

# Deep learning in spaceborne GNSS-R: Recent methodologies and atmospheric products

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EGU General Assembly 2022

Atmospheric and Environmental Monitoring with Space-Geodetic Techniques  
and Contributions to Extreme Weather Studies (G5.2)

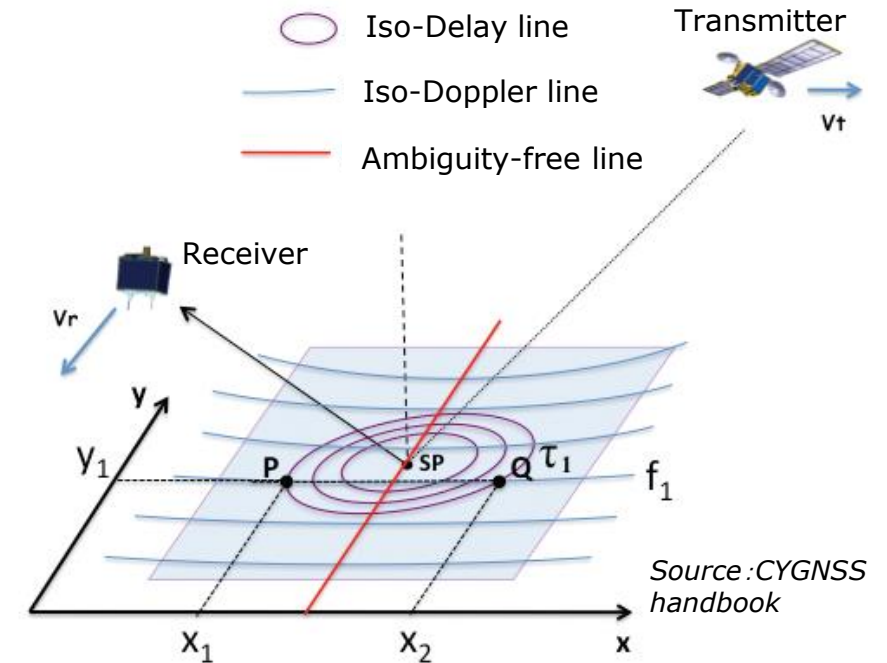
