THE CYGNSS MISSION LEVEL 2 WIND SPEED RETRIEVAL ALGORITHM

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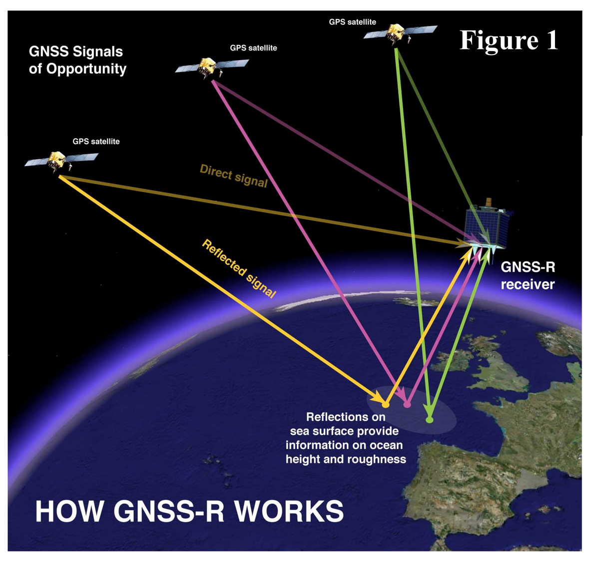
INTRODUCTION

1. GNSS-R: Concept & Principles

❖GNSS-R exploits signal of opportunity from navigation constellations (GPS, GLONASS, Galileo) scattered from the sea surface to derive **ocean roughness,** related to **wind speed and waves (figure 1).**

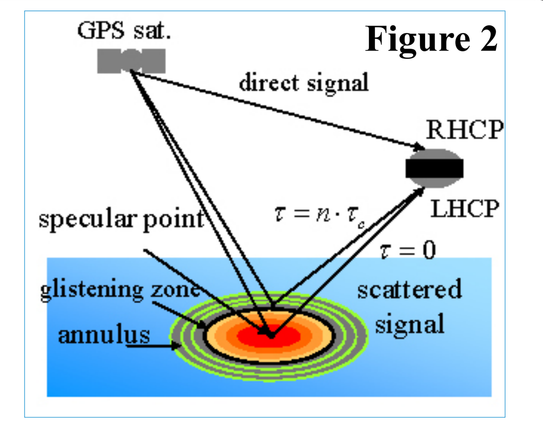
❖**GNSS-R has dense space-time sampling capabilities, uses L-Band signals that penetrate well through the rain, and only calls for simple low-cost/low-power GNSS-R receivers.**



2. GNSS-R Geometry & Delay-Doppler Maps

❖The bistatic scattered power comes mainly from a **Specular Point (SP)** and an area around it called **Glistening Zone (GZ, figure 2)**

❖GNSS-R Data are represented in the form of 2D **Delay-Doppler Maps (DDM)** of scattered power as a function of delay and Doppler frequency (see Figure 3).



❖GNSS-R uses forward scattering, hence when the wind increases:

a) **the scattered power at the specular point (DDM peak) decreases;**

b) **The scattered power from the glistening zone (DDM horseshoe branches) increases;**

