

Atmosphere and Ocean Monitoring using GNSS reflected signals: Current Status and Prospects at GFZ

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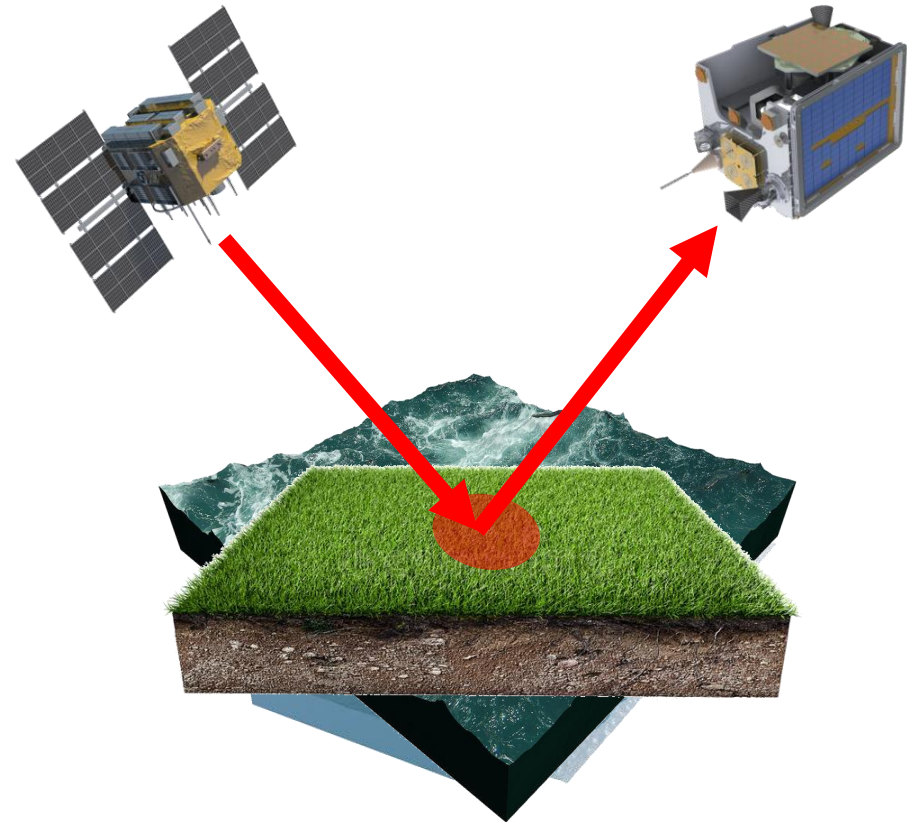
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What is GNSS-R?

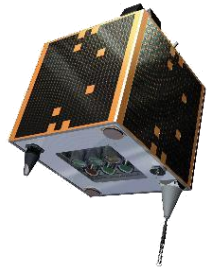
- The exploitation of GNSS signals after **reflection** off the Earth's surface
- A bistatic radar technique
- **Multistatic**
- Cross correlation of the reflected signal with a local replica or the direct GNSS signal
- Correlation power inversely proportional to the ocean roughness (diffuse scattering case)
- **Cost-effective**
- **High spatiotemporal resolution**



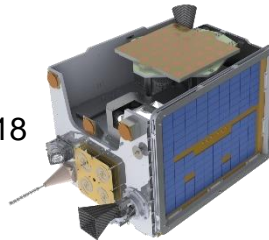
GNSS-R Satellite Missions

GNSS-R satellite missions

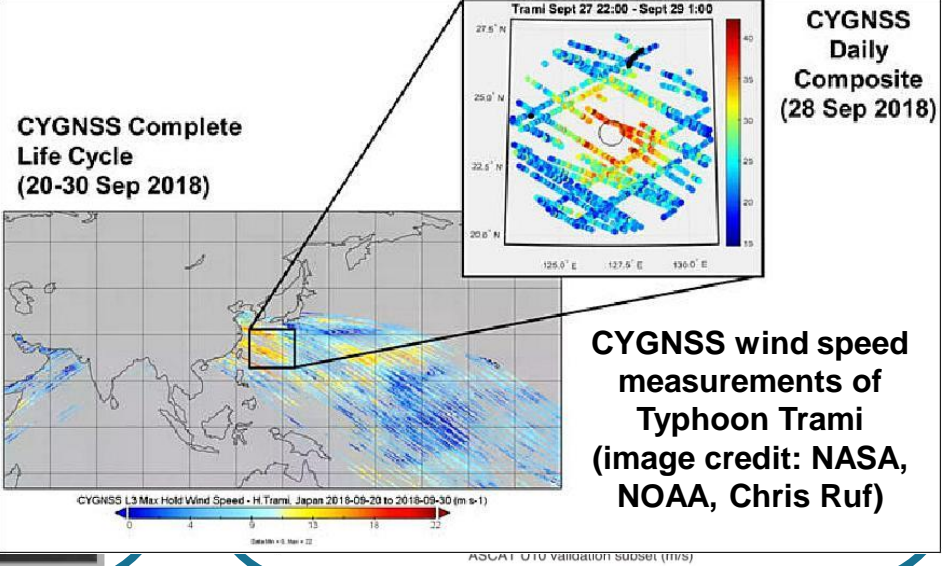
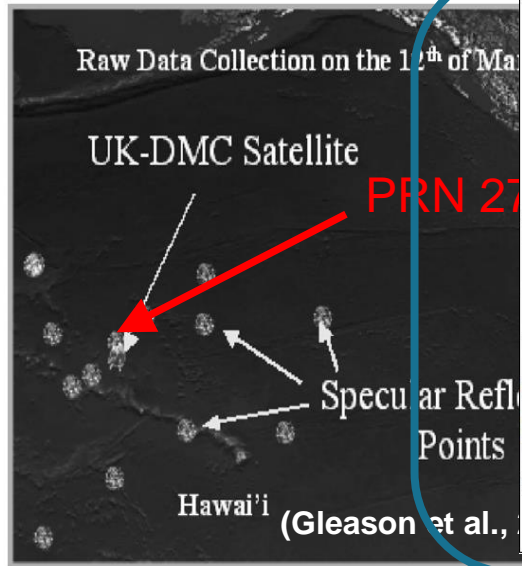
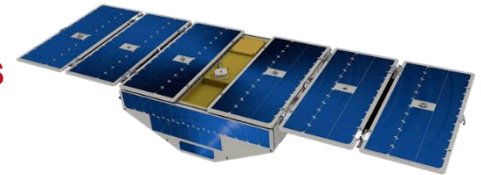
UK-DMC
2003/2004



TDS-1
2014-2018



CYGNSS
2016-...



Monostatic back scatterometry

SeaSAT 1978
110 days

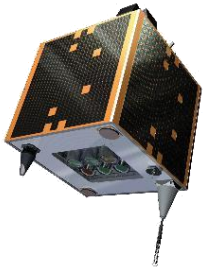
Ku-band
NSCAT
August 1996

QuikSCAT
Jun 1999-Nov 2009

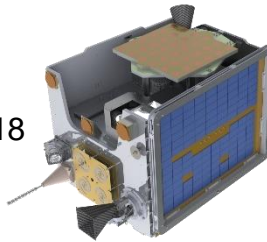
OceanSat-2
Sep 2009

GNSS-R satellite missions

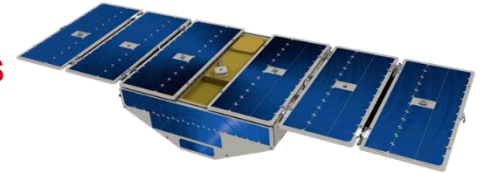
UK-DMC
2003/2004



TDS-1
2014-2018



CYGNSS
2016-...



