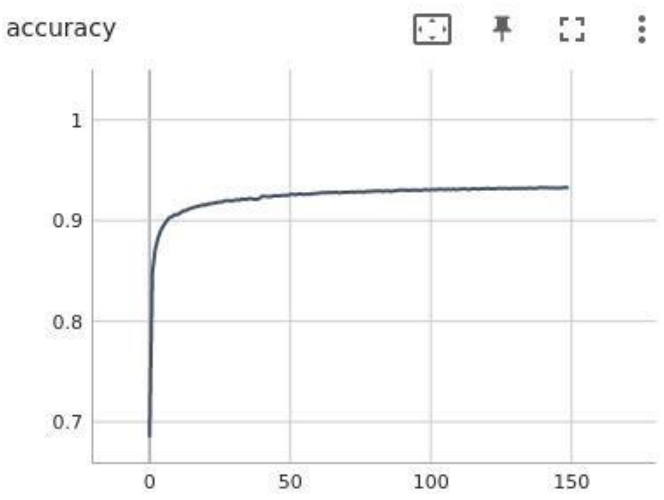


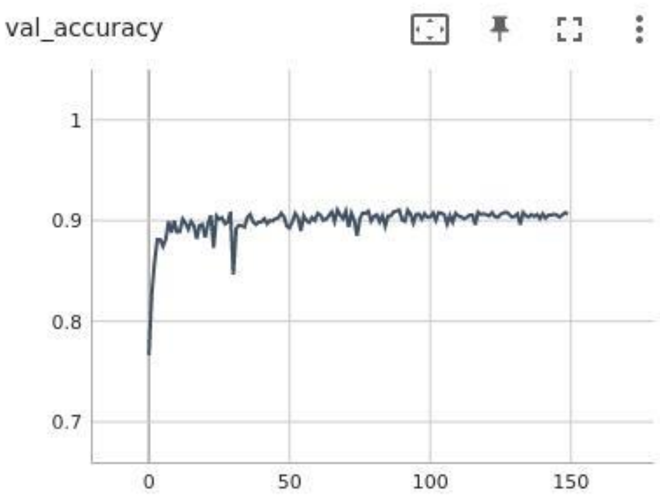
Ilustration: https://www.frontiersin.org/articles/10.3389/fpsyg.2021.663359/full



Training process

- Use **guild.ai and tensorboard** to monitor progress and compare runs
- Train with a total of 178,308 tiles for a maximum of 150 epochs
- Validate with 182,523 tiles (keep model with best validation accuracy)





Confusion matrix for tiles dataset (testing split)

- Test on a total of 178,142 tiles

		Ground truth				
		unfiltered	filtered	clutter	wt	total
	unfiltered	0.4313	0.0225	0.0080	0.0006	0.4625
Neural	filtered	0.0163	0.1705	0.0124	0.0047	0.2041
Network	clutter	0.0027	0.0056	0.1760	0.0048	0.1892
	wt	0.0005	0.0043	0.0075	0.1316	0.1440
	Total	0.4510	0.2030	0.2041	0.1418	