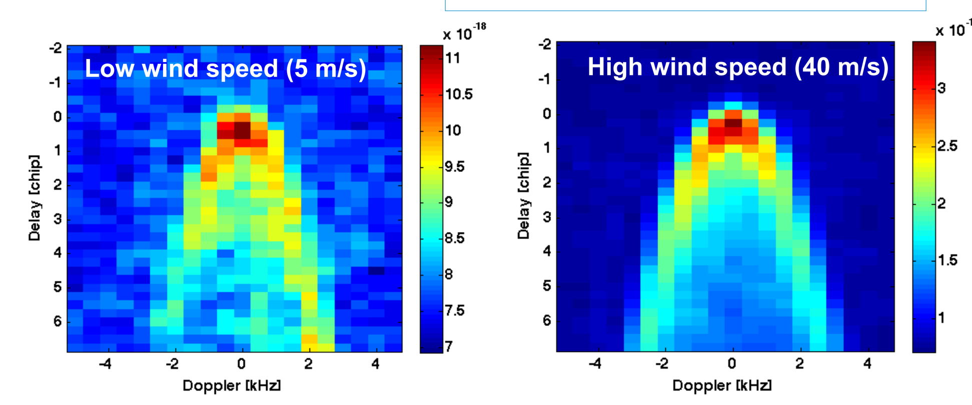


Figure 3. Example of DDMs simulated using the CYGNSS E2ES

3. Overview of CYGNSS

CYGNSS will measure ocean surface wind speed in all precipitating conditions, including those experienced in the TC eyewall, with sufficient frequency to resolve genesis and rapid intensification (Fig. 4a);

CYGNSS uses 8 satellites in LEO at 35° inclination (Fig. 4b), each carrying a GPS-R receiver able to track up to 4 simultaneous reflections per second (Fig. 4c);

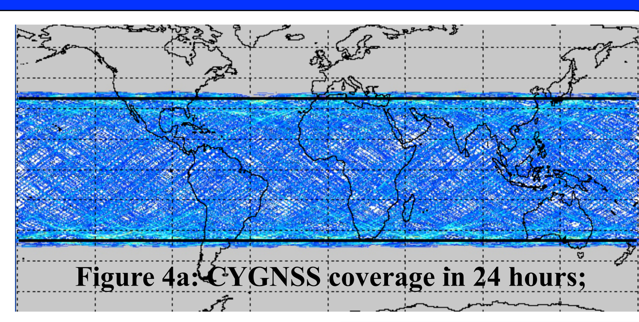
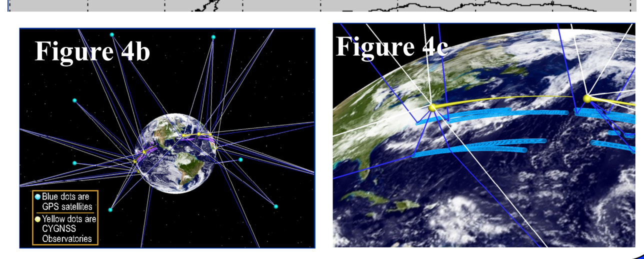


Figure 4a: CYGNSS coverage in 24 hours;



4. CYGNSS Specifications

Table 1 shows the mission objectives and expected performances;

Figure 5 illustrates some specifications for each CYGNSS observatory;

Table 1

Science Objective	Scientific Measurement Estimated Performance	
	Observable	Physical Parameter
Measure ocean surface winds under TC conditions	Precip	< 100 mm/hr (25 km footprint)
	Windspeed uncertainty	Greater of 2 m/s or 10% of windspeed
	Spatial resolution	Variable 5-50 km (ground processing)
	Windspeed dynamic range	< 70 m/s (Cat 5)
Measure ocean surface winds in TC inner core with high temporal frequency	Mean revisit time	4 hr
	Earth coverage	> 70% coverage of all historical TC storm tracks

LEVEL 2 WIND RETRIEVAL ALGORITHM

5. DDM Observables

DDMA (Delay-Doppler Map Average)

The *DDMA is the average value over a given delay-Doppler window around the specular point;*

LES (Leading Edge Slope)

The LES is the slope of the leading edge of the Integrated Delay Waveform (IDW), obtained by integrating (incoherently) the DDM along the Doppler dimension

Delay-Doppler Window for DDMA and LES

Chosen as a trade-off to:

- ✓ **Comply with spatial resolution** (25 km x 25 km);
- ✓ Maximise the received signal;
- ✓ Minimise inclusion of noise-only delay-Doppler pixels;