C-band

L-band

Bistatic Radar Equation

Received Power as a function of delay and Doppler frequency

Masking due to the transmitting and antenna gains

Bistatic radar cross section

$$\langle |Y(\tau, f)|^2 \rangle_{nc} = \frac{P_t G_t \lambda^2 T_i^2}{4\pi^3} \iint_A \frac{G_r \Lambda^2(\tau) S^2(f)}{R_t^2 R_r^2} \sigma^0 dA$$

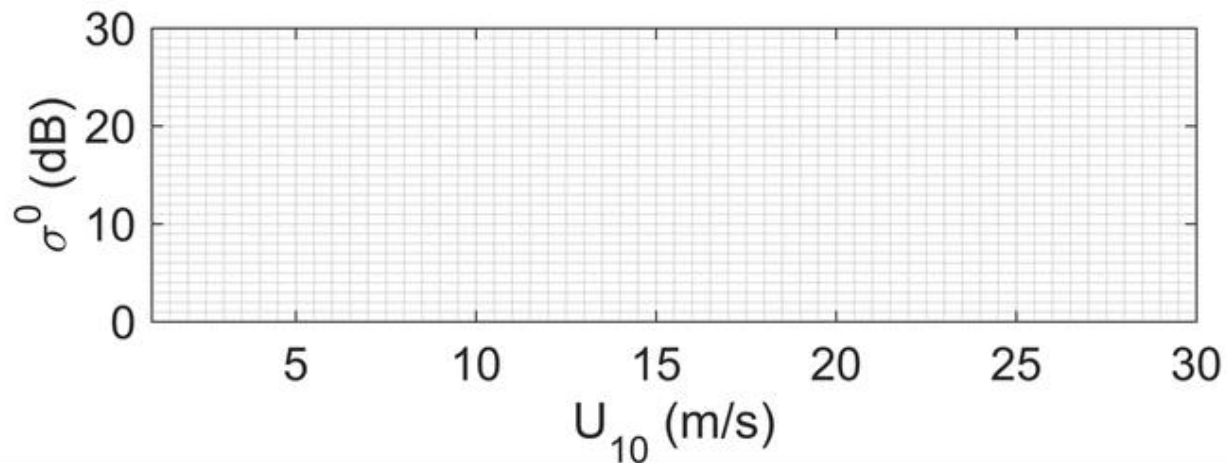
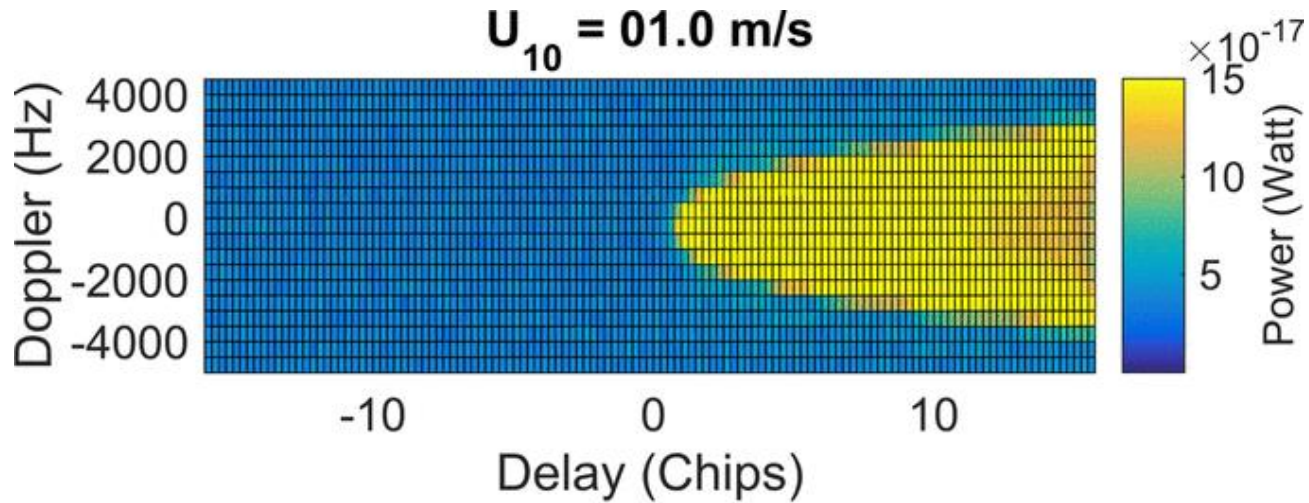
(Zavorotny and Voronovich, 2000)

Transmitting power

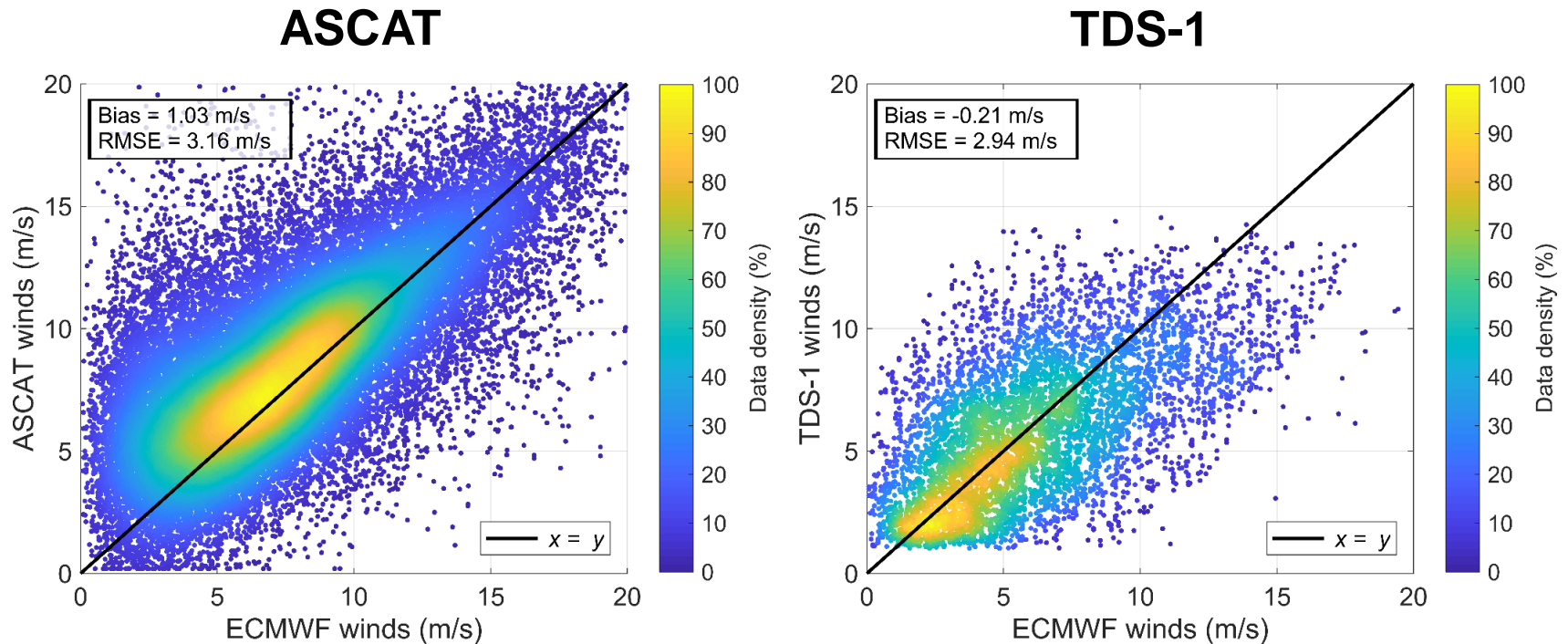
The glistening zone
 (the area scattering GNSS signal)

