The NOAA Track-Wise Wind Retrieval Algorithm and Product Assessment for CyGNSS

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Abstract—A novel approach in addressing cyclone global navigation satellite system (CyGNSS) intersatellite and GPS-related calibration issues is proposed, based on a track-wise $\sigma^o$ bias correction method. This method makes use of both ancillary data from numerical weather prediction models and a semiempirical geophysical model function. Care is taken, so the track-wise $\sigma^o$ bias correction maintains CyGNSS signal sensitivity. Both intersatellite and GPS-related calibration issues are removed after correction. Long-term $\sigma^o$ downward trend, observed throughout the CyGNSS mission, is greatly reduced. Using the corrected $\sigma^o$ measurements, a wind retrieval method is also presented and its product thoroughly assessed for a three-year period against European Centre for Medium-Range Weather Forecasts (ECMWFs), Advanced Scatterometer (ASCAT) A/B, Advanced Microwave Scanning Radiometer (AMSR)-2, GMI, WindSat, hurricane weather research and forecasting (HWRF) model, and the stepped frequency microwave radiometer (SFMR) winds. The overall wind speed bias and standard deviation of the error (stde) against ECMWF are 0.16 and 1.19 m/s, while these are $-0.11$ and 1.12 m/s against ASCAT A/B, respectively. The same metrics against AMSR-2/GMI/WindSat (combined) are $-0.19$ and 1.11 m/s, respectively. The bias and stde against soil moisture active passive (SMAP) are $-0.38$ and 1.90 m/s, respectively. In the tropical cyclone environment, the bias and stde against HWRF are $-0.54$ and 2.90 m/s, and $-4.71$ and 5.88 m/s with SFMR. Finally, CyGNSS wind performance is gauged in the presence of rain. Below 10 m/s, the bias between CyGNSS and ECMWF increases as the rain rate increases. Between 10 and 15 m/s, biases are mostly absent. Above 15 m/s, results are inconclusive due to the low number of collocated rain samples. Overall, the presented CyGNSS wind speed product both exhibits consistency and reliability, showing promise of using GNSS-R derived winds for operational purposes.

Index Terms—Geophysical measurements, global positioning system, microwave reflectometry, radar measurements, remote sensing, scattering, sea surface, wind.

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Fig. 1. Graphical representation of the CyGNSS spacecraft. Adapted from [1].

I. BACKGROUND

On December 15, 2016, the Cyclone Global Navigation Satellite System (CyGNSS) mission, a constellation of eight low Earth-orbiting small satellites, was launched into space (see Fig. 1). One of CyGNSS’s major purposes is to provide reliable global wind speed measurements, including in the tropical cyclone environment, with increased daily temporal revisits. In order to achieve that, each of these eight spacecrafts carries a port and starboard side antennas capable of receiving up to four simultaneous specular reflections, from right-hand-circularly polarized L-band signals (1.575 GHz) transmitted from the GPS satellite constellation. The received signal associated with each specular point location is recorded in the delay-Doppler map (DDM) space, from which the normalized bistatic radar cross section (NBRCs) is estimated.

Using such an observable, the sea surface wind speed can be inferred using a geophysical model function (GMF), which relates the NBRCs to the wind speed as a function of incidence angle and additional geophysical parameter, such as the significant wave height. Due to the mechanism associated with bistatic specular reflections, the received power originates from waves scattered from within the so-called glistening zone, with the strongest signal being reflected from its center (i.e., nominal specular point). As the surface roughens, the glistening zone becomes larger, thereby decreasing the amount of received power, leading to a monotonous decrease in NBRCs as the sea surface wind speed increases. There are two noticeable effects from this relationship: first, the NBRCs shows higher sensitivity in the low wind speed regime (e.g., below 4–5 m/s), where a small change in wind speed corresponds to a large change in NBRCs. Conversely, for higher wind speed regimes, a large change in wind speed...
corresponds to a small change in NBRCS. Since the signal-to-noise ratio (SNR) naturally decreases as the wind speed increases, robust wind retrieval methods must be implemented in order to provide a reliable and consistent wind speed product to the scientific community.

Since May 2017, a few CyGNSS Level 1 science data record versions have been released to the public, namely v1.0 and v1.1 (both provisional versions), later v2.0 [2], and at the time of writing v2.1 [3] and v3.0 [4]. In [5], the NBRCS calibration from the v2.0 dataset was carefully assessed where the presence of inter-satellite NBRCS biases was observed; a dependence between NBRCS and instrument noise floor (NF) was also identified and believed to be the main drive for this bias. This issue was reported to CyGNSS scientists and engineers, and a temporary solution for this problem was provided and implemented in the version 2.1 release [6].

Improvements in the characterization of the GPS effective isotropically radiated power (EIRP) were also noted, starting with v2.0, where $\sigma^o$ biases between GPS block types IIR, IIR-M, and IIF were reduced [5]. However, the so-called flex power events have been troublesome, particularly with block IIF GPS [7]; since January 2017, 10 out of the 12 block IIF GPS have had their power level temporarily altered in strategic locations around the globe. Since these power fluctuation levels are unknown and unpredictable, specular reflections from IIF GPS have always been problematic for the CyGNSS mission. In fact, the v2.1 Level 2 wind speed product flags all retrieved wind samples from $\sigma^o$ measurements originating from such GPS, roughly representing 40% of the total dataset [8].

Despite the above-mentioned calibration improvements, we have reported a $\sim$ -5-dB decrease in v2.1 NBRCS between May 2017 and January 2019 across all satellites. This issue resulted in a nonnegligible increase in the wind speed bias between CyGNSS and numerical weather prediction (NWP) models across the same time period (i.e., $\sim +2$ m/s) [9]. Furthermore, we have noted the ever presence of inter-satellite NBRCS biases, albeit much smaller than in previous versions. Yet, these still translate into nonnegligible inter-satellite wind speed biases and thereby result in an inconsistent and unreliable wind speed product [9].

This article proposes a method that directly addresses these various calibration issues by applying a so-called track-wise bias correction to v2.1 CyGNSS $\sigma^o$ measurements, first introduced in [10]. Section II describes the methodology behind it. Section III provides the details regarding the quality control (QC) steps implemented in our proposed wind retrieval algorithm. Sections IV–VII provide a comprehensive performance assessment and evaluation of the estimated NBRCS, retrieved wind speed globally and in the tropical cyclone environment, and finally in the presence of rain, respectively. Section VIII finally concludes and discusses possible future work.

II. METHODOLOGY

Our so-called track-wise $\sigma^o$ bias removal procedure requires a careful assessment of the $\sigma^o$ measurement quality on a per track basis; we define a track to be a set of NBRCS measurements obtained from contiguous specular reflections originated from a given GPS, received by a CyGNSS spacecraft antenna (see Fig. 2). Each spacecraft registers approximately 1000–1100 tracks per day. Along each of these tracks, the CyGNSS NBRCS has been reported at a 1-Hz sampling rate, resulting in approximately $\sim$-6-km spacing between adjacent NBRCS measurements. Since July 2019, the sampling rate has been increased to 2 Hz, resulting in a $\sim$-3-km spacing between adjacent NBRCS measurements. Since the expected NBRCS spatial resolution varies between 25 and 40 km (depending on incidence angle) [12], either sampling strategy inevitably results in highly correlated NBRCS measurements.

We first minimize this artifact by averaging the NBRCS on a 25-km grid size on a per track basis while excluding poor-quality NBRCS measurements (e.g., “poor overall quality flag”) provided in the Level 1 data is triggered—see Section III-A for additional details)—and excluding very short tracks with 15 samples or less. A boxcar smoothing window is then applied on the gridded NBRCS in order to reduce remaining large fluctuations between the adjacent samples along each track. In addition, a given track may be split into subtracks whenever data gaps greater than 10 s are present along the track. This track splitting step has been deemed necessary as we found some discrepancies in the NBRCS when a track is crossing land or a set of islands. Furthermore, tracks may also be split based on the receiver antenna gain; on longer gridded tracks, the corresponding time series of the receiver antenna gain usually follows the shape of a negative parabola, which includes areas of low gain on both ends of the time series. We have noted in several instances higher fluctuations in the NBRCS when the Rx gain is dropping on either end, potentially impacting the overall retrieval performance. Consequently, these longer tracks may be split at the peak of the Rx gain if and only if at least both split track lengths are at least 500 km long and the total length of the original gridded track is at least 1750 km long. These strict conditions are used in order to avoid overfitting of the data.

