

Article

Evaluation of L-Band SMAP Scatterometer Tropical Cyclone Wind Retrieval Using UHR σ° Measurements

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Highlights

What are the main findings?

- Tropical cyclone winds can be retrieved using a Geophysical Model Function developed from Soil Moisture Active/Passive Ultra-High Resolution measurements.
- The results confirm findings from other studies that cross-pol backscatter measurements have a stronger correlation with high-to-severe winds compared to horizontal and vertical-pol measurements.

What are the implications of the main findings?

- L-band scatterometer backscatter measurements offer advantages for tropical cyclone wind retrieval because L-band signals are less affected by rain, still show a strong relationship with high-to-severe wind speeds, and provide wind-direction information. This is an improvement over SAR measurements, which have to use auxiliary information to retrieve wind direction.
- These results suggest that if the cross-pol SNR can be increased, the L-band wind estimates have the potential to achieve desirable error tolerances for satellite-based wind measurement over the ocean.

Abstract

Tropical cyclones pose a significant hazard to coastal populations and shipping infrastructure. By helping provide timely warnings, ocean scatterometers can mitigate this threat with ocean wind estimates. In this study, the Soil Moisture Active/Passive (SMAP) mission is used to evaluate the effectiveness of wind estimates using L-band scatterometry for tropical cyclones. Standard-resolution SMAP scatterometer normalized radar backscatter (σ°) measurements are enhanced to a much finer spatial resolution using the Ultra-High Resolution (UHR) algorithm, from which high-to-severe winds are estimated. The influence of σ° polarization (Horizontal HH-, Vertical VV-, and Cross X-pol) on wind estimates at high-to-severe winds is assessed. In this study, a new wind model is created with tropical cyclone Best-Track data, SMAP σ° measurements, and Numerical Weather Prediction winds. The Best-Track-derived wind model and SMAP UHR σ° measurements are used to create a Geophysical Model Function (GMF), and wind retrieval is performed. Analysis of wind retrieval estimates demonstrates that the HH- and VV-pol σ° tend to saturate at high-to-severe winds while X-pol measurements do not. Retrieved UHR winds generally align with the Best-Track derived wind model, although the errors can exceed desirable tolerances for speed and direction (i.e., less than 10% m/s and 20° Root Mean Square Error). Ultimately, these results suggest that L-band scatterometer wind estimation has potential for tropical cyclone monitoring by increasing the SNR of X-pol σ° measurements.



Received: 17 August 2026

Revised: 6 October 2026

Accepted: 12 October 2026

Published: 15 October 2026

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Keywords: scatterometry; SMAP; wind retrieval; tropical cyclones

1. Introduction

Tropical cyclones can cause widespread damage, leading to significant infrastructural, economic, and human losses. The most deadly tropical cyclones killed 300,000 people [1,2] and it has been shown that a “robust” mortality rate increase persists up to 15 years after tropical cyclones [3]. The safety of populations near the coast and ships at sea can be increased with earlier warnings and better monitoring of tropical cyclones using remote sensing.

Space-borne scatterometers improve tropical cyclone warnings because they operate independently of daylight and under most weather conditions [4–6]. Scatterometers are active microwave sensors that measure the normalized radar backscatter (σ°) of the ocean surface. The observed σ° is closely related to the surface roughness generated by near-surface winds. Using a Geophysical Model Function (GMF), the near-surface winds are inferred from the σ° measurements [7–9].

Unfortunately, there are some drawbacks to using traditional C- or Ku-band scatterometers for tropical cyclone monitoring. First, such scatterometers are susceptible to adverse rain effects [10,11]. In the presence of rain, attenuation and modification of wind-induced scattering introduce wind estimation errors. Second, scatterometers typically use horizontally or vertically polarized measurements (HH- or VV-pol), which experience saturation at high-to-severe wind speeds [12,13].

Previous studies have shown that radars and radiometers operating at lower microwave frequencies, such as L-band, are less sensitive to rain because they operate at a longer wavelength (The effects of rain on L-band scatterometer measurements have been studied using SMAP measurements showing that rain has minimal effects at L-band [14]) [15–19]. Additionally, recent studies using C-band and L-band Synthetic Aperture Radar (SAR) have demonstrated that cross-polarization (X-pol) measurements exhibit a stronger correlation with high-to-severe wind speeds than HH- and VV-pol measurements [12,13,20,21]. In this study, the performance of wind estimates using L-band scatterometer X-pol σ° measurements is evaluated near tropical cyclones.