Distances to the transmitter and receiver satellites

Delay-Doppler Maps

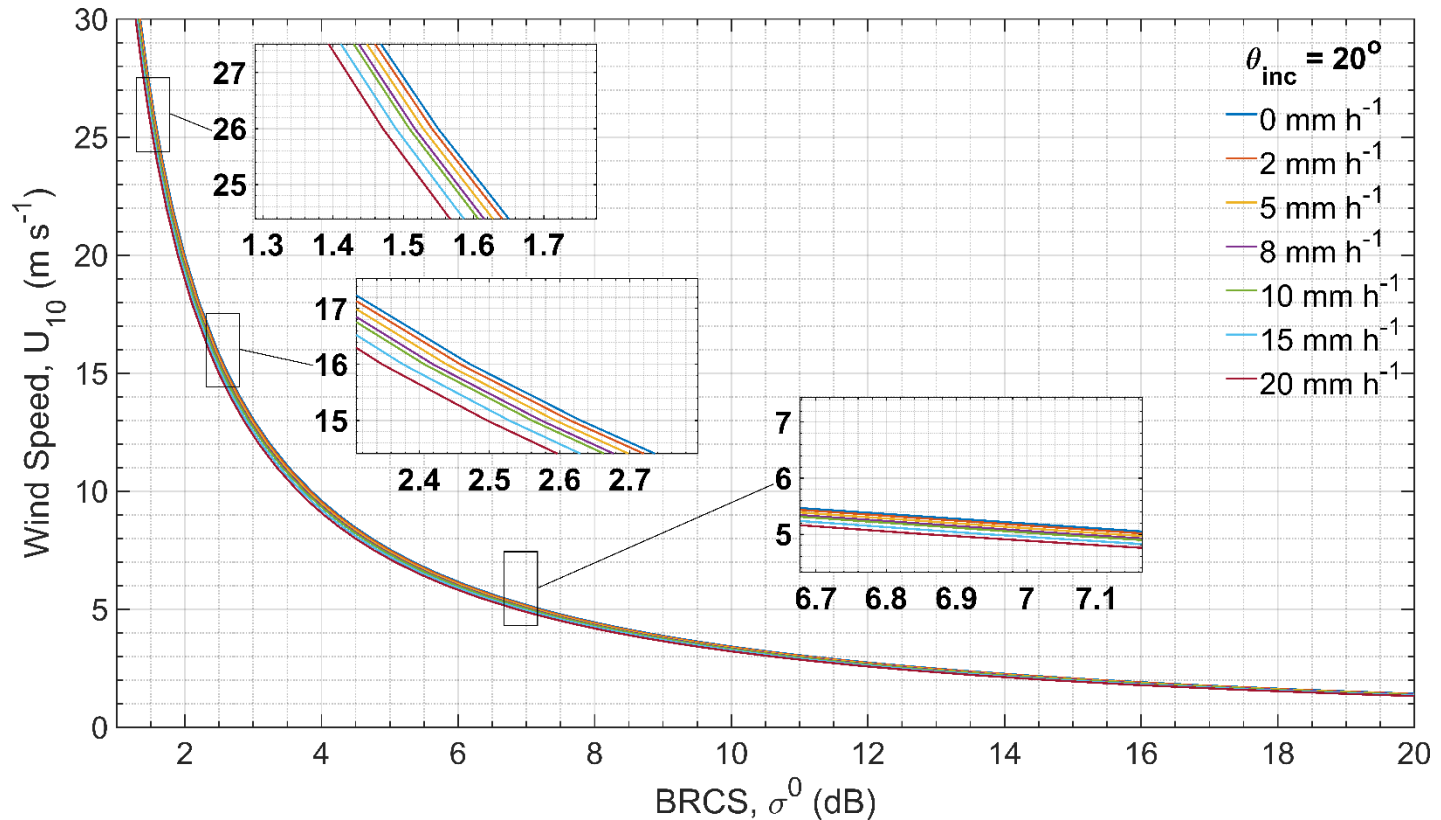


Comparison during rainfalls



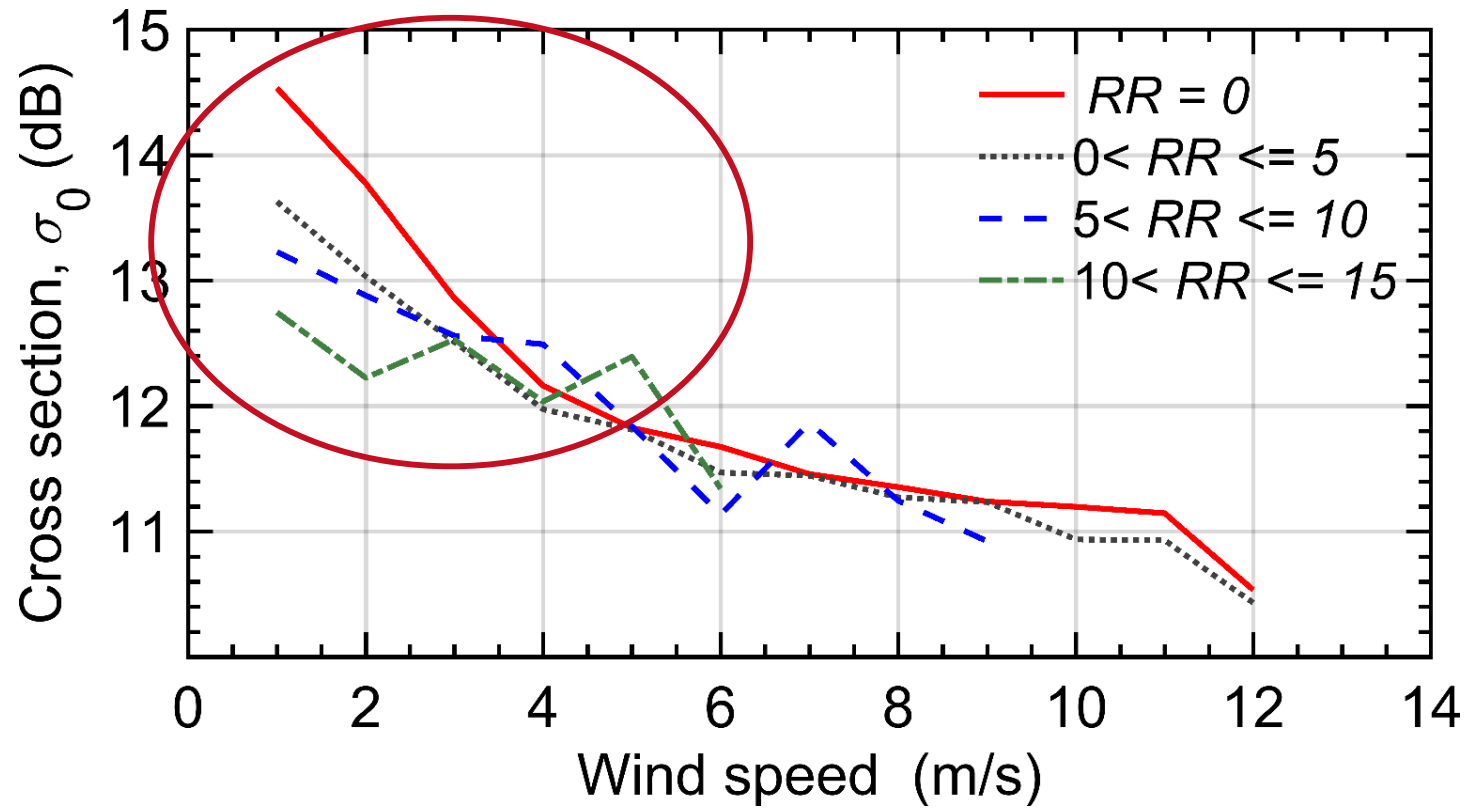
ASCAT (left) and TDS-1 (right) winds versus ECMWF winds during rainfalls (Asgarimehr et al., 2018).