Once the data are gridded on a 25-km grid along each track, the predicted $\sigma^o$ is then estimated using collocated
Fig. 3. CyGNSS $\sigma^o$ as a function of sea surface wind speed for varying Hs (1–9 m), given a 32° and 47° incidence angle [see plots (a) and (b), respectively]. These figures show that the NBRCS is highly sensitive below 5 m/s. Conversely, the opposite is true for wind speeds greater than 15 m/s. As an example, around 20 m/s wind speed and given Hs = 5 m and $\theta_i$ = 32° [see plot (a)], the rate of change of the NBRCS is $-0.64 \text{ dB/(m/s)}$; around 25 m/s, it is $-0.048 \text{ dB/(m/s)}$ given the same Hs and $\theta_i$ = 32°. As can be seen, any moderate change in estimated NBRCS along a given CyGNSS track in the higher wind speed regime (e.g., >20 m/s) could result in a large wind speed change. Additional details about the GMF derivation are provided in [11].

Fig. 4. (a) Time series of the v2.1 nongridded and gridded $\sigma^o$ with and without bias correction, including estimated $\sigma^o$ from the GMF, along track ID 357 from CyGNSS 3 on July 4, 2017. Ancillary data, such as model wind (shown in blue), significant wave height (shown in yellow), and the incidence angle at the specular point (shown in magenta), are also provided along the track. (b) Both $\sigma^o$ with and without bias correction, including estimated $\sigma^o$ from the GMF, as a function of the model wind speed. (c) Scatterplot of the retrieved CyGNSS winds (with and without the bias correction applied in the $\sigma^o$ space) versus the model winds.

sea surface wind speed, such as European Centre for Medium-Range Weather Forecasts (ECMWFs) and significant wave height (Hs) from the Ifremer implementation of the Wave watch 3 model [13] and knowledge of the incidence angle of specular reflection ($\theta_i$). This step is made possible with the use of a 3-D lookup table (LUT), or semiempirical GMF, relating the wind speed, Hs, and $\theta_i$ to CyGNSS $\sigma^o$. This GMF is constructed using the standard CyGNSS Level 1 NBRCS product, collocated with 1/4° winds from an NWP model such as ECMWF and 1/2° Hs from the Ifremer implementation of the Wave watch 3 model, which utilizes the ECMWF winds as input. The relationship between $\sigma^o$ and wind speed is then bin averaged along both the Hs and $\theta_i$ dimensions using a 1 m and 5° bin sizes, respectively (see Fig. 3 and [11] for more details). A median filtering step, with a width of 3, is applied to the retrieved wind samples along each gridded CyGNSS track to minimize potential spikes from highly varying $\sigma^o$ samples.

Fig. 4(a) shows the measured (in black) and predicted (in red) $\sigma^o$ time series for a selected track with specular reflections originated from GPS unique space vehicle number (SVN)-46 (pseudo random noise (PRN) 11) and received by observatory #3 on July 4, 2017. As can be seen, a non-negligible bias exists between the measured and predicted $\sigma^o$ along the track. As discussed in Section I and [5], calibration issues either from poorly characterized transmitted power and/or receiver antenna (Rx) gain, including possible NBRCS dependence to the instrument NF, are most likely the cause of these biases. By making use of the predicted $\sigma^o$ associated with the tail of the distribution of the collocated model wind speed samples (representing 35% of the sample size), a bias between the two $\sigma^o$ time series is then computed and applied to the measured $\sigma^o$, resulting in a bias corrected $\sigma^o$ shown in green in Fig. 4(a) and (b). It is important to note that this bias correction method does not alter the “shape” of the $\sigma^o$ time series, thereby preserving the sensitivity of the received signal along the track.

Using the aforementioned 3-D GMF LU, the wind speed is then inferred using straightforward inversion and linear interpolation techniques, requiring $a$ priori knowledge of Hs and the reported incidence angle along the track. Fig. 4(c) shows the scatterplot of the retrieved CyGNSS wind speed (with and without the bias correction applied in the $\sigma^o$ space) versus model winds. We note the very poor correlation between the overestimated retrieved wind without bias correction and modeled wind along the track. The benefit of the track-wise $\sigma^o$ bias correction method is clear in this example, where agreements between the retrieved wind and modeled wind are notably improved.

III. QUALITY CONTROL

As previously mentioned, one of the main reasons behind the use of the track-wise $\sigma^o$ bias correction method is to address the various lingering calibration issues found in the CyGNSS data. However, there are certain inherent limitations in the current state of the data in which the track-wise $\sigma^o$ bias correction method cannot overcome. This section addresses these issues and also discusses the preretrieval and postretrieval QC steps performed on the data.
or negative adjusted accordingly, resulting in most instances to a positive out the CyGNSS mission, the spacecraft roll angle was power positive orientation for high solar beta angles through-

gets below ∼3 dB [see plot (a)]. The specular reflections were transmitted from SVN-53 with pm code 17. Plots (b)–(d) provide three DDM plots for three different Rx gains along the track. The well-known horseshoe pattern is usually associated with DDMs. Note, however, how this pattern degrades as the Rx gain decreases. In addition, note how the correlation between the measured and predicted σo decreases once the Rx gain is below ∼3 dB [see plot (a)].

A. Preretrieval QC

1) CyGNSS SNR Variability: While developing our track-wise-based wind retrieval algorithm, we discovered that the quality of the σo decreases substantially as the Rx gain decreases below ∼3–4 dB (as a reminder, CyGNSS peak Rx gain is ∼15 dB). The same can be said when the SNR gets below ∼2 dB. As an illustration, Fig. 5(a) shows σo, corresponding Rx gain, and SNR time series along a track containing specular reflections from SVN-53 (PRN 17 – block IIR-M), received by observatory #2 on September 12, 2017. Three DDMs [see Fig. 5(b)–(d)], selected at different times along the same track, are also included in this figure, each of which are associated with an approximate Rx gain of 13.7, 5, and 2 dB, respectively. The DDM retrieved at the peak Rx gain along the track [Fig. 5(b)] exhibits the well-known and expected horseshoe pattern. However, this pattern deteriorates as the Rx gain decreases, as shown in Fig. 5(c) and (d). Even though the horseshoe pattern is still recognizable in these images, the quality of the estimated σo from these DDM pixels degrades as the Rx gain decreases. In fact, a closer look at the σo time series reveals poor correlation with estimated σo when the Rx gain gets below 4–5 dB. Further analysis was performed with a larger data sample showing similar results, where CyGNSS σo cannot be trusted if its associated Rx gain is below ∼3 dB and/or its associated SNR gets below ∼1 dB. Therefore, data meeting the following criteria are rejected: (Rx ≤ 3 dB ∧ SNR < 9 dB) ∨ (SNR < 1 dB ∧ Rx < 7 dB).

2) High Solar Beta Angle Period: In order to maintain a power positive orientation for high solar beta angles throughout the CyGNSS mission, the spacecraft roll angle was adjusted accordingly, resulting in most instances to a positive or negative ∼220 roll angle [6]. Fig. 6 shows the daily averaged roll angle time series [see plot (a)], including the daily averaged σo time series per spacecraft antenna [see plots (b) and (c)]. It can be seen from Fig. 6(b) and (c) that the daily averaged σo notably increased whenever the roll angle was large. Furthermore, daily averaged σo from the starboard antenna appeared to be more affected than the port side during these maneuvers. This indicates possible calibration issues in the receiver antenna gain patterns when the attitude is nonideal during high solar beta angles. Until further analysis of the σo quality in a high roll angle situation is performed, we have decided to exclude all σo samples associated with any attitude variable angle greater than 5°.

3) Azimuth Angle-Dependent Flag: σo samples associated with the starboard side antenna have the azimuth angle of specular reflection set to be varying between 0° and 180°, whereas σo samples on the port side have the azimuth angle set to be varying between 180° and 360°. However, we have discovered instances of starboard side σo samples associated with azimuth angle greater than 180°, and as port side σo samples associated with azimuth angle less 180°. Such σo samples are rejected prior to performing the retrieval, given the fact that both starboard and port side antenna patterns are poorly characterized at these azimuth locations.