Delay/Doppler range of [-0.25 0.25] chips and [-1000 1000] Hz is selected

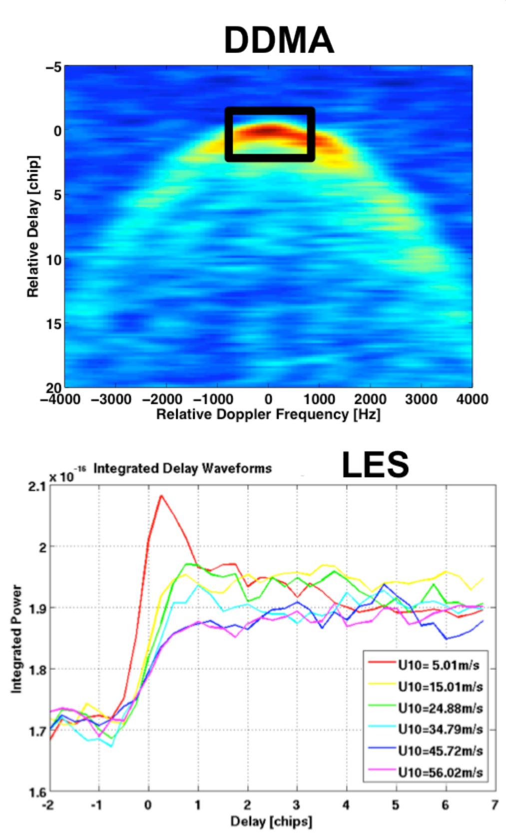
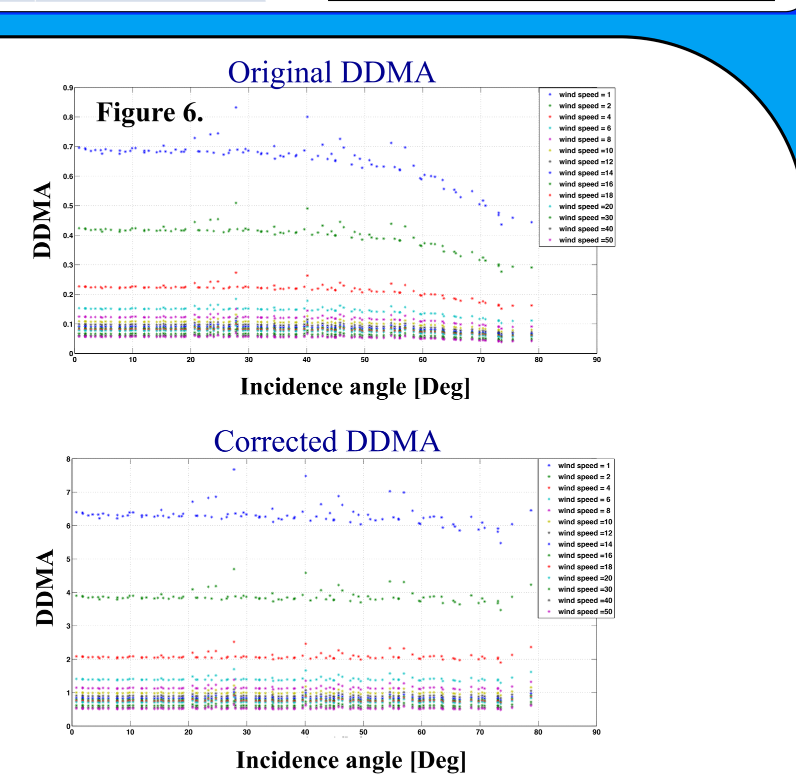


Figure 5. Illustration of DDMA (top) and LES (bottom)