Data from the Soil Moisture Active/Passive (SMAP) [22] radar is used to perform this analysis. SMAP operated a radiometer and a radar, but the radar failed early in the mission after three months (mid-April to early-July 2015) [23]. Both conventional scatterometer and SAR σ° measurements are reported by SMAP, but only scatterometer measurements are reported over the ocean (A limited number of SAR measurements were collected within 1000 km of coast and only on ascending passes [12]). SAR measurements have extremely fine spatial resolution (1 km grid) compared to scatterometer measurements (6×30 km), but do not have azimuth-look directions. Most SMAP studies have focused on SAR measurements [12,20,24] or have used scatterometer measurements as an intermediary step in combined active/passive processing (Scatterometer measurements differ from SAR measurements. SAR processing linearly combines backscatter measurements within a single, very narrow range of azimuth-look directions to form images of σ° for locations within a narrow ground-swath. Scatterometer measurements have a coarser spatial resolution and are collected at multiple different, widely spaced azimuth directions for each point in a wide swath [7]) [25–27]. An in-depth evaluation of SMAP σ° direction dependence measurements has recently been performed but focused only on non-tropical cyclone wind speeds [14]. Existing studies have not focused on the scatterometer measurements near

tropical cyclones. Thus, an evaluation of SMAP σ° wind direction dependence using scatterometer measurements at high-to-severe wind speeds is desired.

In this study, the Brigham Young University Ultra-High Resolution (UHR) algorithm [28,29] is used to process SMAP scatterometer σ° measurements surrounding tropical cyclones to a 2.5 km grid. A trade-off exists in using UHR σ° measurements. The use of the UHR algorithm increases the spatial resolution of σ° measurements, making meso-scale features more distinct, providing more data for processing, and enabling detection of higher wind speeds at a cost of higher measurement noise. These advantages support the use of UHR σ° measurements to create a new GMF tuned to high-to-severe wind speeds with both speed and direction. The fine resolution of UHR measurements comes at the cost of an elevated noise level.

The circumstances of this study (the limited lifespan of SMAP, and high-to-severe tropical cyclone winds) preclude the use of commonly used vector wind reference datasets (See Appendix A). In this study, a new vector wind reference dataset is created using Best-Track databases. Best-Track tropical cyclone databases contain post-storm estimates of storm location and wind intensity determined using data from a variety of sources. The tropical cyclone Best-Track databases are reported by the National Hurricane Center (NHC) and Joint Typhoon Warning Center (JTWC). We acknowledge it is uncommon for Best-Track data to be used as the reference vector wind dataset, although in previous studies, Best-Track databases have been used in scatterometer analysis of tropical cyclones [12,30].

First, Section 1.1 discusses pertinent information about scatterometer wind retrieval, the SMAP configuration, and Best-Track databases. Second, UHR processing is performed and compared with conventional σ° resolution measurements in Section 2.1. Third, Section 2.2 describes the Best-Track derived wind model and summarizes the process to create a tropical cyclone-tuned GMF using SMAP UHR measurements. Finally, Section 3.1 analyzes the wind retrieval performance using SMAP scatterometer σ° measurements and quantifies the capabilities of tropical cyclone L-band wind retrieval.

1.1. Background

1.1.1. Scatterometer Wind Retrieval Using a GMF

Space-borne scatterometers have been used since the 1970s to estimate global near-surface vector winds [31,32]. Near-surface winds can be estimated because wind causes stress on the ocean surface, inducing waves that are observable by scatterometer σ° measurements. The σ° response over the ocean is typically proportional to the near-surface wind speed with a modulation depending on the wind and azimuth-look directions. A grouping of multiple σ° measurements from a spatially limited area with a variety of observation geometries is called a Wind Vector Cell (WVC). Vector wind retrieval is performed for each WVC using a GMF.

A GMF maps σ° measurements to near-surface vector winds. A GMF can be either derived theoretically or compiled empirically. Theoretical GMFs have been more difficult to derive and have proven to be less reliable than empirical GMFs [7]. The GMF is designed to capture the relationship between the near-surface vector wind and the observed σ° [33]. In this study, the L-band tropical cyclone-tuned GMF is created empirically with SMAP σ° measurements collocated with a Best-Track derived reference vector wind database.