B. Postretrieval QC

1) Star Tracker Flag: CyGNSS microsatellites use a star tracker for primary attitude knowledge [12]. Unfortunately,
the sensor location on each CyGNSS spacecraft allows Sun incursion in its field of view, thereby making the star tracker lose lock on a near orbital basis. Despite having additional Sun sensors used to help during such events, these sensors provide coarse attitude information [14].

A nano star tracker attitude flag is therefore included in the Level 1 data. When this flag gets set, it essentially means that the reported attitude parameters may not be trusted even if their reported ranges are nominal. Fig. 7 reports the daily percentage of CyGNSS data, per observatory, where the star tracker flag is set. As can be seen, the levels oscillate between 0% and ∼25% and remain similar across sensors. The preliminary analysis showed that the reported NBRCs values had poor correlation with predicted $\sigma^o$ measurements whenever the star tracker flag was set. In order to retain as many retrieved samples as possible, a pointwise bias between the predicted and measured $\sigma^o$ samples is computed. If the absolute value of the bias is found to be above 0.55 dB, the corresponding wind speed sample is then flagged. As an illustration, Fig. 8(a) shows the time series of predicted and measured $\sigma^o$ samples, along with the corresponding CyGNSS retrieved winds and collocated ECMWF winds. Fig. 8(b) reports the corresponding time series of the attitude parameters and Rx gain. As can be seen in Fig. 8(a), retrieved wind samples are flagged when the measured $\sigma^o$ noticeably deviates from estimated $\sigma^o$, as previously described. Such samples are highlighted with a red “x” symbol in Fig. 8(a).

2) Detecting Unrealistic Wind Speed Samples: Even when the Rx gain is greater than 3 dB, it is still possible to obtain $\sigma^o$ measurements associated with SNR level below 2 dB. This is especially problematic when the wind speed at the sea surface becomes high (e.g., greater than 15 m/s). If calibration issues are present, an unexpected change in the $\sigma^o$ level can lead to an abrupt and unrealistic change in wind speed along a given track. A flag has been implemented to detect unrealistic wind speed samples whenever the Rx gain is above 3 dB and the SNR is below 2 dB. Whenever this condition is met, the rate of change of the wind speed along each track ($du_{10}/dt$) is evaluated for each wind speed sample. A wind speed sample is then flagged if and only if it is surrounded by derivatives with different signs (see Appendix A for additional details on the flagging algorithm). It is important to note that this algorithm is designed to preserve as much of the along-track wind field characteristics as possible. Fig. 9 shows an example of a CyGNSS track where a retrieved wind speed sample significantly deviates from the remaining retrieved wind samples along the track (see the sample circled in red). Notice the corresponding sudden drop in measured $\sigma^o$. As shown in this figure, the reported Rx gain was varying between 4.5 and 8.5 dB, while the SNR was varying between 1 and 3 dB along this track.

3) Tracks Crossing Flex Power Events: As previously mentioned, the transmitted power from block IIF GPS may incur an unpredictable (to the user) change of power level at anytime. These power level changes are intermittent and may occur in specific regions of the world. This may in turn cause problems when a CyGNSS track passes through a transition region, where the received signal power may exhibit a sudden change of power level. Fig. 10 shows this problem where $\sigma^o$, the SNR, and the NF time series, from track identification (ID)
Fig. 10. Time series of the $\sigma^\circ$ (shown in black), NF (shown in green), SNR (shown in brown), and model wind (shown in blue) along track ID#846 from observatory #3 on July 30, 2017. The transmitted signal originated from SVN 72 using prn code 8 (block IIF). Note the sudden jump in the $\sigma^\circ$, NF, and SNR, highlighting a track crossing a flex power event.

846 (SVN 72|PRN 8 received by observatory #3 on July 30, 2017), all show a simultaneous sudden change of signal strength. As can be seen, the $\sigma^\circ$ level change is important, in this case as high as 2 dB. Our current track-wise bias removal algorithm is unable to compensate for such a drastic power level change. As a temporary workaround, an algorithm has been implemented in order to identify tracks affected by this problem. This algorithm makes use of the rate of change of the NF ($d\text{NF}/dt$) along each track. In general, this rate of change is small along any given track. However, the latter can be quite large when a sudden jump in the NF is detected. The current version of this algorithm is set up so that the whole track is rejected if $d\text{NF}/dt$ passes a preset threshold at any given time along a block IIF track.

4) Additional Filtering Strategy: Inspired from the filtering technique presented in [15], an error probability LU is implemented in order to remove unwanted wind speed samples for which previously described methods cannot account for. Due to its complexity, details regarding this filtering method are provided in Appendix B.

C. QC Overall Statistical Impact

Using data from May 2017 until May 2020, Table I reports a 31.2% of data permanently flagged out. As can be seen, both the Rx gain/SNR and high roll angle related filters are the major contributors to the overall percentage. Furthermore, it is interesting to note that samples associated with the starboard antenna but showing on the port side are four times likely to occur, compared to the other way around (i.e., compared the 2.9% figure to the 0.7% figure shown in Table I). Table II reports 4.6% of data being flagged from the postretrieval QC process, such as from data with the star tracker flag set and unrealistic wind speed samples.

We realize that the overall amount of data being removed or flagged is quite substantial and undesirable. Future work will be carried out to reassess the data quality in each of these scenarios and see whether the overall filtering criteria can be loosened. We are hopeful that a substantial portion of high roll data can be recovered, particularly from the port side as it exhibited less $\sigma^\circ$ anomaly, as discussed in Section III-A2. As for the low Rx gain/SNR data, this will be a challenging task since DDMs become quite noisy very quickly as the Rx and/or SNR go down.

IV. $\sigma^\circ$ PERFORMANCE ASSESSMENT

We now assess the potential impact of this bias correction method on the $\sigma^\circ$ quality and consistency, by analyzing several aspects of CyGNSS $\sigma^\circ$ measurements from all eight observatories. This work is performed using a three-year period from May 2017 to May 2020.

A. Time Series

Figs. 11 and 12 report the time series of the daily averaged $\sigma^\circ$ bias (i.e., measured $\sigma^\circ$–predicted $\sigma^\circ$) per observatory and per block type, respectively. In both figures, this bias is provided with and without the track-wise bias correction applied. According to [16], a new flex power mode has been implemented on both GPS block types II-F and IIR-M starting on February 14, 2020. As can be seen from Figs. 11 and 12, this new flex power mode is clearly affecting CyGNSS $\sigma^\circ$ levels.

Fortunately, once the track-wise bias correction is applied across all observatories, the intersatellite $\sigma^\circ$ biases and $\sigma^\circ$ biases between GPS block types, including the downward trend in $\sigma^\circ$ over time, are almost completely eliminated (see top plots of Figs. 11 and 12). We do note, however, that a very small residual daily averaged $\sigma^\circ$ bias remains ($\sim-0.06$ dB).
**B. Statistical Distributions**

We now take a look at the distribution of the $\sigma^o$ per spacecraft antenna and GPS block type. Fig. 13 shows the corresponding normalized histograms of the $\sigma^o$ estimated over the sea surface without and with the track-wise bias correction (see plots (a)–(f) and (g)–(l), respectively). In addition, plots (m)–(r) show the corresponding normalized ECMWF wind speed histograms. The impact of the track-wise bias correction is shown in Fig. 13(g)–(l), where all normalized $\sigma^o$ histogram curves are now aligned together with an improved agreement between their respective distribution. It is worth mentioning, however, the presence of a slightly higher median $\sigma^o$ value from block IIF [see Fig. 14(a), (d), (g), and (j)] due to the regularly occurring flex power events mentioned in Section I; note the different spatial distributions of these biases between the port and starboard side antennas. We also note that for a given spacecraft antenna and orbital node, the spatial distribution of the $\sigma^o$ bias correction is similar between block IIR-M and IIR [i.e., compare Fig. 14(b) and (c), (e) and (f), (h) and (i), and (k) and (l)].

For the latter two GPS block types, the largest biases are found along the eastern Asian continental coastline, including portions of the Indian Ocean and the Western Pacific basins. At the time of writing, the authors have not determined a direct cause for the occurrence of these large biases in these geographical locations.