6. Wind Retrieval Algorithm

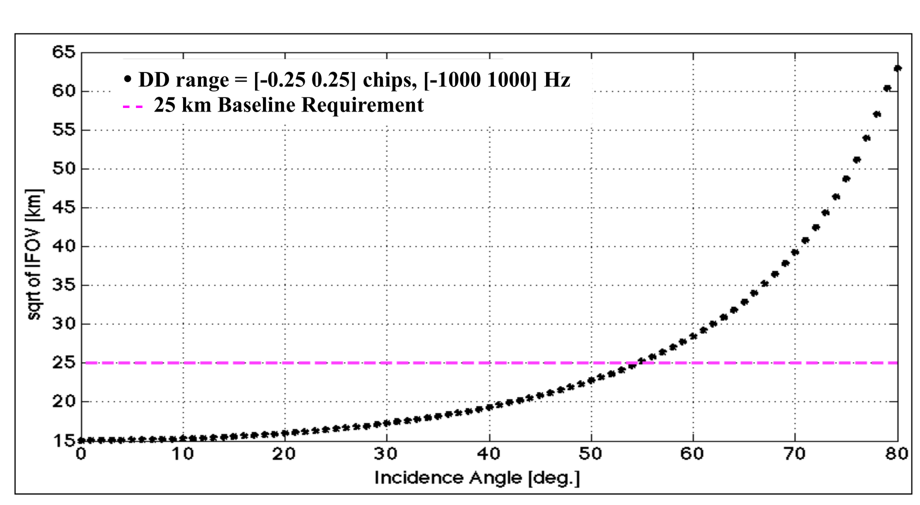
6.1 L2a Correction

The L2a correction suppresses the dependence of th observables on incidence angle (see figure 6).



6.2 Time averaging of observables

If a single sample has a scattering area lower than 25 km x 25 km, observables can be averaged in time to produce an Equivalent Field Of View (EFOV) with the desired resolution (figure 7). Some geometries (Incidence angle greater than 54.5° do not meet the resolution requirements.



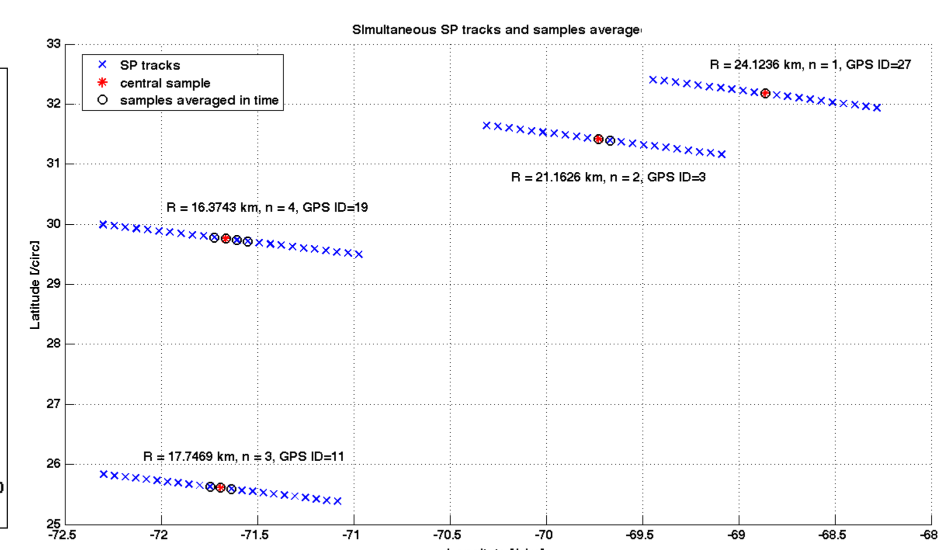


Figure 7 (left): plot of the sqrt of scattering area as a function of incidence angle, for the delay-Doppler window selected. The 25 km CYGNSS baseline requirement is also shown. (right): Graphical illustration of how time averaging works.