In this study, two kinds of GMFs are considered: Speed+Direction (SD), and Speed-Only (SO). A SD GMF relates σ° to both speed (U_s) and direction ($\mathcal{X}_r$), while a SO GMF relates σ° only to speed, with no direction dependence. An SD GMF ($\mathcal{M}$) is typically modeled using harmonic decomposition with four harmonics in which the coefficients (A_i) are a function of wind speed [34],

$$\mathcal{M}(U_s, \mathcal{X}_r) = \sum_{i=0}^{N-1} A_i \cos(i\mathcal{X}_r). \quad (1)$$

Since the SO GMF does not model wind direction, it is equivalent to the A_0 from the harmonic decomposition.

Maximum Likelihood Estimation (MLE) is typically used for wind retrieval using a GMF [7], although Maximum A Posteriori (MAP) is also a common approach [35]. In this study, MLE is used to estimate L-band winds. SD estimation can generate multiple solutions called “ambiguities”. The ambiguity solutions are generally separated by 90° in wind direction [14]. An ambiguity selection scheme is used to select the estimate from the various ambiguities [8]. In this study, the estimate is determined by selecting the closest ambiguity to the “true” wind direction. This scheme is chosen for simplicity and reproducibility.

1.1.2. Scatterometers and Tropical Cyclones

Traditional ocean scatterometers have been used to monitor tropical cyclones since the launch of the SeaSat scatterometer in 1978. As an example, QuikSCAT, a Ku-band pencil beam scatterometer launched in 1999, improved the identification and estimation of the location and intensity of tropical cyclones [6,36]. Roughly 20% of tropical cyclones identified by the NHC in 2006 used QuikSCAT data to estimate the storm location, size, or intensity. Unfortunately, QuikSCAT was limited by rain contamination and saturation of wind estimates at severe wind speeds (saturation > 40 m/s). Wind retrieval from C-band σ° has also demonstrated non-negligible rain contamination and wind saturation [37].

Rain can alter the expected wind-induced σ° at C- and Ku-band due to two effects: volume scattering from falling hydrometeors and surface alterations to the wave spectra [11]. The falling raindrops cause volume scattering and attenuation, diminishing the strength of the signal that reaches and returns from the surface. The surface-induced wind spectra are attenuated by alterations from raindrops. Surface impact effects (waves, stalks, and ripples) lead to a distorted σ° response from the desired wind-only backscatter response. For example, at 30 m/s and a rain rate of 8 mm/h, the wind speed estimate error is roughly 5 m/s for Ku-band, and 1 m/s for C-band (The effects of rain seem to be minimal at L-band compared to C- and Ku-bands) [15]. High wind speeds are often associated with rain, highlighting the importance of accounting for rain in wind estimation using microwave wind scatterometers near tropical storms.

L-band wind retrieval has shown that at low-to-intermediate wind speeds (between 2 and 20 m/s), HH- and VV-pol σ° measurements are proportionally related to wind speed [14]. However, when wind speeds exceed 25 m/s, the HH- and VV-pol σ° response falls off with wind speed. Previous studies using C-band and L-band SAR suggest that X-pol measurements exhibit a stronger correlation with severe-to-intense wind speeds [12,13,38–40]. These results (The results also demonstrate that X-pol measurements at wind speeds below 5 m/s have an insufficient SNR to be used reliably in scatterometer wind retrieval [13,38]) suggest that accurate wind retrieval is possible at wind speeds up to 45 m/s, and potentially as high as 60 or 70 m/s. In this case, the L-band X-pol measurements may decrease wind estimate error compared to C- and Ku-band wind estimates.

1.1.3. Soil Moisture Active/Passive Radar

The SMAP mission was launched on 31 January 2015, with a radar and radiometer [22]. The radar is an L-band quad-polarized rotating pencil beam scatterometer. The four polarizations operated by the SMAP radar are HH-, VV-, HV-, and VH-pol. In this study, HV- and VH- σ° measurements are averaged (X-pol) to increase the Signal-to-Noise Ratio (SNR). SMAP orbits at an altitude of 685 km, has an incidence angle of 40° , and a ground

swath width of 1000 km. With a 98.1° orbit inclination, SMAP achieved global coverage roughly every 2–3 days with complete orbit repeat every eight days [41]. Even though SMAP was originally designed to measure soil moisture content, early SMAP studies demonstrated wind retrieval is possible with an L-band sensor [15].