**D. Relationship to Incidence Angle**

We now assess the incidence angle dependence in CyGNSS $\sigma^o$. As a reminder, for a given wind speed, theoretical models have predicted $\sigma^o$ to remain constant up to $\sim 40^\circ$ and eventually monotonically decrease thereafter (see [12] and [17]). Plots (a), (e), and (i) from Fig. 15 show the bin averaged $\sigma^o$ as a function of incidence angle per spacecraft antenna, GPS block type, and spacecraft orbital node. As expected, the largest bias corrections are associated with block IIF [see Fig. 14(a), (d), (g), and (j)] due to the regularly occurring flex power events mentioned in Section I; note the different spatial distributions of these biases between the port and starboard side antennas. We also note that for a given spacecraft antenna and orbital node, the spatial distribution of the $\sigma^o$ bias correction is similar between block IIR-M and IIR [i.e., compare Fig. 14(b) and (c), (e) and (f), (h) and (i), and (k) and (l)].

For the latter two GPS block types, the largest biases are found along the eastern Asian continental coastline, including portions of the Indian Ocean and the Western Pacific basins. At the time of writing, the authors have not determined a direct cause for the occurrence of these large biases in these geographical locations.
Fig. 13. Plots including normalized $\sigma^o$ histograms per CyGNSS spacecraft antenna and GPS block type. v2.1 gridded $\sigma^o$ from May 2017 to May 2020, without and with the track-wise bias correction, was used to generate plots (a)–(f) and (g)–(l), respectively. Plots (m)–(r) report the corresponding normalized histograms of collocated ECMWF per CyGNSS spacecraft antenna and GPS block type. Plots (g)–(l) show that the track-wise bias correction reduced the biases between instruments, antenna, and block type. The source for the remaining shifts between the various histograms (e.g., compare the IIR-M PORT median $\sigma^o$ versus IIR PORT) appears to be geophysical and not due to lingering calibration issues, as lower median $\sigma^o$ [shown in plots (g) through (k)] correlates with higher wind speed medians [see the corresponding plots (m)–(q)].
bin (6–6.5 m/s). From these plots, we make the following observations.

1) The incidence angle dependence in $\sigma^o$ differs from what has been modeled, where its level oscillates as the incidence angle increases. In [5], a different pattern was even reported using v2.0 data, alluding to changes made to the receiver antenna gain pattern of the spacecrafts while transitioning to v2.1.

2) Just like v2.0 showed (see [5]), noticeable $\sigma^o$ biases remain between instruments.

3) For a given instrument, $\sigma^o$ biases exist between the starboard and port side antennas.

4) Bin averaged $\sigma^o$ levels from block IIF are quite different between the starboard and port side antennas, most likely due to the inhomogeneous geographical coverage of flex power events [see Fig. 14(a), (d), (g), and (j)].

Plots (b), (f), and (j) report bin averaged CyGNSS $\sigma^o$ as a function of incidence angle with the track-wise bias correction applied. Compared to plots (a), (e), and (i), the $\sigma^o$ bias correction greatly reduces intersatellite biases, biases between a given spacecraft antennas, and GPS block type. However, the oscillations in the CyGNSS $\sigma^o$ as a function of incidence angle remain. This is to be predicted since the GMF, used in the track-wise $\sigma^o$ bias correction algorithm, is based on v2.1 CyGNSS $\sigma^o$, which inherently carry this pattern.

Similar plots are generated, this time showing the bin averaged $\sigma^o$ bias as a function of incidence angle [see plots (c), (d), (g), (h), (k), and (l) from Fig. 15]. The same observations are made, except that the $\sigma^o$ oscillations disappear once the track-wise $\sigma^o$ bias correction is applied [see plots (d), (h), and (l)].
V. GLOBAL RETRIEVED WIND SPEED PERFORMANCE EVALUATION

First made available on the National Oceanic and Atmospheric Administration (NOAA) Manati website [18] and subsequently on the Physical Oceanography Distributed Active Archive Center (PO.DAAC) [19], the v1.1 NOAA CyGNSS retrieved wind speed product based on our track-wise $\sigma^o$ correction is now compared to a series of rain-free wind speed products from both active and passive microwave sensors, namely the Advanced Scatterometer (ASCAT) A/B scatterometer wind product from NOAA [20], the low-frequency wind product from the Advanced Microwave Scanning Radiometer (AMSR)-2 [21], the low-frequency wind product from the Global Precipitation Measurement Microwave Imager (GMI) [22], WindSat Polarimetric Radiometer “All-weather” wind product (Windsat) [23], and the Soil Moisture Active

Fig. 15. Bin averaged $\sigma^o$ as a function of incidence angle. Plots generated for each spacecraft antenna, separated by GPS block type for a given wind speed bin without [see plots (a), (e), and (i)] and with the track-wise bias correction [see plots (b), (f), and (j)]; bin averaged $\sigma^o$ bias are also plotted without [see plots (c), (g), and (k)] and with the track-wise bias correction [see plots (d), (h), and (l)].

Fig. 16. Daily averaged wind speed bias (i.e., CyGNSS–ECMWF) time series separated by spacecraft and receiver antenna (see top row). Bottom rows show the time series of the daily averaged standard deviation of the bias, also separated by spacecraft and receiver antenna.
Passive (SMAP) wind product [24] from remote sensing systems (REMSS). NWP model winds from the ECMWF are also used in the evaluation process.

Both statistical and geographical distribution analyses are presented. The time period used thereafter for all analyses with sensor data is May 1, 2017–July 31, 2019, and May 2017–May 2020 for NWP data. Finally, the spatial and temporal collocation criteria used with sensors are 25 km and 90 min, respectively, while ECMWF winds are interpolated in space and time with CyGNSS winds.

A. Wind Speed Statistical Analysis

We begin this analysis by exploring the time series of both the wind speed error and its standard deviation against ECMWF. Fig. 16 shows such time series separated by observatory and receiving antenna, whereas Fig. 17 shows time series separated by the GPS block type and receiving antenna. We first note that there are no discernible intersatellite biases throughout the whole three-year period, as well as no discernible inter-GPS block type biases despite the presence of flex power events (see the top row of Fig. 12). A ~0.16 m/s residual daily averaged bias remains throughout the whole mission. This bias appears to show a ~0.05–0.1-m/s steady increase over the three-year period; further investigation is needed to identify its source. Finally, the standard deviation of the error remains stable at ~1.2 m/s over the three-year period.

Since CyGNSS NBRCS shows some dependence on the incidence angle, we want to verify whether CyGNSS winds exhibit any dependence on such metric. Fig. 18 shows a series of 2-D histograms comparing CyGNSS and ECMWF winds for different incidence angle ranges between 0° and 80°. We first note the absence of noticeable wind speed bias across all incidence angle ranges, as reported in Fig. 18, where all biases remain below |0.35 m/s|. We further note the standard deviation of the error (stde) ranging between 1.38 and 0.98 m/s, which is highest at the lowest incidence angle range (0°–10°) and keeps decreasing as the incidence angle range increases (excluding the poorly sampled 70°–80° range). Coincidentally, the mean ECMWF wind speed decreases as the
Fig. 19. 2-D histograms of CyGNSS wind speed against ASCAT A/B, REMSS (i.e., AMSR-2, GMI, and WindSat combined), SMAP, and ECMWF. The time periods used for this figure are May 1, 2017–July 2019 for all sensors, and May 2017–May 2020 for ECMWF. All sensor data are rain-free. All figures are generated for both CyGNSS ascending [see plots (a)–(d)] and descending node [see plots (e)–(h)]. Statistics are reported in each plot legend.

Fig. 20. Wind speed error plots against ASCAT A/B, REMSS (i.e., AMSR-2, GMI, and WINDSAR combined), SMAP, and ECMWF (see plots (a)–(d), respectively). All sensor data are rain-free. These plots report the bias (in black), standard deviation (in magenta), and root mean square of the error (in green); These metrics are computed using a 0.5-m/s bin size along the x-axis. The “error” is defined as the difference between CyGNSS and the sensor/model wind speed. A red curve is added to each plot, representing the CyGNSS mission baseline requirement indicating the maximum achievable standard deviation at any given wind speed [12].

incidence angle increases, pointing to the fact that higher wind regions on the globe may have been scanned at lower incidence angle. This could be a factor in increasing the stde since the CyGNSS signal sensitivity decreases as the sea surface roughness increases.