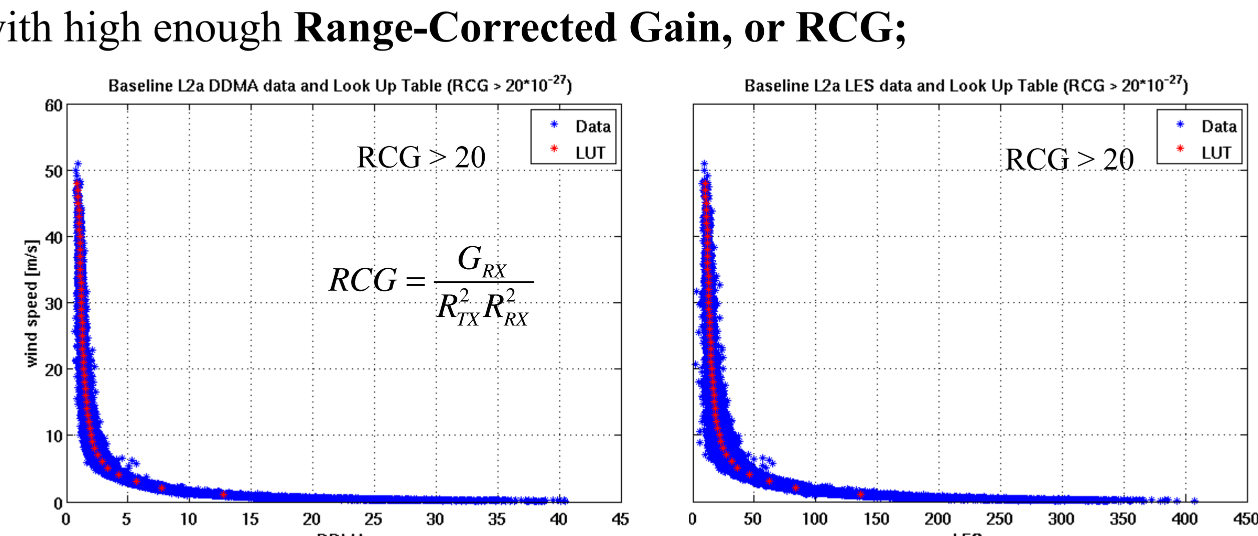
6.3 Training Data, Geophysical Model Function and Minimum Variance Estimator

I. The DDMA and LES are computed from DDMs generated using the CYGNSS E2ES and a **Nature Run wind field [1]** that simulates 13 days of a full life-cycle of a Tropical Cyclone;

II. The whole dataset of observables is split into **training and test dataset;**

III. An empirical **Geophysical Model Function or GMF** (Look-Up Table) is derived from the training dataset of each observable with high enough **Range-Corrected Gain, or RCG;**

IV. Winds retrieved from DDMA and LES are linearly combined to generate a **Minimum Variance Estimator** [2], which exploits the degree of decorrelation between the retrievals from the two observables



$$RCG = \frac{G_{RX}}{R_{TX}^2 R_{RX}^2}$$

Figure 8 training DDMA (left) and LES (right) data with RCG> 10(blue stars) shown together with their empirical GMF (red stars) derived in the form of a Look-Up table

V. An **adaptive implementation** of the MV Estimator is used, with different Covariance Matrices (and different coefficients) estimated for different ranges of RCG (see figure 9)

MV estimator — MV coefficients — DDMA/LES estimates

$$\hat{u}_{MV} = \vec{m} \cdot \hat{u}$$

Elements of inverse covariance matrix — inverse covariance matrix of DDMA and LES retrieval errors

$$\vec{m} = \left(\sum_{i=1}^{N} \sum_{j=1}^{N} \boxed{C_{ij}^{-1}} \right)^{-1} \boxed{C^{-1}} \cdot \vec{1}$$

Correlation coefficient matrix	RCG interval
$R_i = \begin{bmatrix} 1.0000 & 0.0807 \\ 0.0807 & 1.0000 \end{bmatrix}$	3*10^-27 <= RCG < 5*10^-27
$R_i = \begin{bmatrix} 1.0000 & 0.1067 \\ 0.1067 & 1.0000 \end{bmatrix}$	5*10^-27 <= RCG < 10*10^-27
$R_i = \begin{bmatrix} 1.0000 & 0.1164 \\ 0.1164 & 1.0000 \end{bmatrix}$	10*10^-27 <= RCG < 20*10^-27
$R_i = \begin{bmatrix} 1.0000 & 0.3690 \\ 0.3690 & 1.0000 \end{bmatrix}$	RCG >= 20*10^-27