Rain attenuation



Rain attenuation effect at different rain rates and incidence angle of 20 degrees (Asgarimehr et al., 2019).

Rain signature

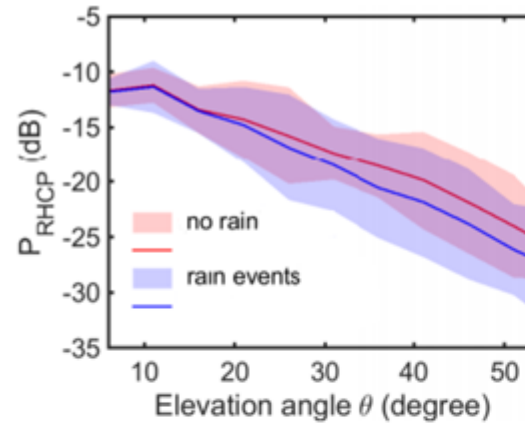


Average bistatic radar cross section versus wind speed at different rain rates RR (Asgarimehr et al., 2018).

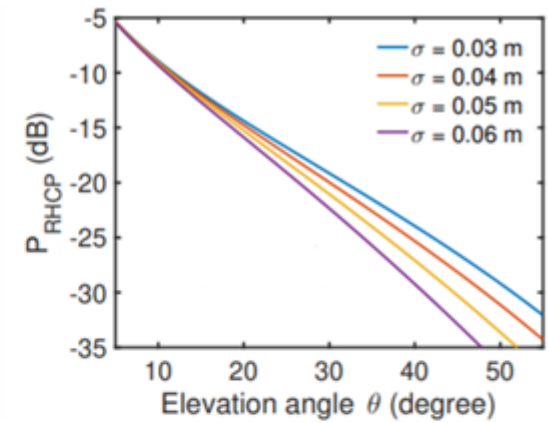
Rain signature – dual polarization observations



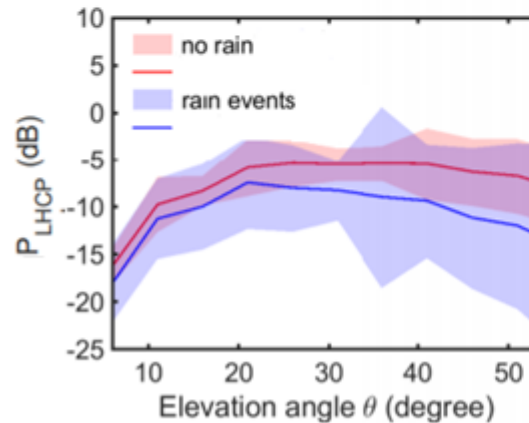
An eastward view of the GNSS-R experiment setup at Onsala space observatory, Sweden.



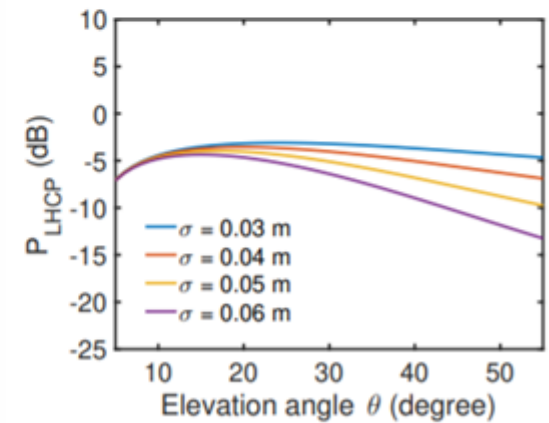
(a)



(b)

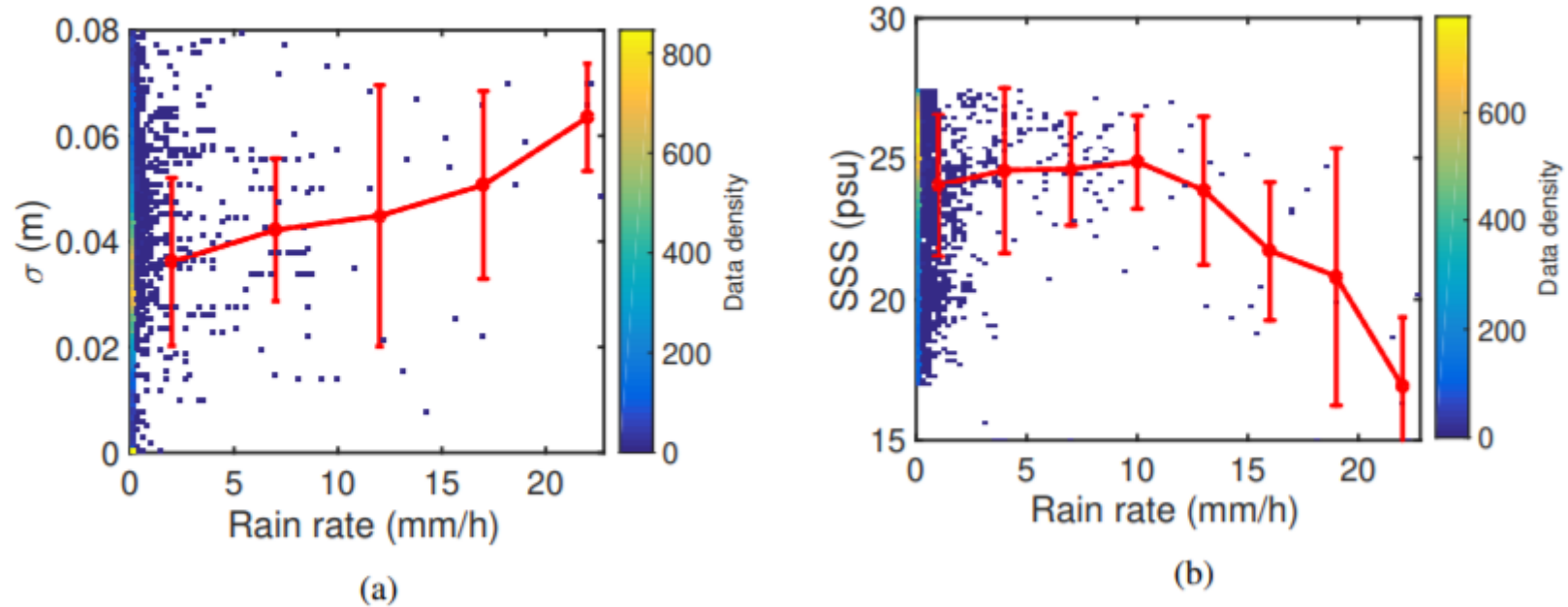


(c)



(d)