We now compare CyGNSS winds with each aforementioned sensor and model winds. The data are separated per CyGNSS orbital node, as shown in Fig. 19. These plots show a good overall agreement between each respective sensor/model wind speed and CyGNSS, where most of the data lie along the 1:1 line. The best performance, in terms of stde, is achieved against both ASCAT A/B and REMSS sensor winds [see Fig. 19(a), (b), (e), and (f)] ranging between 1.10 and 1.12 m/s. Slightly improved wind speed biases are obtained against ASCAT A/B, compared to REMSS wind speeds (i.e., −0.11 m/s versus 0.18–0.19 m/s). The performance against ECMWF shows similar overall biases but slightly worse overall standard deviation compared to both ASCAT A/B and REMSS (i.e., 1.18–1.19 m/s versus 1.10–1.12 m/s). We note that the performance is consistent between orbital nodes across all sensors and model. Comparisons with SMAP winds lead to overall biases of −0.41 and −0.36 m/s and overall standard deviations of 1.89 and 1.90 m/s for the ascending and descending orbits, respectively. These larger errors may be mostly attributed to the land impact on the SMAP data [see the negative wind speed biases shown in Fig. 25(c) and (g) along the coastal regions]. Interestingly, the 2-D histograms from Fig. 19(c) and (g) do report that the majority of points found along the 1:1 line are below the 12-m/s threshold where the SMAP wind speed retrievals are stated to be unreliable.

Fig. 20 shows the bias, standard deviation, and root mean square of the error (i.e., CyGNSS-sensor/model wind) as a function of each respective sensor/model wind speed. A red curve is added to each plot, representing the CyGNSS mission baseline requirement indicating the maximum achievable standard deviation at any given wind speed [12]. From best to worst performance in terms of bias error, the bias remains close to zero up to 25 m/s when compared against ECMWF. This is to be expected since ECMWF winds were utilized in the GMF development, as well as in the track-wise $\sigma^*$ bias correction algorithm. Next is both REMSS and ASCAT A/B with bias errors remaining close to zero up to $\sim$12 m/s. The bias error remains slightly above 0 m/s for all SMAP winds.
below \(\sim 5\) m/s. The standard deviation of the error (stde) between CyGNSS and ASCAT A/B is similar to the one between CyGNSS and ECMWF, up to \(25\) m/s; slightly worse performance is observed with REMSS winds where the stde becomes greater than \(2\) m/s when REMSS winds are greater than \(17\) m/s. The worst performance is again observed with SMAP with an stde becoming greater than \(\sim 14\) m/s. As with the 2-D histograms, the performance is generally the same across CyGNSS orbital nodes.

We are now interested in assessing the yearly consistency in wind speed retrieval across all eight CyGNSS observatories since May 1, 2017. Fig. 21 shows the median [see plots (a) and (b)] and the standard deviation [see plots (c) and (d)] of the wind speed difference with each sensor/model for each CyGNSS observatory and CyGNSS orbital node. These yearly statistics are color-coded in blue, red, and green, for the years 2017, 2018, and 2019, respectively. The following observations are made.

1) The median of the wind speed error is smallest when compared against ECMWF, which is to be expected since the latter is used in both the GMF tuning and \(\sigma_o\) bias correction algorithm.

2) The median of the wind speed error remains constant across all eight observatories when compared against ASCAT A/B, REMSS, and ECMWF.

3) There are some slight median differences, between observatories, when compared with SMAP, probably due to data coverage.

4) When comparing time period, the median results are consistent when compared against ASCAT A/B and REMSS. With ECMWF, very small median differences are noticeable between years but remain well within the measurement error.

5) The median differences, between the years 2017 and 2018/2019, are more pronounced when compared against SMAP.

6) The stde from 2019 shows a \(\sim 0.1\)-m/s deviation for SMAP, ECMWF, and ASCAT A/B compared to previous years across all eight observatories particularly for the ascending orbit [see Fig. 21(c)].

7) As shown in the previous figures, the stde is the highest with SMAP and lowest with both REMSS and ASCAT A/B.

Fig. 22 shows the double difference of the median of the wind speed error between the port and starboard side antennas.
for each CyGNSS observatory such that

\[
\text{Med}(U_{10\text{Obs}} - U_{10\text{mod}/\text{sens}})_{\text{PORT}} - \text{Med}(U_{10\text{Obs}} - U_{10\text{mod}/\text{sens}})_{\text{STAR}}. \tag{1}
\]

In this equation, \(U_{10\text{Obs}}\) and \(U_{10\text{mod}/\text{sens}}\) represent the observed wind speed reported by a CyGNSS observatory and the wind speed reported by either NWP model or sensor, respectively. This statistic is also separated by sensor and model, year, and CyGNSS orbital node. The purpose of this figure is to verify the absence of systematic bias between the observatory antennas. As shown in this figure, the double differences are all within \(+-0.1\) m/s despite the apparent noisiness of the curves. Since these biases are well within the measurement error, we conclude that there are neither noticeable performance differences nor systematic biases between the CyGNSS antennas when using the track-wise \(\sigma^o\) correction algorithm.

Finally, the median and standard deviation of the wind speed error are now computed per GPS block type. The statistics are once again separated by CyGNSS orbital node and year, as shown in Fig. 23. We first note that both the median and std are greatest for the block IIF GPS, then IIR-M, and smallest with IIR, across all years regardless of sensor and model. The differences are, however, very small (<0.05–0.075 m/s) for a given sensor/model, once again, well within the measurement error. We then conclude that the wind retrieval performance shows no noticeable biases across the GPS block.

### B. Spatial Wind Speed Distribution Analysis

To conclude our global wind speed analysis, we now explore the geographical distribution of both the wind speed bias and std against the same set of sensors/model. Fig. 24 first shows the spatial distribution of the density of collocated data with each sensor/model, separated by CyGNSS orbital node. In all cases, the figures show that the coverage is greatest at the highest latitudes (i.e., >25°). Among the collocated sensor data, the overall coverage is greatest with REMSS (since it encompasses AMSR-2, GMI, and WindSat winds), then ASCAT A/B, and finally SMAP. ECMWF collocated winds evidently report the most coverage overall since these are obtained via a bilinear spatial and temporal interpolation method, with a longer analysis period spanning between May 2017 and May 2020.

Figs. 25 shows the spatial distribution of the bias of the error. As we previously observed throughout this section, the performance between orbital node is almost identical (i.e., compare plots (a) versus (e) and (b) versus (f)), except within the southeastern Asian coastal region where strong positive biases are only present during descending CyGNSS passes, as shown in Fig. 25(h). Radio frequency interference may be the source for such errors. For a given orbital node, we note large areas of negative biases around the equator and higher latitudes with REMSS [see plots (b) and (f)], except within the southeastern Asian coastal region where strong positive biases are only present during descending CyGNSS passes, as shown in Fig. 25(h). Radio frequency interference may be the source for such errors. For a given orbital node, we note large areas of negative biases around the equator and higher latitudes with REMSS [see plots (b) and (f)], except within the southeastern Asian coastal region where strong positive biases are only present during descending CyGNSS passes, as shown in Fig. 25(h). Radio frequency interference may be the source for such errors.
Fig. 25. Spatial distribution of the wind speed bias between CyGNSS and each sensor/model, separated by CyGNSS orbital node. Note that all sensor data are rain-free. A $2^\circ$ grid size was selected to generate these plots.

Fig. 26. Spatial distribution of the standard deviation of the error. Plots are organized in a similar fashion as

ECMWF are smaller in general, except for the Inter Tropical Convergence Zone (ITCZ) and east of Asia. Even though these biases are large, we surmise that the CyGNSS winds may in fact be more reliable than model winds within the ITCZ since this area is known to be a challenging forecast region given the frequency and unpredictability of convective activity. The large biases found east of Asia are still being investigated at the time of writing.