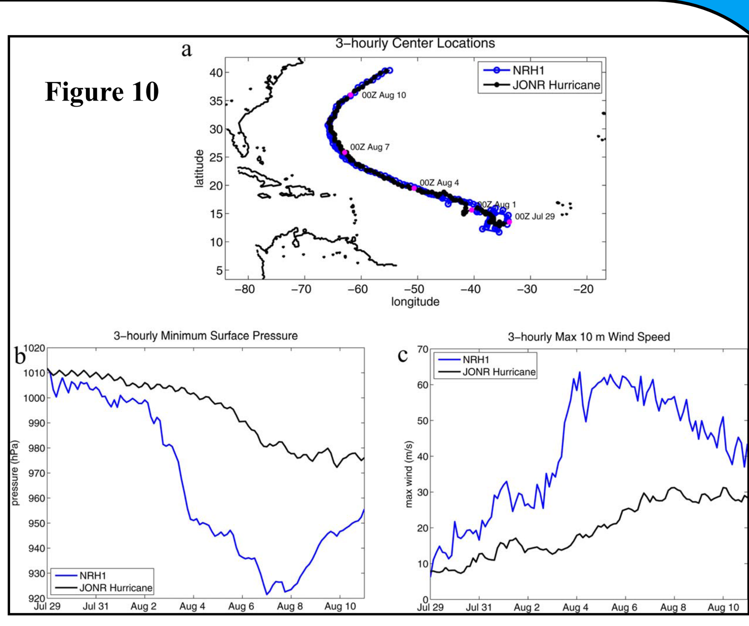
Figure 9. Correlation Coefficient Matrices of DDMA and LES wind speed retrievals, for different intervals of RCG

7. Results

Figure 10 (black box) shows the characteristics of the 13 Day Tropical Cyclone simulated with the Nature Run model, and used to train and test the algorithm;

Figure 11 (red box) shows the resulting performances of the algorithm;

Table 2 highlights that the algorithm meets the baseline requirements on the average RMS error (which must be the greatest between 2 m/s and 10% of the measured wind);



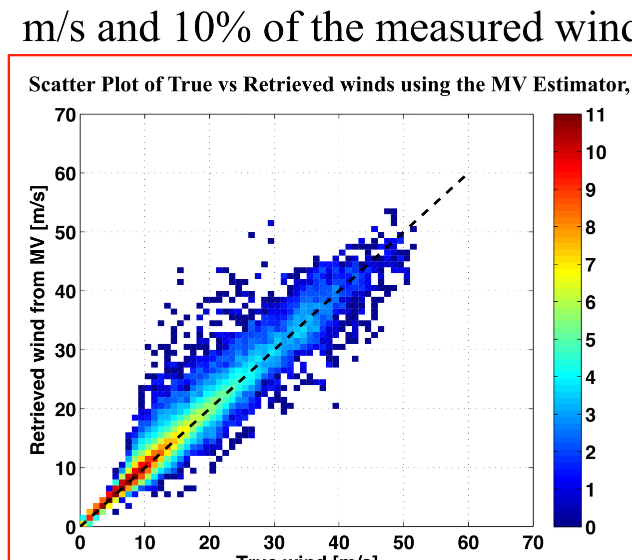


Figure 11

Wind speed range	<20m/s	>20m/s
RCG lower bound	>5	>10
Avg. RMS error	1.4 m/s	9.2%

Table 2. RCG lower bounds that need to be selected for the wind speed to meet the baseline requirements