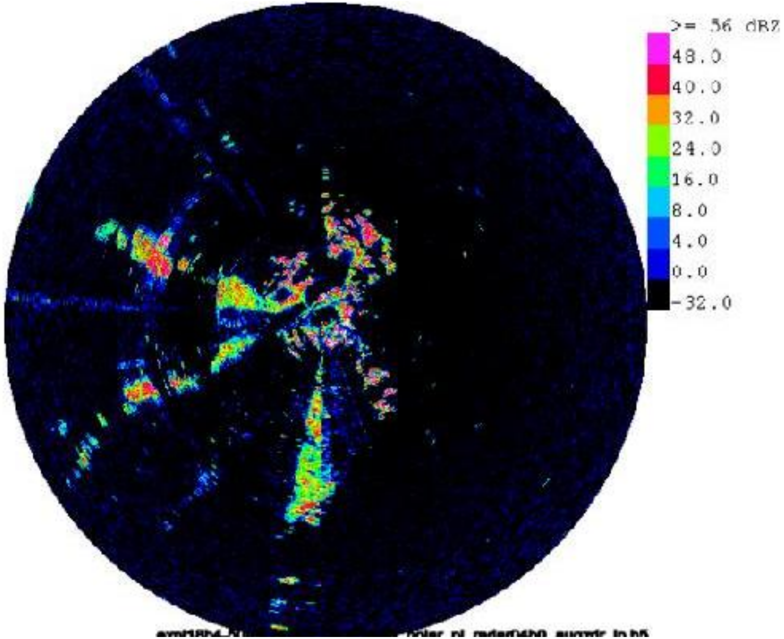
overall accuracy: 0.9096

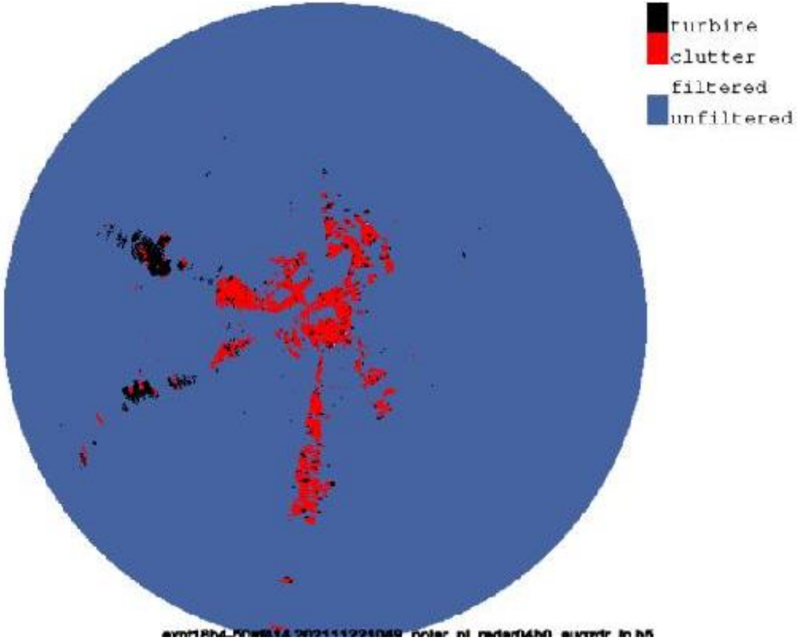
ground truth: n_unfiltered=80,353, n_filtered=36,167, n_clutter=36,360, n_wt=25,262

accuracy: unfiltered=0.9563, filtered=0.8401, clutter=0.8624, wt=0.9283

Dry case – beam 0 (0.5°)