Fig. 26 shows the spatial distribution of the standard deviation of the error. Plots are organized in a similar fashion as
A. Performance Against HWRF

During the lifetime of a tropical cyclone, the operational HWRF model provides 6-h analysis wind fields complemented with 3-h forecast fields. Three spatial domains are provided, each with its own grid spacing: first a so-called parent domain roughly spanning an $80^\circ \times 80^\circ$ area at a $0.1-0.135^\circ$ grid spacing, a middle nest domain spanning $\sim 25^\circ \times 25^\circ$ area centered around the eye of a tropical cyclone at a $0.03-0.045^\circ$ grid spacing, and finally an inner nest domain spanning an $\sim 8^\circ \times 8^\circ$ also centered around the eye of a tropical cyclone at 0.011–0.015° grid spacing. For our analysis, we selected the spatial domain with the highest grid resolution (i.e., inner nest domain) and regridded the wind field down to 0.25° for a fair comparison with the 25-km CyGNSS wind product.

Fig. 27 shows the spatial distribution of the collocation points (using a 2° grid size), including the bias and standard deviation of the wind speed error (i.e., $U_{\text{CyGNSS}} - U_{\text{HWRF}}$). First, we note that most of the collocations are found in the Eastern Pacific (EP) and Atlantic (AL) basins. Overall, the spatial distribution of the wind speed error bias is low, with randomly scattered high biased areas. We also note more instances of high stde in the Western Pacific basin. A possible explanation for this error is the reduced complexity used in the HWRF model implementation for this basin, compared to both AL and EP [27]; for the latter case, additional sensor measurements (e.g., data from flight overpasses) may be implemented whenever available.

Fig. 28 shows a series of 2-D histograms comparing CyGNSS versus HWRF wind, separated by year [see Fig. 28(a)–(c)], and for the period May 2017–May 2020 [see Fig. 28(d)]. The performance is similar for all years, although the overall standard deviation per year is worse for 2018 compared to 2017 and 2019. Note that these statistics, for the year 2017, included only storms from the AL and EP basins, while all basins were available for the other years. In addition, the 2018 EP season was a very active season with 23 named storms, which included 10 major hurricanes [28]. In fact, a closer look at Fig. 28(b) shows a slight shift of the scatter to the right compared to the other years. We also note from Fig. 28 that above $\sim 15-20$ m/s, the scatter begins to deviate from the one-to-one line, where CyGNSS winds become lower than HWRF.

In Fig. 29, we report the bias, standard deviation, and root mean square of the wind speed error as a function of HWRF wind. We note that the bias of the wind speed error becomes negative after about 11 m/s, while both the stde and rmse become greater than 2 m/s when HWRF winds are greater than 18 and 15 m/s, respectively.

Despite the tendency for CyGNSS to underestimate the wind speed in the high wind regime (i.e., above 15 m/s), its performance remains consistent and predictable against HWRF, as reported in Fig. 28. Statistical correction methods, such as a cumulative distribution function matching approach and possible GMF revisions, could be used in the future to remove these negative biases and improve its overall performance.

B. Comparison Against SFMR

The SFMR wind measurements, usually considered the reference in high wind research analysis [26], are now used to gauge CyGNSS ability in reliably measuring the wind speed in the vicinity of tropical cyclones. For this analysis, we also include collocated winds from the ECMWF, ASCAT A/B, and the REMSS sensors (i.e., AMSR-2, GMI, and WINDS SAT). Fig. 30 shows four scatterplots where three different quadru-

![Fig. 27. Spatial distribution of the collocated data with HWRF [see plot (a)]. The spatial distribution of the bias and stde of the wind speed error is also provided (see plots (b) and (c), respectively). A 2° grid size was selected to generate these plots.](image-url)
Fig. 28. 2-D histograms of CyGNSS wind speed against 1/4° HWRF. Plots are separated by time period; one plot per year [see (a)–(c)], with plot (d) combining the whole mission from May 1, 2017 to May 1, 2020. Statistics are reported in each plot legend.

At first glance, Fig. 30(a) shows that CyGNSS, ECMWF, and ASCAT A/B all follow the same trend where all wind samples (below 15 m/s) are close to the one-to-one line. Above that threshold, all three wind sources underestimate the wind speed compared to SFMR, with ECMWF deviating the most when SFMR winds are greater than 35 m/s. In fact, the reported statistics show that the worst bias (−6.99 m/s) and stde (5.24 m/s) are obtained with ECMWF. Although quite similar to CyGNSS, the best overall results are obtained with ASCAT.

The comparison between CyGNSS, ECMWF, and REMSS in Fig. 30(b), shows the scatter remaining more or less along the one-to-one line across all SFMR winds, albeit with larger stde compared to Fig. 30(a), except for ECMWF; REMSS, CyGNSS, and ECMWF report a 4.11, 5.53, and 3.63 m/s stde, respectively.

The comparison between CyGNSS, ECMWF, and SMAP as shown in Fig. 30(c) shows a tight scatter compared to the previous two plots. While ECMWF reports the lowest stde (3.69 m/s), the reported stde for SMAP is abnormally high at 7.50 m/s most likely due to a ~70-m/s SMAP collocated wind sample.

A much larger sample population was obtained between CyGNSS, ECMWF, and HWRF, when compared against SFMR, as shown in Fig. 30(d). The lowest bias is obtained with HWRF (−2.44 m/s), while CyGNSS bias is noticeably larger at −5.21 m/s. ECMWF shows the largest bias (−7.48 m/s) and stde (6.14 m/s) against SFMR. The lowest stde is obtained with CyGNSS (5.47 m/s), with HWRF being a close second at 5.48 m/s. Despite the few CyGNSS outlier samples shown in Fig. 30(d), CyGNSS versus SFMR scatter remains close to the one-to-one line albeit with a negative bias. The outlier samples may be explained by the inherent relationship between the NBRCS and the wind speed (see Fig. 3), where the rate of change of the NBRCS becomes very low as the wind speed increases. This means that a small change in NBRCS may result in a large change in wind speed. This issue can especially be augmented with a noisy signal (e.g., low Rx gain situation). Nevertheless, future improvements may be obtained using a more sophisticated wind retrieval approach, which will be explored in an upcoming product version.

C. Case Studies

We now present four case studies, each with its own detailed and informative plots, including HWRF’s inner nest domain background winds overlaid with CyGNSS overpasses, SFMR winds, storm track positions from Best Track data, and 34, 50, and 64 kt wind radii for each storm quadrant. In each case study, the CyGNSS overpasses include any available wind samples ±3 h from the indicated timestamp. Since all eight observatories do not make simultaneous overpasses, the symbol size of the CyGNSS wind samples provided in each plot, and signals approximate time gap between a CyGNSS overpass and the indicated timestamp. Timestamps are also provided along the SFMR tracks. Finally, scatterplots are also provided to help gauge CyGNSS high wind performance against both HWRF and SFMR, both of which have been regridd to a 0.25° and 25-km resolution, respectively, so as to provide a fair comparison against CyGNSS.

1) Harvey Overpass: The first case study, shown in Fig. 31(a1) shows a CyGNSS overpass over hurricane Harvey on August 25, 2017, around 06:00 Coordinated Universal Time (UTC). Harvey was considered a hurricane some time
on August 24 and reached category 3 status by midday on August 25 [29]. The SFMR reported a maximum wind speed of 52.8 m/s around 8:47 UTC on August 25. Reported north–east and south–east quadrant wind radii, as shown in Fig. 31(a), agree well with HWRF background winds. Approximately 13 CyGNSS tracks are depicted on this figure, most of which appear to correlate well with HWRF background winds, despite the large time difference between several CyGNSS tracks and the HWRF background image.

Fig. 31(a2,3,4) shows the scatterplots of CyGNSS versus HWRF winds, CyGNSS versus SFMR winds, and HWRF versus SFMR winds along CyGNSS tracks, respectively. Fig. 31(a2) reports in general a good agreement between CyGNSS and HWRF, while the overall scatter between CyGNSS and SFMR as shown in Fig. 31(a3) is noisier. This may be explained by the fairly large time difference between CyGNSS and SFMR samples, where most of them are greater than 30 min.

2) Michael Overpass: Fig. 31(b1) shows all available CyGNSS overpasses over hurricane Michael on October 9, 2018 at 12:00 UTC ± 3 h. These overpasses occurred around the time Michael regained rapid intensification [30], where the SFMR reported around 14:17 UTC a maximum wind of 56.9 m/s. Most of the CyGNSS tracks, as shown in Fig. 31(b1), once again visually blend well with HWRF background field.