23.05.2022, Vienna

# Deep learning in spaceborne GNSS-R

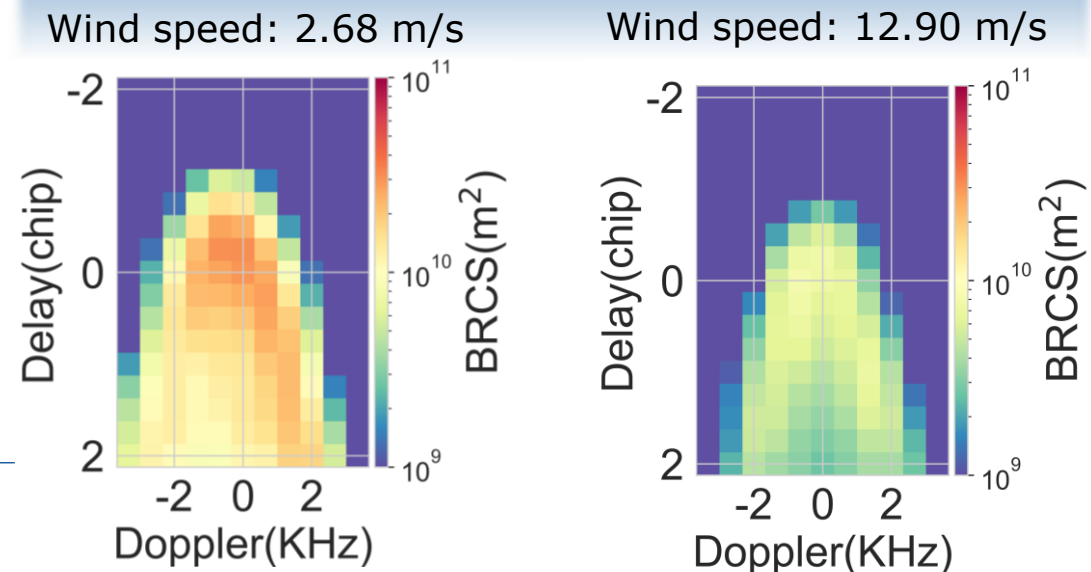


## CYGNSS - Cyclone Global Navigation Satellite System

- Initial dedicated GNSS-R constellation for ocean wind speed determination
- 8 Low Earth Orbiting microsatellites