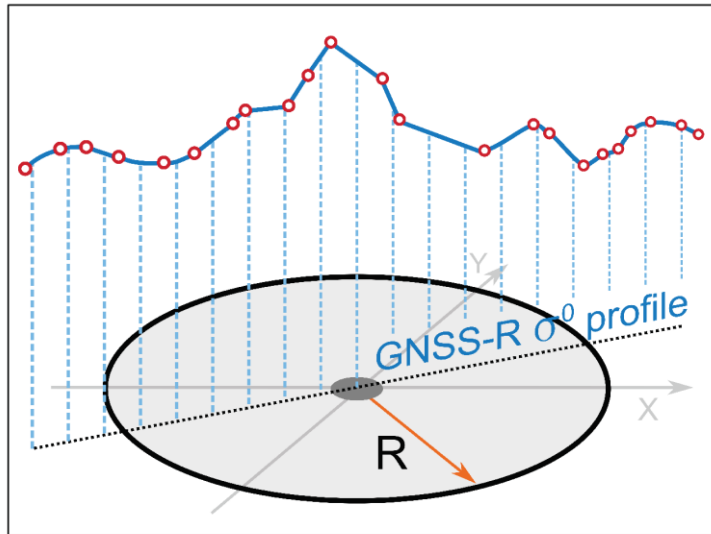
Rain Signatures – dual polarization observations



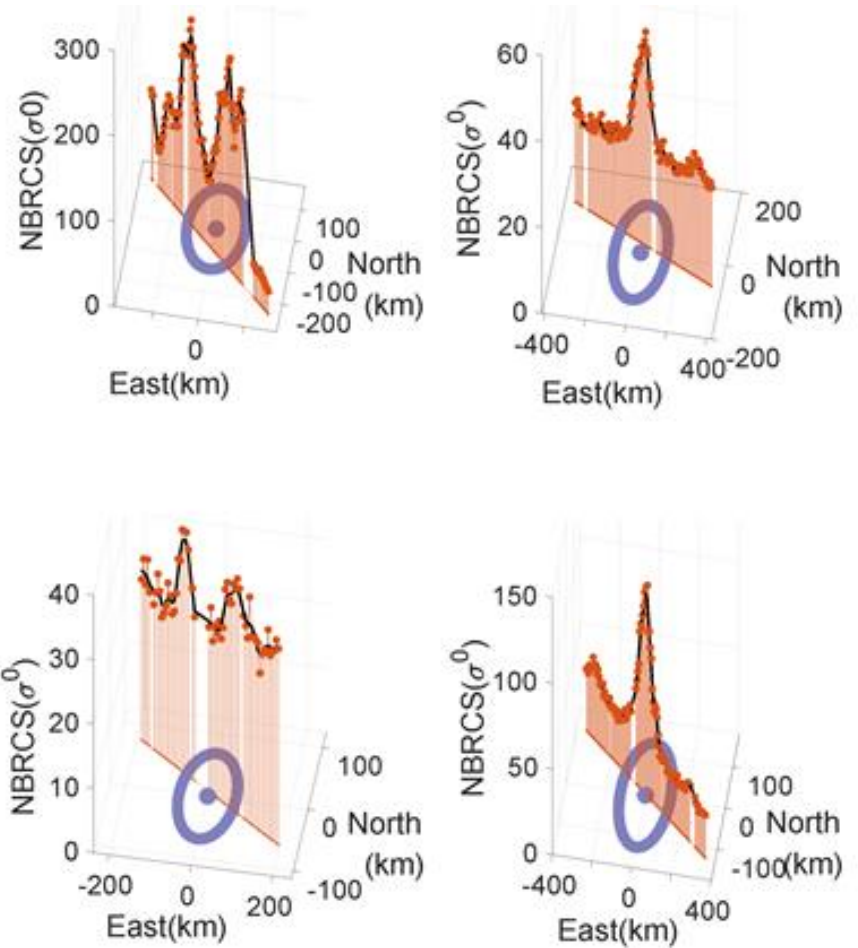
The power of reflected RCHP (a) and RHCP (b) signals and their ratio (c) vs elevation angle at different Sea Surface salinity (SSS)

Ocean Eddies

- Feasibility of sensing mesoscale ocean eddies using GNSS-R measurements

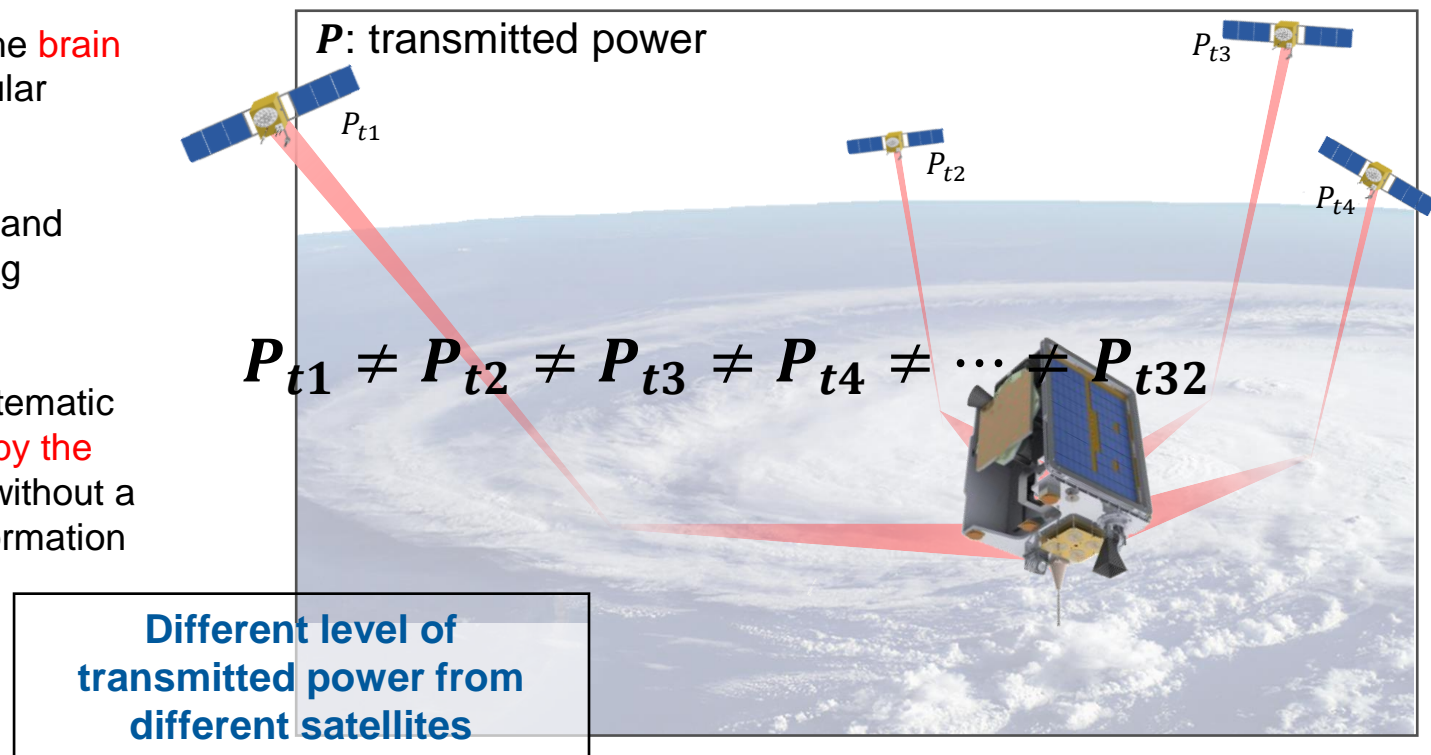


- NBRCS jumps at the eddy center (single-jump behavior)
- NBRCS jumps at the eddy edges with a lower value at the center (double-jump behavior)