One CyGNSS track, however (see closest CyGNSS track south of the storm center), reports noticeably higher wind samples compared to both HWRF and SFMR with speeds up to 48.9 m/s. A closer inspection of this track showed that the samples were retrieved at a questionable region of the port side antenna pattern, where the incidence angle range was below 15° and the azimuth angle was close to 180°. Having said that, most of the DDMs along this track did not exhibit any abnormal patterns, except those closest to the eye of the storm; as a matter of fact, the radio frequency interference (rfi) flag was set for a few ddm around this area. Although data from such DDMs are excluded from the wind retrieval processing, it is possible that adjacent nonflagged DDMs are still corrupted to some extent.

Apart from this track, a comparison of CyGNSS winds with HWRF shows a good agreement for most wind samples up to 40 m/s, as reported in Fig. 31(b2). We note that most uncorrelated samples shown on this scatterplot are associated with low SNR levels (i.e., <2 dB), which are usually linked to poor-quality DDMs. Fig. 31(b3,4) shows the scatterplots of CyGNSS and HWRF winds versus SFMR, respectively, using a 90-min time window. In both cases, most data points remain more or less close to the one-to-one line, with a few outliers.

3) Dorian Overpass: Hurricane Dorian was the first major AL hurricane in 2019 and the most powerful and devastating hurricane on record striking the Bahamas. Fig. 31(c1) shows a CyGNSS overpass on August 29, 2019, ±3 h around 12:00 UTC, where Dorian was considered a Category 1 Hurricane. Peak SFMR winds were estimated around 42.5 m/s measured at 14:52 UTC. As shown in Fig. 31(c1), essentially, all CyGNSS tracks correlate well with the included HWRF background winds. Fig. 31(c2) supports this claim where all wind samples remain close to the one-to-one line. The same can be said when comparing the few collocated CyGNSS/SFMR samples, as shown in Fig. 31(c3).

4) Laura Overpass: Hurricane Laura was a category 4 AL tropical cyclone recorded as one of the strongest storm to hit the U.S. state of Louisiana in 2020. Fig. 31(d) shows a CyGNSS overpass on August 25, 2020, ±3 h around 12:00 UTC when Laura was about to be upgraded as a category 1 hurricane. As can be seen from the figure, SFMR winds did report winds above 32.9 m/s in several locations along the flight path (see purple-colored sections), while the HWRF model predicted much lower winds. In fact, Fig. 31(d) shows HWRF clearly underestimating the wind speed along the CyGNSS tracks. The same can be said of CyGNSS, as shown in Fig. 31(d1). We note the presence of a few outliers (look for white and gray wind samples on the upper left quadrant of the Figure). Further investigations showed that these samples originated from observatory #3, which appeared to be malfunctioning at random around that time period.

VII. PERFORMANCE IN THE PRESENCE OF RAIN

Using rain rates from AMSR-2, GMI, and WindSat combined (referred to as REMSS), we now assess NOAA CyGNSS wind performance against ECMWF in the presence of rain. The time period used for this analysis begins in May 2017–July 2019. Due to the possibility that most rain
Fig. 31. Four case studies illustrating CyGNSS capabilities in retrieving sea surface winds in hurricane force wind conditions. A case study is included for each of the following hurricanes: Harvey in 2017, Michael in 2018, Dorian in 2019, and Laura in 2020. Each time, all available CyGNSS overpasses are shown within a 380 km radius from the best track estimated storm center location, ±3 h from the indicated timestamp. HWRF background inner nest domain winds are included. Best track storm positions are also included along with best track wind radii. Finally, any available SFMR flights within that same time window are also included.
Fig. 32. Spatial distribution of REMSS rain rates collocated with both CyGNSS and ECMWF [see plot (a)] and with both ASCAT and ECMWF [see plot (c)]. Wind speed error plots between CyGNSS and ECMWF and between rain-free ASCAT and ECMWF are also shown for different REMSS rain rate intervals (see plots (b) and (d), respectively). Analysis period is May 1, 2017–July 31, 2019.

A. Global Analysis

Fig. 32(a) and (c) shows the spatial distribution of all collocated rain events between CyGNSS and ECMWF, and between ASCAT and ECMWF, respectively. Fig. 32(b) and (d) shows the bias of the wind speed error between CyGNSS and ECMWF and between ASCAT and ECMWF, respectively, as a function of the average wind speed. These error curves are generated for different rain rate intervals. From Fig. 32(b), we observe that the bias of the error increases as the rain rate increases for average winds below 5 m/s. The opposite occurs for average winds above \( \sim 14 \) m/s. The biases show little dependence on rain rates between 5 and 14 m/s. If we assume the ECMWF model winds to be correct below 5 m/s, then the increased retrieved wind speeds are a result of decreased NBRCS due to the rain droplets increasing the ocean surface roughness. If this is true, then CyGNSS is indeed affected by rain in the low wind regime. Conversely, if we assume the ECMWF model winds to be unreliable below 5 m/s, then these positive biases may originate from rain effects compounded with microscale events inherently difficult to resolve with NWP models. This can be particularly prevalent along the ITCZ where NWP models are known to struggle. In fact, Fig. 32(a) shows that a nonnegligible amount of data is sampled along the ITCZ. Given the current dataset, it is unfortunately impossible to identify the actual contribution to the decrease in CyGNSS \( \sigma'' \) from either microscale events or rain droplets. However, in both scenarios described above, it is clear that rain is present. We can then safely conclude that CyGNSS is in fact affected by rain, but the extent of these effects cannot be properly quantified at this time.

Due to the use of a C-band carrier frequency, the ASCAT sensor has been known to show minimal rain sensitivity [31]. Fig. 32(d) compares ASCAT to ECMWF for various rain rates interval. Note that these wind samples have been triply collocated with CyGNSS as well, resulting in a much lower data population compared to Fig. 32(a) and (b). A similar observation is made in the lower wind regime, where the bias of the error increases as the rain rate increases, which aligns with our conclusion above. For winds greater than 15 m/s, results are somewhat inconclusive and difficult to interpret due to the low number of collocated samples.

B. Analysis Under Tropical Cyclone Condition

A similar analysis is performed first between CyGNSS and HWRF, as shown in Fig. 33. In the lower wind regime, a similar pattern is observed, where the wind speed bias increases with increasing rain rates. In Fig. 34, a different perspective is provided by comparing the wind speed error, between CyGNSS and SFMR/HWRF, to SFMR rain rates (while excluding all rain rate samples associated with SFMR winds below 15 m/s). We note the largest bias with SFMR, which steadily becomes more negative as the rain rate increases. A somewhat similar result is obtained with HWRF, albeit with a smaller overall bias. However, the results from both of these figures must be interpreted with caution since the number of collocated samples is very low, particularly for the higher rain rate events (e.g., 10 mm/h).
VIII. Conclusion

In this article, we have presented a novel method designed to improve the quality and reliability of CyGNSS $\sigma^o$ measurements, in order to generate a high-quality CyGNSS wind product. The proposed track-wise bias correction addresses the ongoing calibration issues previously reported, including the exclusion of $\sigma^o$ measurements from block IIF GPS, challenges in properly characterizing the GPS EIRPs, and the 16 CyGNSS receiver gain patterns. The resulting track-wise bias corrected $\sigma^o$ pdf per sensor, per antenna, and per GPS block type all agree between each other with almost identical medians. The impact is particularly noticeable for block IIF-related $\sigma^o$ measurements, which showed distorted $\sigma^o$ pdf before applying the track-wise bias correction. Corrected $\sigma^o$ measurements also showed resiliency against the impact of the recent flex power event (i.e., mid-February 2020) associated with blocks IIF and IIR-M. Finally, the track-wise bias correction method has shown its capability to remove unwanted intersattelite $\sigma^o$ biases as a function of incidence angle.

Using the bias corrected $\sigma^o$ measurements from CyGNSS, a wind speed retrieval approach was presented based on the use of a semiempirical GMF relating $\sigma^o$ to wind speed as a function of both the incidence angle of specular reflection and the significant wave height. Both preretrieval and postretrieval QC steps have been described in this article. Overall QC steps account for 36.7% of data.