- Each satellite can track 4 GNSS signals at most -- 32 wind measurements per second
- Approx. revisit time: 2.8~7.2 hours
- Designed wind speed retrieval accuracy: 2 m/s
- Cost-effective
- High spatiotemporal resolution



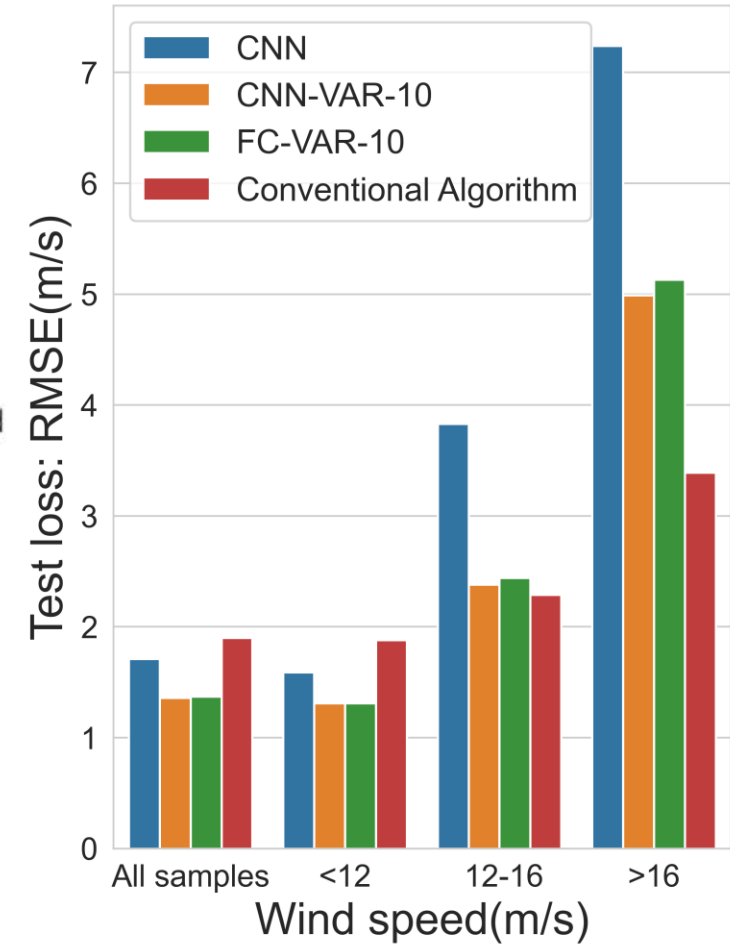
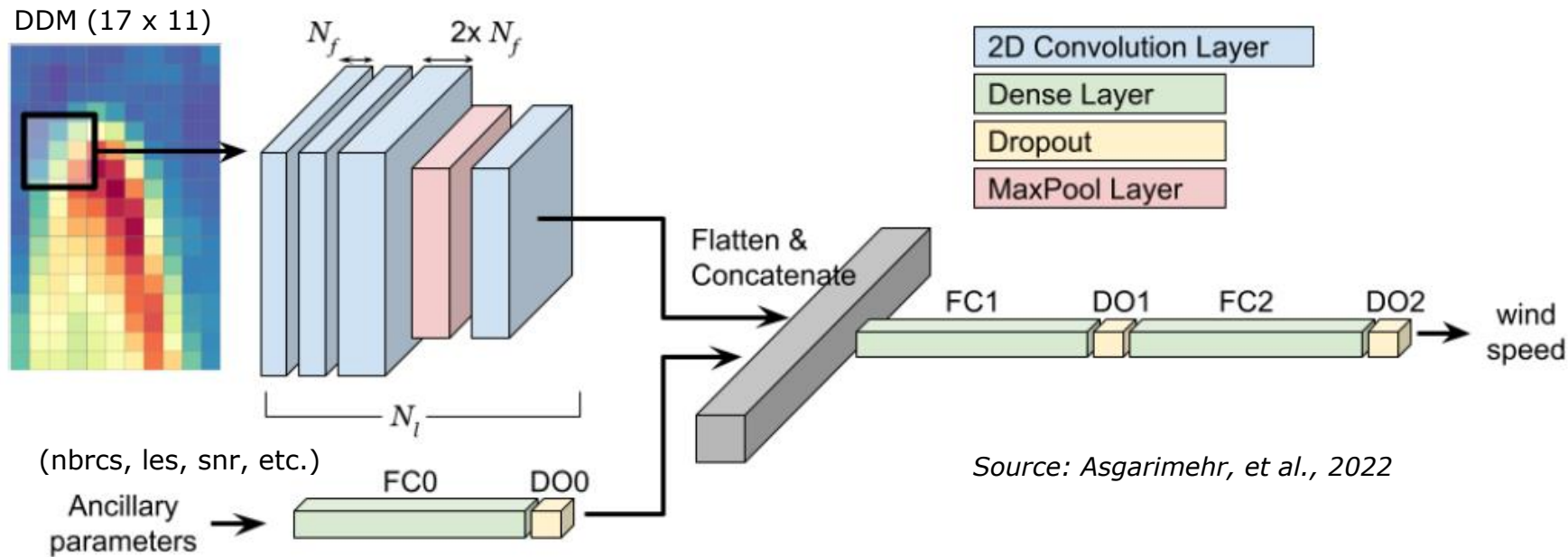
### Delay-Doppler Map (DDM)