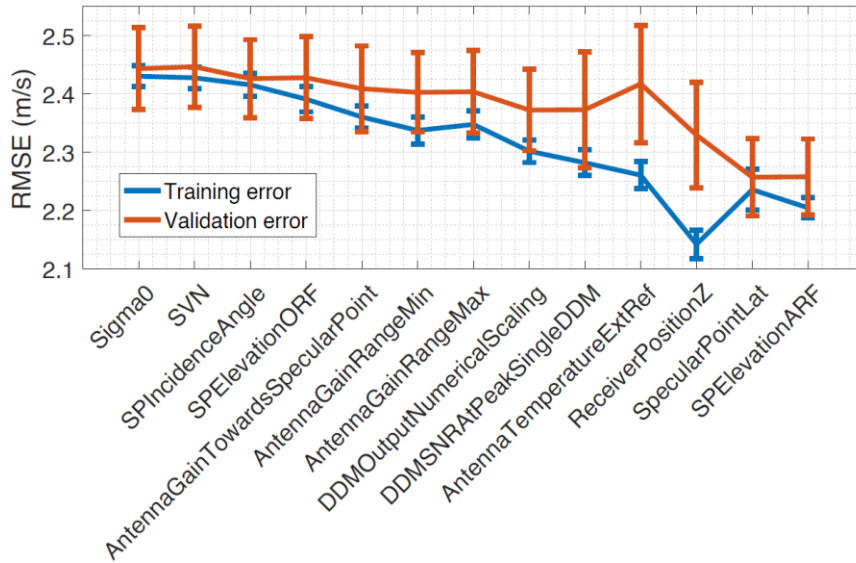


Why Machine Learning?

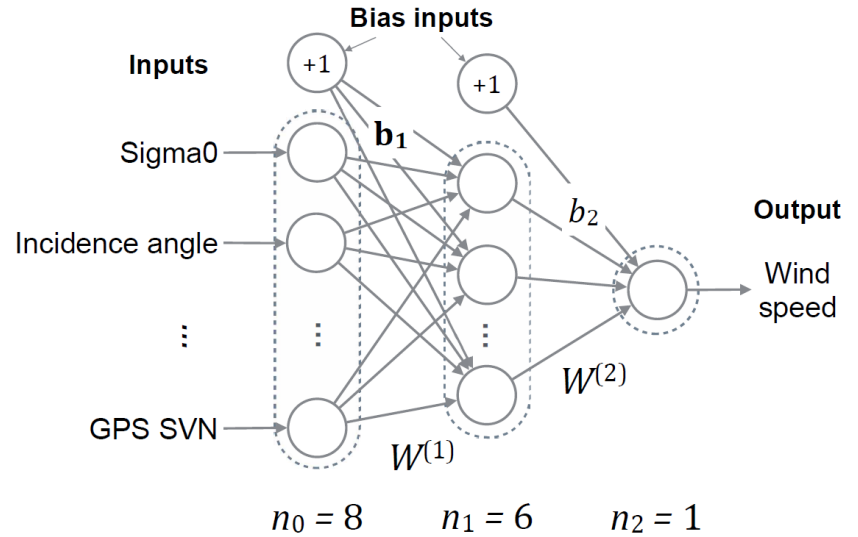
- **Potential disagreements** between the true and the predefined functions
- No direct information on affecting factors and potentially unknown effects
- Inspired by how the **brain** performs a particular learning task
- A non-parametric and statistical modeling approach
- Capturing the systematic patterns **dictated by the data themselves** without a need to direct information



Machine Learning



Successively incorporation of variables

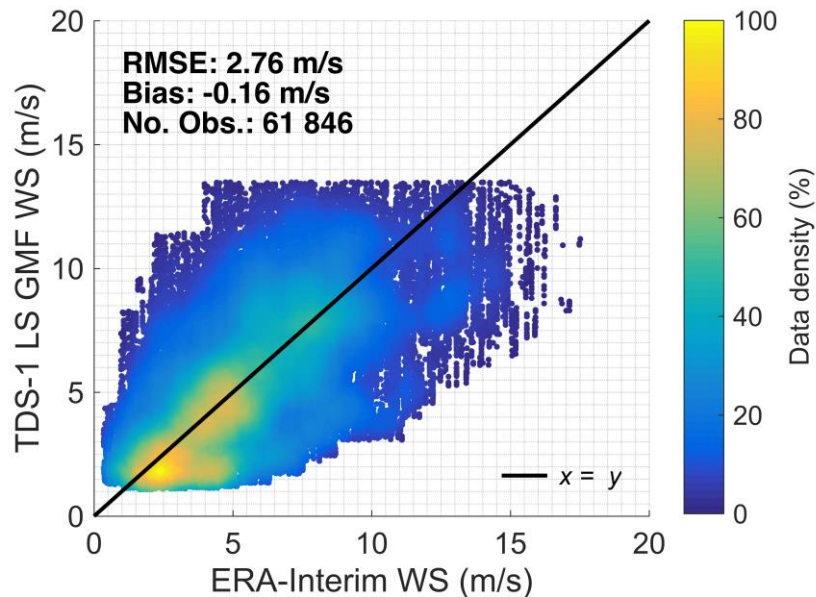


Optimal architecture

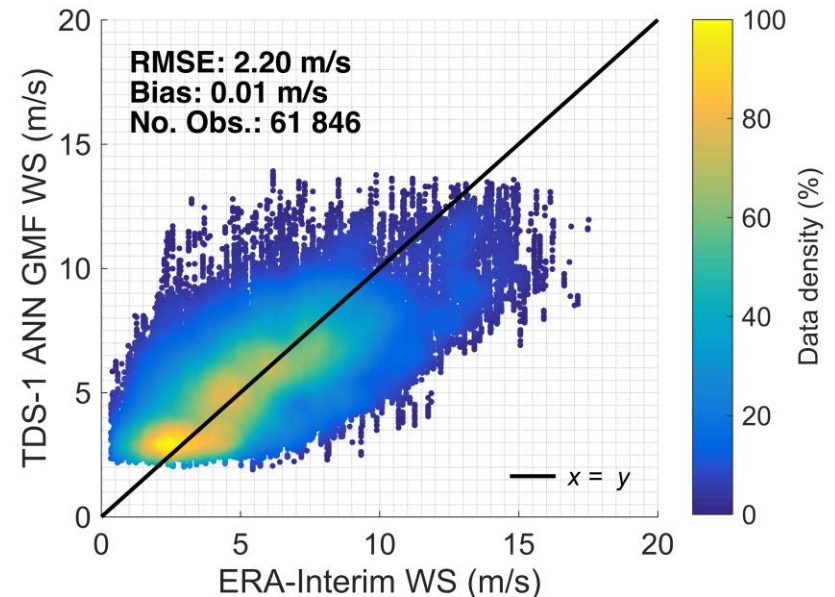
(Asgarimehr et al., 2020)