A comprehensive analysis of CyGNSS retrieved winds was also provided, both on a global scale as well as within the tropical cyclone environment. The performance was compared using a three-year data period from May 2017 to May 2020. Both sensor derived winds and NWP model winds were used in this analysis, namely winds from the ASCAT A/B, SMAP, AMSR-2/GMI/WindSat (REMSS), SFMR, ECMWF, and HWRF. Daily averaged wind speed biases between CyGNSS and ECMWF showed small biases throughout, on the order of 0.15 m/s across all sensors. The dependence between block types has also disappeared. We did note a steady, albeit small, increase in the wind speed bias over the three-year period, however. The steady decline in $\sigma^o$ may be the culprit. Further investigation is needed to confirm this claim.

The standard deviation of the error with ECMWF (stde) has been consistently maintained around 1.2 m/s across all sensors throughout the three-year period. When compared against sensors, the best performance was tied between REMSS and ASCAT A/B with stde varying between 1.10 and 1.12 m/s. Worse performance was found against SMAP, due in most part to the less reliable SMAP winds along coastlines. When binning the data using the incidence angle of specular reflection, we observed that the stde between CyGNSS and ECMWF decreased as the incidence angle increased.

The spatial distribution of CyGNSS wind speed biases and stde were also evaluated against sensor winds and ECMWF. First, we observed a consistent disagreement with ECMWF along the ITCZ. Since NWP models are known to struggle in this area, it can be difficult to conclude whether CyGNSS is reliably retrieving sea surface wind speeds along the ITCZ since rain events are a common occurrence there. Second, we have observed persistent high bias locations, specifically east of the Asian continent, possibly due to radio frequency interference.

CyGNSS performance in the tropical cyclone environment has also been assessed against both the HWRF model and SFMR sensor. The overall bias and stde against HWRF for the three-year period were $-0.54$ and $2.90$ m/s, respectively.
CyGNSS winds gradually underestimating the wind speed compared to HWRF in the higher wind speed regime, starting around 15 m/s. Despite the comprehensive collocation exercise performed between CyGNSS and HWRF, the resulting number of collocated samples above hurricane force winds (i.e., greater than 33 m/s) remained low at 3415 total samples with a wind speed bias around −10 m/s. When compared against SFMR, overall bias and stdev were −5.21 and 5.47 m/s, respectively, compared to −7.48 and 6.14 m/s between ECMWF and SFMR, and −2.44 and 5.48 m/s between HWRF and SFMR.

Finally, CyGNSS performance in the presence of rain has been explored using both REMSS and SFMR rain rates. In the lower wind regime (i.e., below 5 m/s), the wind speed bias between CyGNSS and ECMWF increased with increasing REMSS rain rates; between 5 and 15 m/s, wind speed biases quickly decreased regardless of rain rates. For the higher wind regime, the results were inconclusive due to low data sampling. Similar overall trends were obtained when comparing CyGNSS against HWRF using REMSS rain rates. CyGNSS wind speed was then compared to both HWRF and SFMR wind speeds for various SFMR rain rates; both CyGNSS/HWRF and CyGNSS/SFMR wind speed biases remained negative regardless of SFMR rain rates. Although our analysis showed that wind speed underestimation from CyGNSS steadily increased as SFMR rain rate increased, this observation should be interpreted with caution as the total number of SFMR/CyGNSS/HWRF collocated samples remained low despite using a three-year analysis period. Caution should also be used in interpreting our results between ECMWF and CyGNSS using REMSS rain rates since several of these collocated rain samples were located along the ITCZ. Although not proven at this time, it is possible that the rain rate-dependent wind speed biases, below 5 m/s, are due to a compounded effect from both rain rates and possible microscale events undetected by NWP models. This would mean that the rain is in fact impacting CyGNSS measurements, but its extent cannot be properly measured at this time.

Even though the presented results are very promising and show a much improved level of consistency and reliability in CyGNSS winds, performance improvements can still be made by revisiting our current wind retrieval scheme and using an improved GMF relating CyGNSS $\sigma^o$ to wind and wave parameters. In addition, the $\sigma^o$ data quality associated with high solar beta angle periods (i.e., high roll angle data) will be carefully assessed in order to determine the amount of data we can reinstate. Future works will also include a transition from using v2.1 to v3.0 CyGNSS $\sigma^o$. Preliminary analysis of v3.0 CyGNSS $\sigma^o$ shows, yet again, intersatellite $\sigma^o$ biases, including biases between GPS block types. However, v3.0 $\sigma^o$ time series show the absence of trend, which should result in an improved quality wind product.

### Appendix A

**Unrealistic Wind Speed Sample Detection Algorithm**

Each gridded CyGNSS track is first temporarily split into subtracks of up to seven samples each. The median (med) and standard deviation of the retrieved wind speed are computed for each subtrack. Then, each retrieved wind sample is evaluated against the med $+/−$ stdthres threshold, where stdthres represents a “standard deviation threshold” either set to 1 m/s if med is less than 14 m/s or set to 2.5 m/s otherwise. If any samples fall outside the med $+/−$ stdthres threshold, given the SNR is less than 2 dB and the Rx gain is greater than 3 dB along that given subtrack, then the rate of change of the retrieved wind speed ($du_{10}/dt$) is computed along the whole subtrack. For each potentially bad n sample (i.e., found outside the med $+/−$ stdthres threshold), the sign of $du_{10}/dt$...
of adjacent samples $n - 1$ and $n + 1$ are compared. Any wind speed sample $n$ is flagged if the signs of $du_{10}/dt$ samples $n - 1$ and $n + 1$ are different. In addition, any samples found at either edge of each subtrack will be flagged if their wind speed is found outside the med $\pm$ std$_{med}$ threshold.

APPENDIX B

ERROR PROBABILITY LUT GENERATION

The error probability is defined such that

$$p_{err}(\{U_{10}^{ret} - U_{10}^{mod}\} > 2|\{SNR, Rx, \theta_{i\text{-range}}\})$$

where $U_{10}^{ret}$ represents the retrieved wind speed, $U_{10}^{mod}$ is the model wind speed, and $\theta_{i\text{-range}}$ corresponds to four selected ranges of incidence angle

$$\begin{align*}
\theta_i < 20 \\
20 \leq \theta_i < 10 \\
40 \leq \theta_i < 60 \\
\theta_i \geq 60.
\end{align*}$$

This error probability table is generated by first collecting retrieved wind speed data and corresponding Rx gain, SNR, $\theta_i$ information, and collocated model wind from a four-month period from July to October 2017. The data are then separated by the four aforementioned incidence angle ranges and subsequently binned by the Rx gain and SNR using a 0.15-dB bin size for both dimensions. Fig. 35 shows the per-bin percentage of data falling within each aforementioned incidence angle range as a function of Rx gain and SNR. Fig. 36 reports, for each incidence angle range, the 2-D distribution of the per-bin probability of the absolute value of the wind speed error (i.e., $|U_{10}^{ret} - U_{10}^{mod}|$) being greater than 2 m/s. Finally, Fig. 37 reports, for each incidence angle range, the 2-D distribution of the flag where wind speed samples are flagged outright wherever the flag is set to 1. Specific probability thresholds are used to determine whether the flag is set to 1 for a given Rx/SNR bin. Thresholds of 15, 14, 14, and 15% have been selected for the incidence angle ranges $\theta_i < 20$, $20 \leq \theta_i < 10$, $40 \leq \theta_i < 60$, and $\theta_i \geq 60$, respectively; meaning that the data are flagged (i.e., flag = 1) whenever probabilities values shown in Fig. 36 are greater than said threshold.

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Fig. 37. 2-D distribution of the flag given an incidence angle range, Rx gain, and SNR. Plots (a), (b), (c), and (d) show such a metric for the incidence angle ranges $\theta_i < 20$, $20 < \theta_i < 10$, $40 < \theta_i < 60$, and $\theta_i \geq 60$, respectively. The selected bin size for both SNR and Rx gain dimensions is 0.15 dB. The flag is set to 1 whenever the probability of the absolute value of the wind speed error becomes greater than a set threshold. The selected thresholds are 15, 14, 14, and 15%, for plots (a), (b), (c), and (d), respectively.
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