# Deep learning in spaceborne GNSS-R

## -- Model

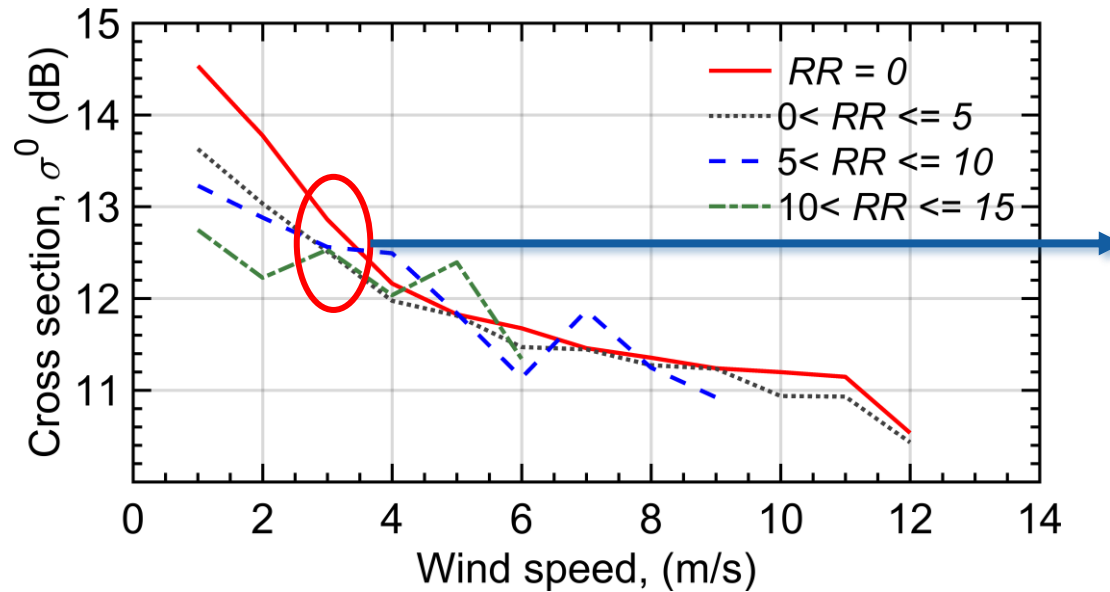
### CYGNSSnet



Model	CNN	CNN-VAR-10	FC-VAR-10	Conventional Algorithm
Observable input (per sample)	1 ddm	1 ddm + 10 Ancillary parameters	10 Ancillary parameters	Derived from CYGNSS L2 data

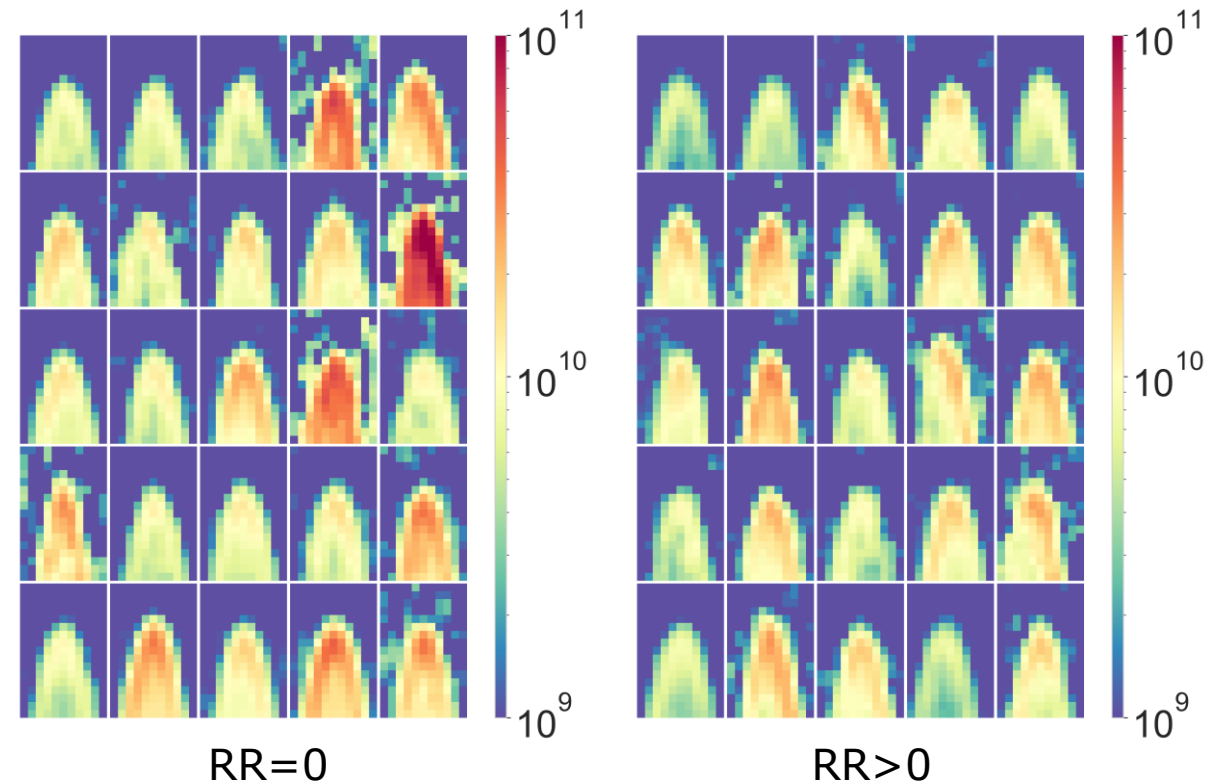
# Deep learning in spaceborne GNSS-R -- Rain Effect

BRCS responds to precipitation with a drop in its value at Low wind speed ( $<4$  m/s)