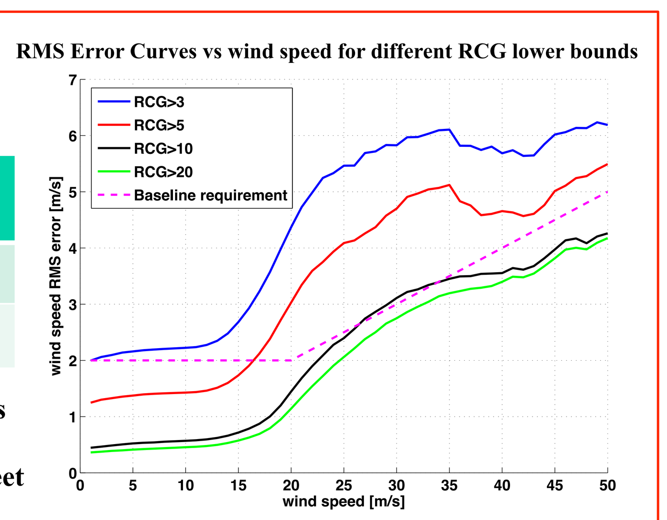
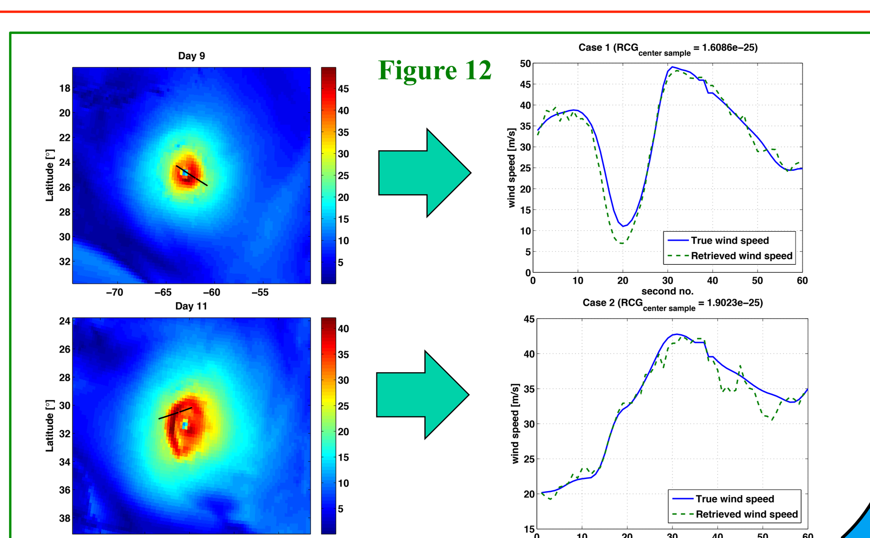


Figure 12 (green box) shows two examples of 1-minute CYGNSS transects near and over the storm center, acquired with high enough RCG (left); The corresponding true and retrieved winds versus time (right) show a good match.



CONCLUSIONS & FUTURE WORK

✧ A wind retrieval algorithm has been illustrated, which uses two different observables: DDMA and LES;

✧ The approach is based on the use of an empirical Geophysical model function (GMF) derived from a set of training data from each observable; the winds retrieved from DDMA and LES are combined into a Minimum Variance (MV) estimator to obtain the best possible performances;

✧ The algorithm has been tested using a dataset independent from the training one. Both training and test datasets have been obtained from the CYGNSS E2ES and a Nature Run wind field simulating a life cycle of a TC. The final average wind speed RMS error meets the CYGNSS baseline requirements

ONGOING & FUTURE WORK:

✧ Application of this algorithm to DDMs generated using the Hurricane Weather Research and Forecasting (HWRF) model [3] and detailed cal/val analysis;

✧ Investigations on ways to improve the present algorithm (i.e. inclusion of more observables, robust GMF derivation), testing of new retrieval algorithms (DDM fitting);

REFERENCES

[1] Nolan, D. S., R. Atlas, K. T. Bhatia, and L. R. Bucci (2013), "*Development and validation of a hurricane nature run using the joint OSSE nature run and the WRF model*", J. Adv. Model. Earth Syst., 5, doi:10.1002/jame.20031.

[2] Clarizia, M. P., Ruf, C.; Jales, P. and Gommenginger, C., "*Spaceborne GNSS-R Minimum Variance Wind Speed Estimator,*" IEEE Trans Geosci. Remote Sens., **52**(n), ppp-ppp, doi: 10.1109/TGRS.2014.2303831, 2014.

[3] S. Gopalakrishnan, Q. Liu, T. Marchok, D. Sheinin, N. Surgi, R. Tuleya, R. Yablonsky and X. Zhang, "*Hurricane Weather Research and Forecasting (HWRF) Model Scientific Documentation*", available at http://www.dtcenter.org/HurrWRF/users/docs/scientific_documents/HWRF_final_2-2_cm.pdf