FNN wind speeds - TDS-1

Conventional approach

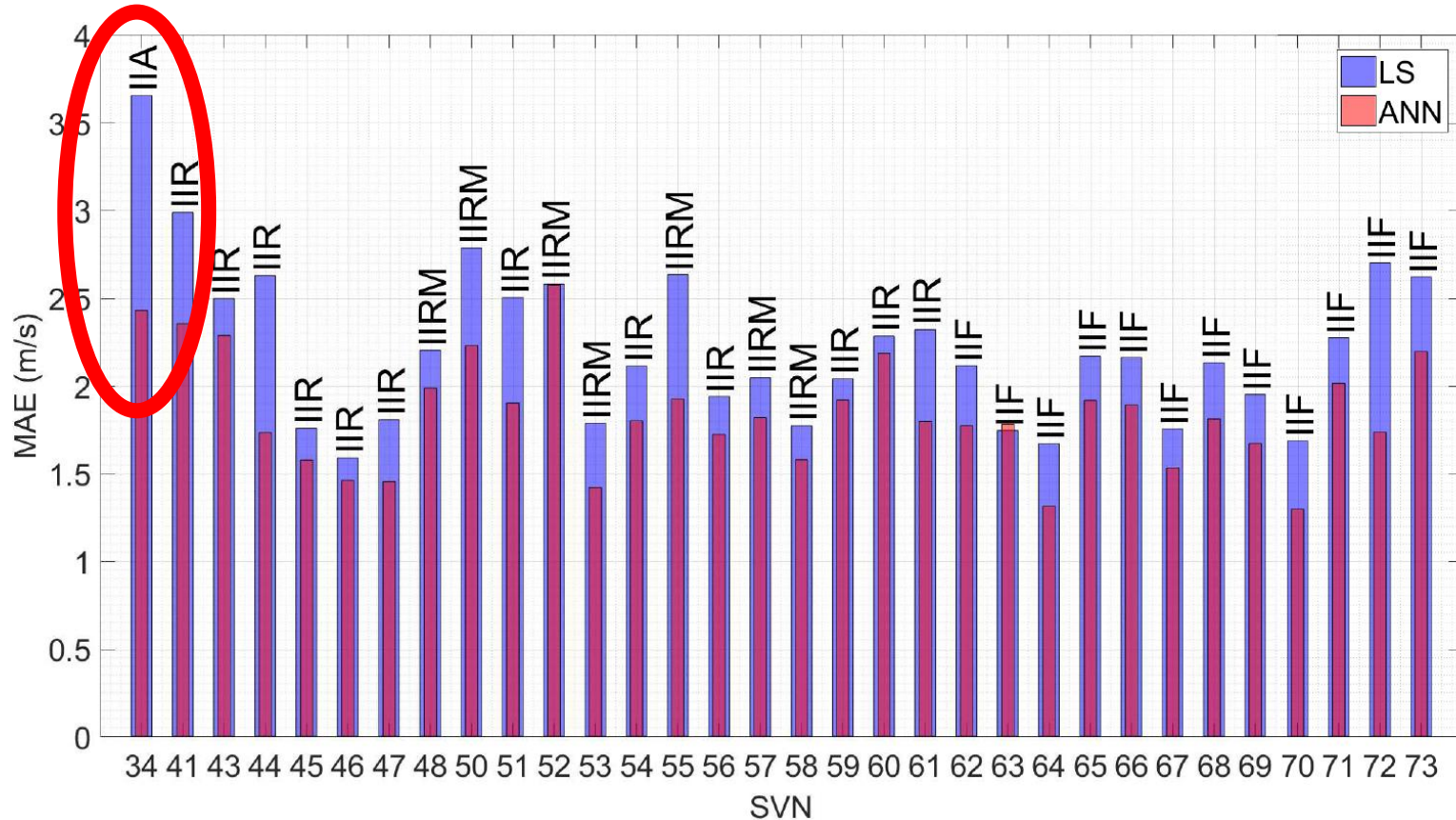


Machine Learning



(Asgarimehr et al., 2020)

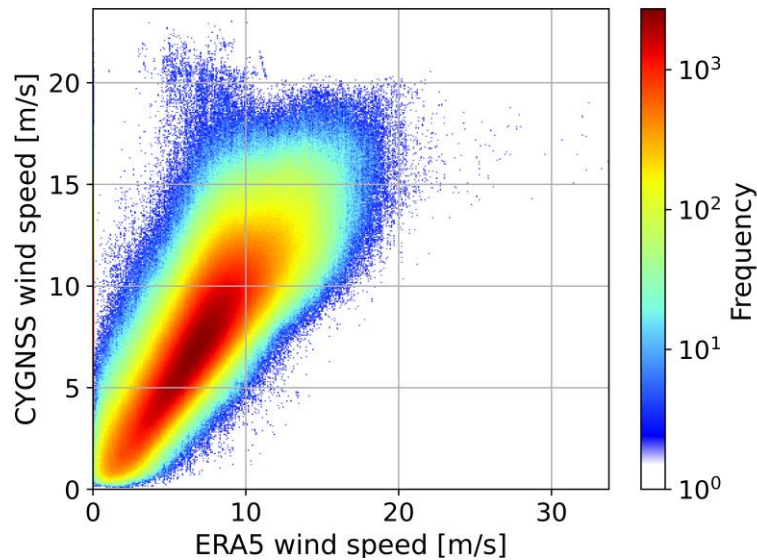
FNN wind speeds



Mean Absolute Error (MAE) of Artificial Neural Network (ANN) and Least Squares (LS) based GMFs for each GPS satellite (Asgarimehr et al., 2020).