Source: Asgarimehr, et al., 2018

DDMs of low wind speed



# Data fusion with precipitation

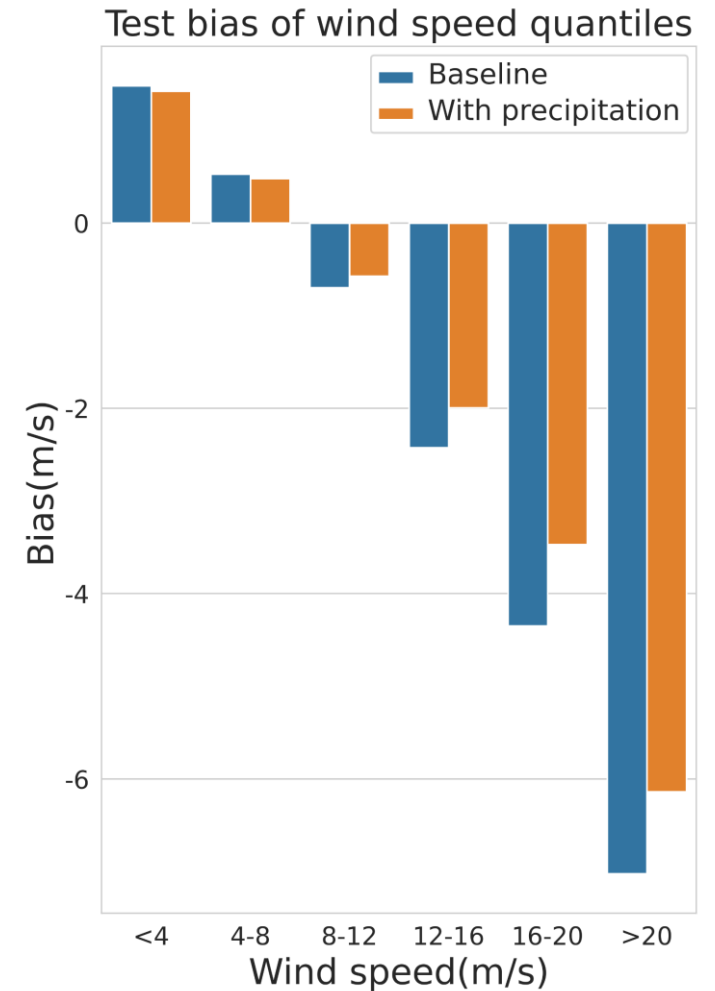
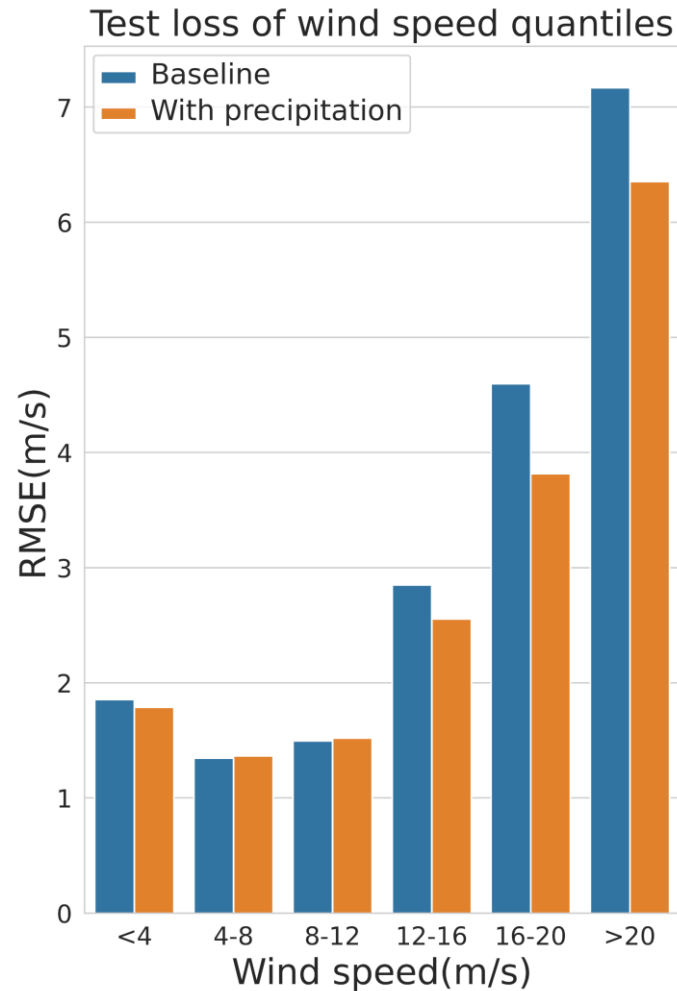
Baseline update:

Dataset version: v3.0

Input DDM: 4 per sample

Input ancillary parameters: 23 per sample

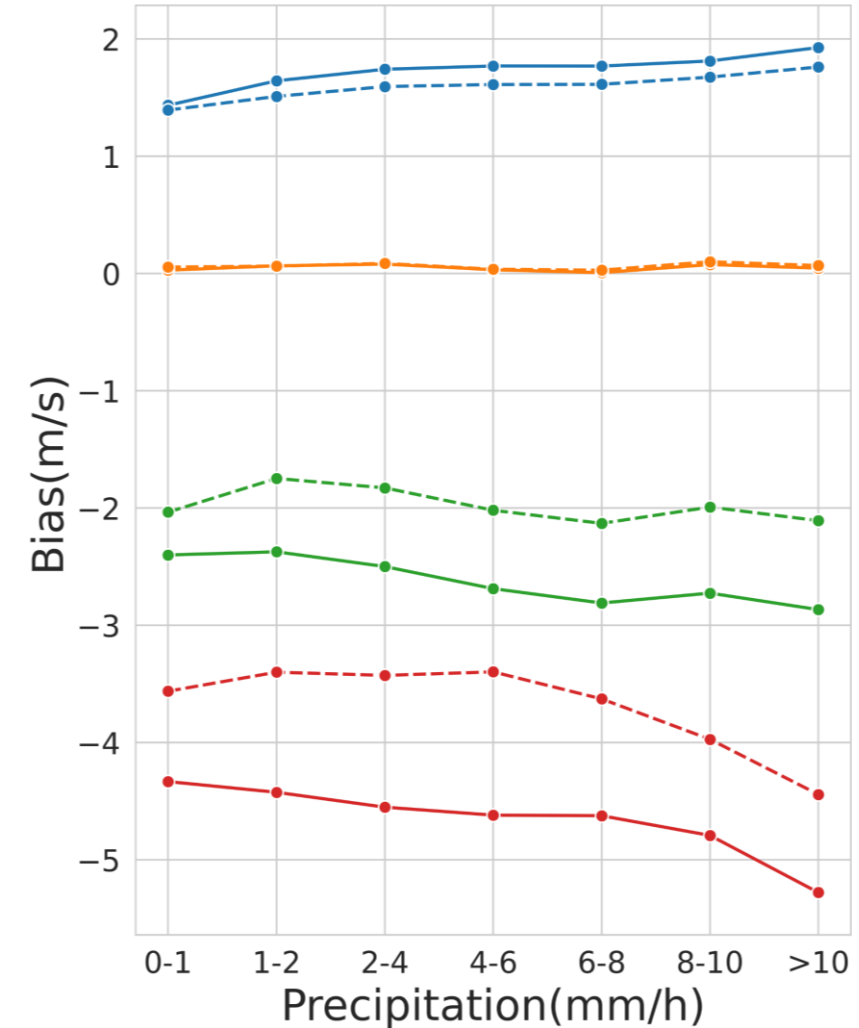
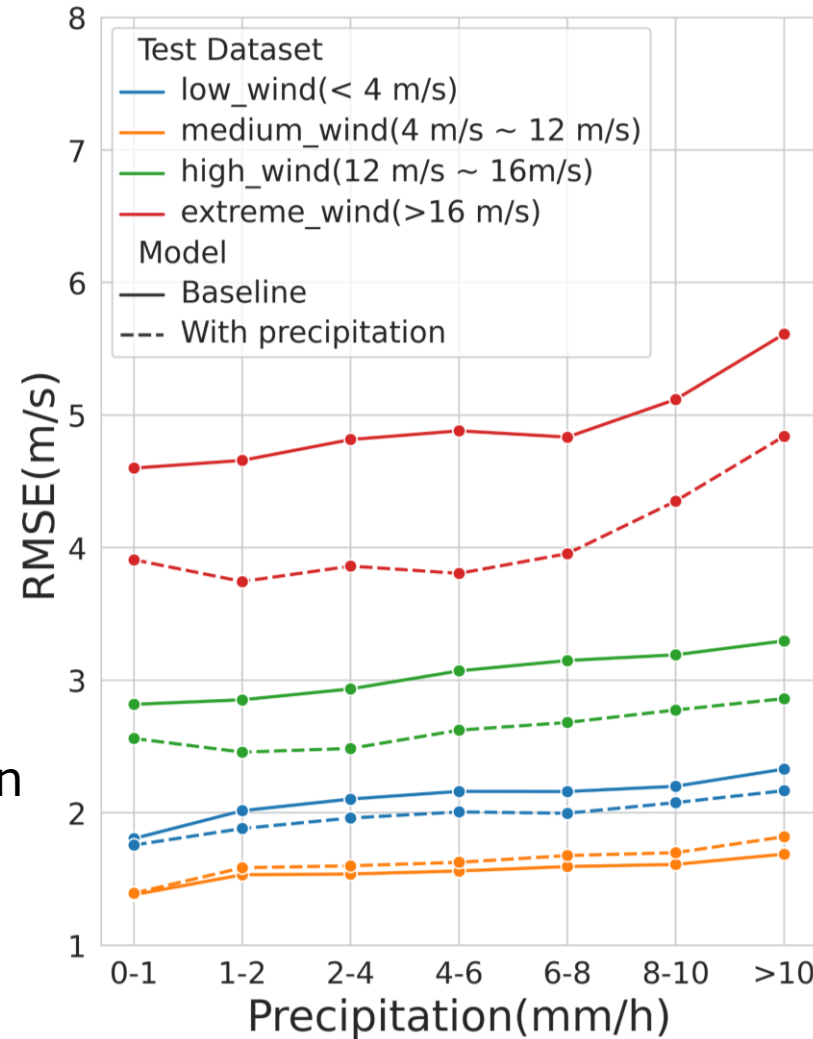
Additional input: GPM precipitation



# Data fusion with precipitation -- Results

Precipitation quantile loss and bias for test samples at different winds peed

Model trained with precipitation data performed better when wind speed is low( $<4\text{m/s}$ ) and higher( $v>16\text{m/s}$ )



# Conclusion

- CyGNSSnet shows a significant improvement in the general RMSE (**28%**) compared to the baseline winds derived from the algorithm based on minimum variance estimations.
- However, reaching MVE accuracy is still a challenge at higher winds.
- Deep learning offers the capability of correcting the effects dictated by the data.
- Data fusion with GPM precipitation data can correct the effect of precipitation and improve the wind speed predictions, especially at low wind speed ( $<4\text{m/s}$ ) and extreme wind speed ( $>16\text{m/s}$ ).

## Future work

- Improve current model performance at medium wind speed ( $4\sim 12\text{ m/s}$ )
- Investigate other potential error source such as swell
- Addressing the unbalanced data
- Combination of physics-based and deep learning methods

### References:

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- Asgarimehr, Milad, et al. "Can GNSS reflectometry detect precipitation over oceans?." *Geophysical research letters* 45.22 (2018): 12-585.
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# Thank you!

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Section 1.1 Space Geodetic Techniques / GNSS Remote Sensing

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