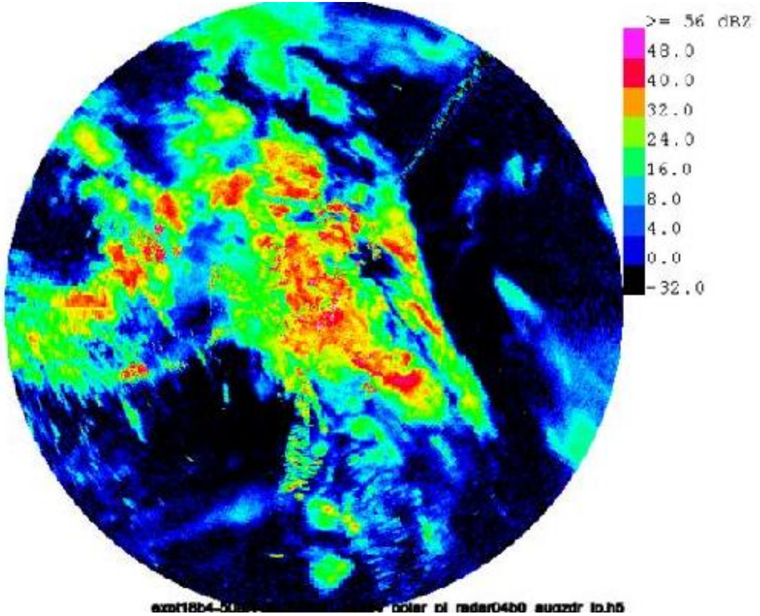
Hameldon Hill
Scale: 300x300km

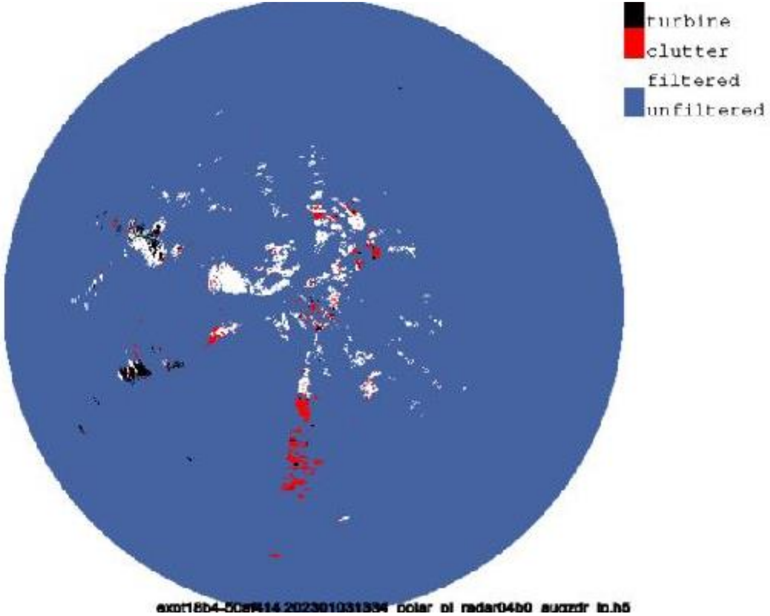




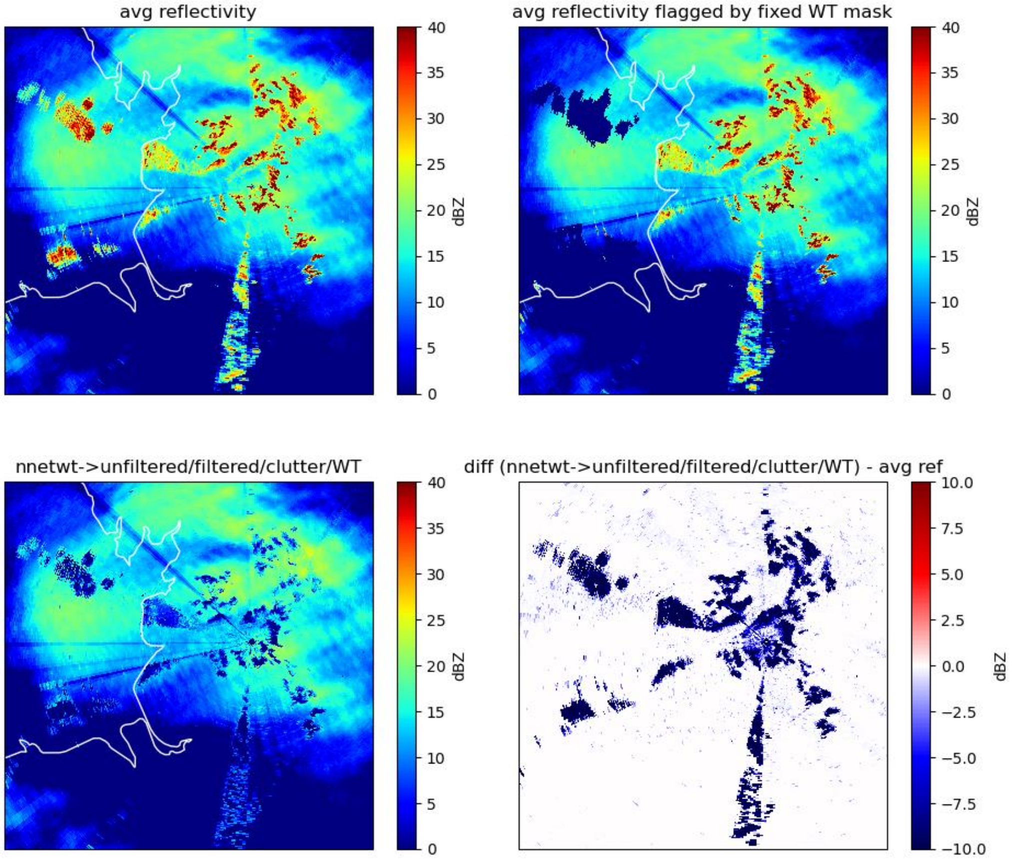
Rainy case – beam 0 (0.5°)

Hameldon Hill
Scale: 300x300km





Mean reflectivity over a 3h period (2023/01/03 12:44-15:39)



- Note: we're not yet using in-filling of censored lower elevation data with higher elevation data

Hameldon Hill
(Beam 0 only)
Scale: 168x168km

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Conclusions and ongoing work

- Increase in wind turbine contamination is unavoidable for NetZero
- Spectral dualpol parameters are useful for detecting wind turbines
- The tiles approach works well for training a neural network to detect both clutter and wind turbines
- We'll try to improve the model further
- Current runtime is ~2min/scan, we plan to do some optimisation