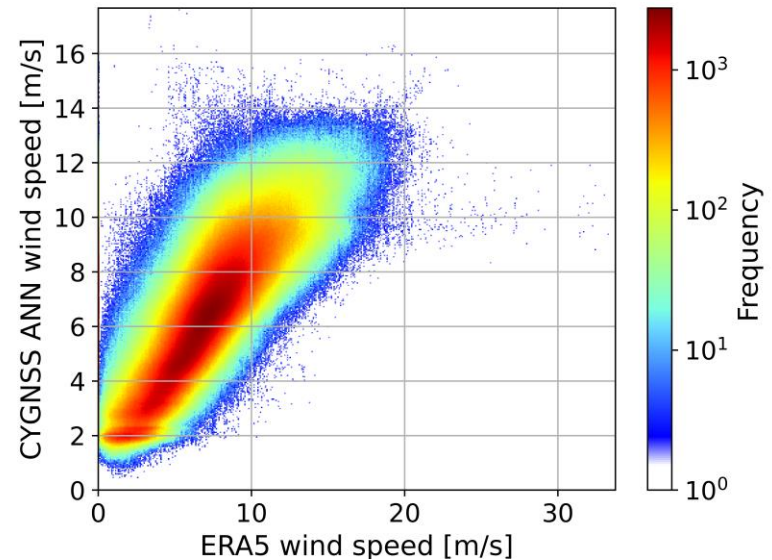
FNN wind speeds - CYGNSS

Conventional approach



RMSE: 2.01

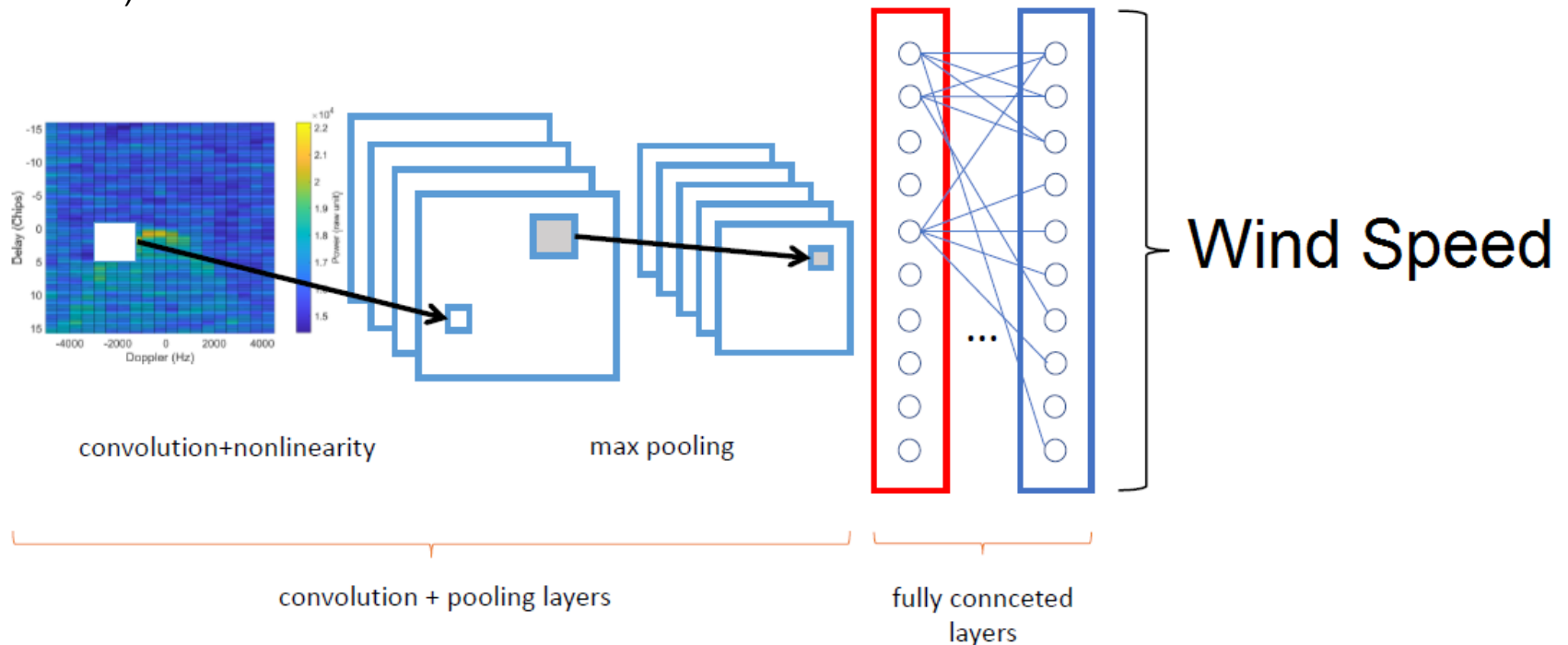
Machine Learning



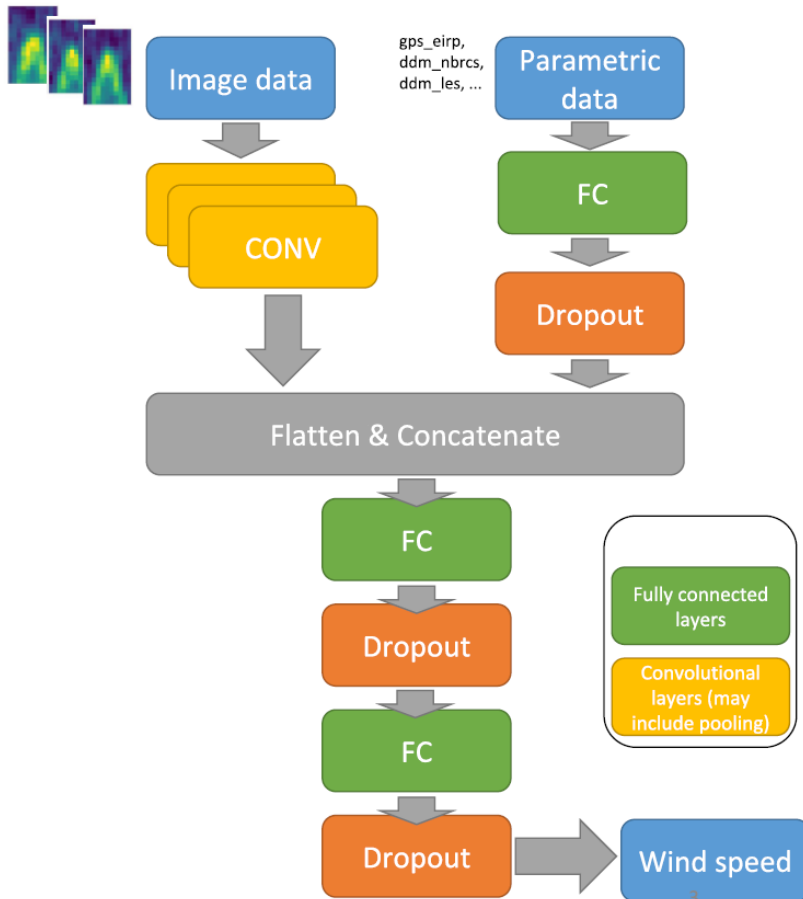
RMSE: 1.81

Deep learning - Convolutional Neural Network

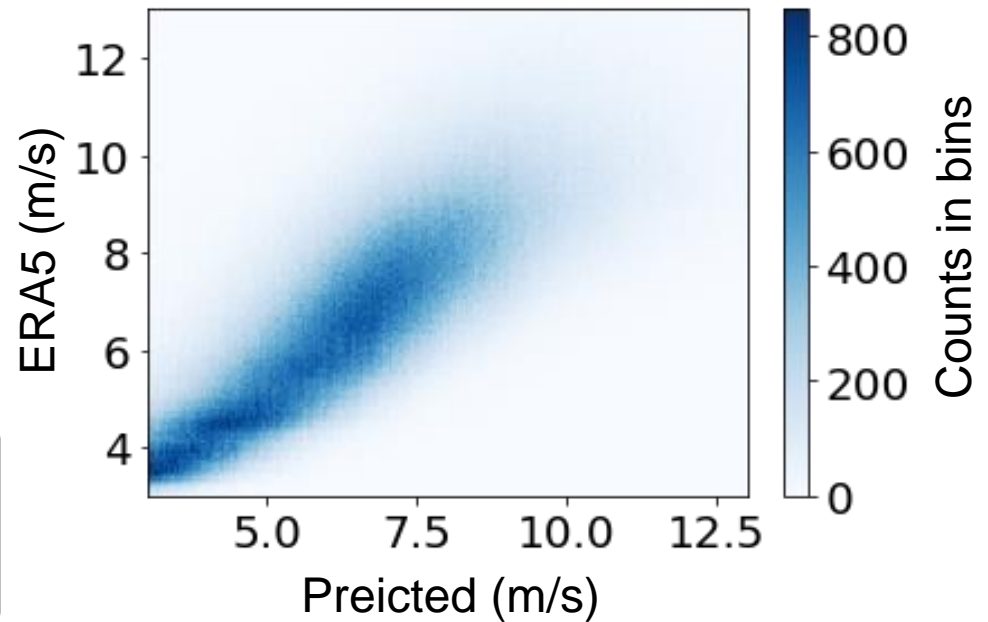
- Most commonly applied to analyzing visual imagery
- Recognition of not only the pixel values, but also the visual patterns (the values with respect to each other).



Deep learning – CNN + FNN



Test data: Oct – Dec 2018



RMSE: 1.62
MAE: 1.18

Concluding Remarks

- Using the TDS-1 and CYGNSS data, GNSS-R wind speed datasets are developed.
- Suitability for extreme weather: the rainy data of TDS-1, show RMSE and bias of **2.94 and -0.21 m/s**, whereas, ASCAT demonstrates a significant degradation to **1.03 and 3.16 m/s**.
- GNSS-R observations are insignificantly affected by **rain attenuation**, less than 3% by rain rates lower than 10 mm/h, which is still ignorable.
- Considerable **splash effect** at winds lower than 6 m/s: **a challenge or opportunity?**
- Spaceborne GNSS-R measurements respond to the existence of eddies.
- Dual polarization measurements show an even higher potential for detecting rain.
- Machine Learning as an alternative inversion approach: significant improvement of **20%** in the general RMSE and 1.2 m/s (32%) for SVN 34.
- The **best** quality of wind products so far are obtained using deep learning, **RMSE of 1.62** with the **CNN+FNN model**.

General Remarks

1 GNSS-R data: more than just additional information

2 The technique is still young!

3 An even more significant role of GNSS-R in ocean monitoring