SMAP reported three σ° spatial resolution measurements: scatterometer footprint ($29 \text{ km} \times 35 \text{ km}$), scatterometer slice ($30 \text{ km} \times 6 \text{ km}$), and SAR ($1 \text{ km} \times 1 \text{ km}$). Slice measurements are calculated from digital processing of the echo return of the measurement power into range bins. SAR processing combines multiple σ° measurements from various azimuth-look directions to improve the σ° spatial resolution (SAR processing can result in a larger SNR compared to the scatterometer product although this comes at a tradeoff of the elimination of multiple azimuth-look direction information). SAR σ° measurements have a single azimuth-look direction, so SAR studies have been restricted to SO wind retrieval. In contrast, the low resolution scatterometer σ° measurements are collected at two widely different azimuth angles at each point in the swath. This enables the potential for direct wind direction retrieval [14]. The low resolution ($6 \times 30 \text{ km}$) of the SMAP σ° measurements is a limiting factor in tropical cyclone retrieval. To ameliorate this, we use the Brigham Young University UHR algorithm to enhance the spatial resolution to support 2.5 km wind retrieval (See Section 2.1).

1.1.4. Reference Vector Wind Dataset

The tropical cyclone Best-Track dataset provides a time-series of location, size, and intensity post-storm estimates using a combination of space-borne, airborne, and ground-based observations (Sources used for Best-Track include: Satellite (Infrared, Optical, Microwave), Ships, Moored buoys, and Coastal weather stations [42]). Both NHC and JTWC compile Best-Track datasets, which provide similar parameters [42–46]. The datasets are revised as new sources have become available, but they have not undergone major revisions since 2015. NHC maintains Hurricane Dataset 2 (HURDAT2), monitoring tropical cyclones near the United States (northern Atlantic, northern and central Pacific), while the other oceans are monitored by JTWC. Moving forward, the Best-Track data reported by NHC and JTWC are referred to as HURDAT interchangeably.

The Best-Track data of major tropical cyclones is reported every 6 h (0000, 0600, 1200, 1800 UTC), and at major storm milestones (e.g., genesis, maximum wind speed, or landfall). The information of interest for this study includes storm positions (latitude and longitude), maximum sustained wind speed, and the radii of three wind speed regimes (34, 50, and 60 kts, in northeast, southeast, southwest, and northwest quadrants). The wind speeds are reported in knots, and the radii are reported in nautical miles (Best-Track maximum sustained winds correspond to 1-min 10 m height wind ($U_{\max 1\text{min}}$) while scatterometer estimated winds correspond to 10 min 10 m height ($U_{\max 10\text{min}}$) winds [15,47]. A conversion factor of 0.93 is recommended by the World Meteorological Organization [48], i.e., $U_{\max 10\text{min}} = 0.93 \times U_{\max 1\text{min}}$).

Tropical storm Best-Track data has previously been used to analyze microwave sensor wind estimates [30]. Typically, the maximum sustained wind speed reported by Best-Track and maximum wind speed estimated from a microwave sensor are compared. This is repeated for multiple passes over multiple storms to evaluate the wind speed estimate performance. Studies generally have not used the Best-Track data as the reference vector wind dataset to create the GMF. This study uses Best-Track data as the reference to generate the GMF and validate vector wind estimates because it is the best option given the circumstances. To achieve this, we create a crude vector wind field model using Best-Track data (See Appendix B).

2. Materials and Methods

2.1. SMAP Tropical Cyclone Collocations and UHR Processing

SMAP measurements are collocated with tropical cyclones by comparing their locations and times with the interpolated times and locations of storm centers. From April to July 2015, 14 major tropical cyclones were observed (see Table 1 and visualized in Figure 1) and have Best-Track information. In this study, SMAP collocations with tropical cyclones require a minimum threshold of 500 standard resolution σ° measurements within 1100 km of the storm center, which restricts the number of passes to 113 of varying quality. We note that 2 of the 14 tropical cyclones during the lifespan of SMAP (Quang and Bill) do not meet the required threshold. Analysis using the SHE wind model requires “high-quality” passes (i.e., the eye of the storm is visibly discernible in the ground swath, not over land; see Section 2.2), which further restricts the number of passes to roughly ~ 30 .

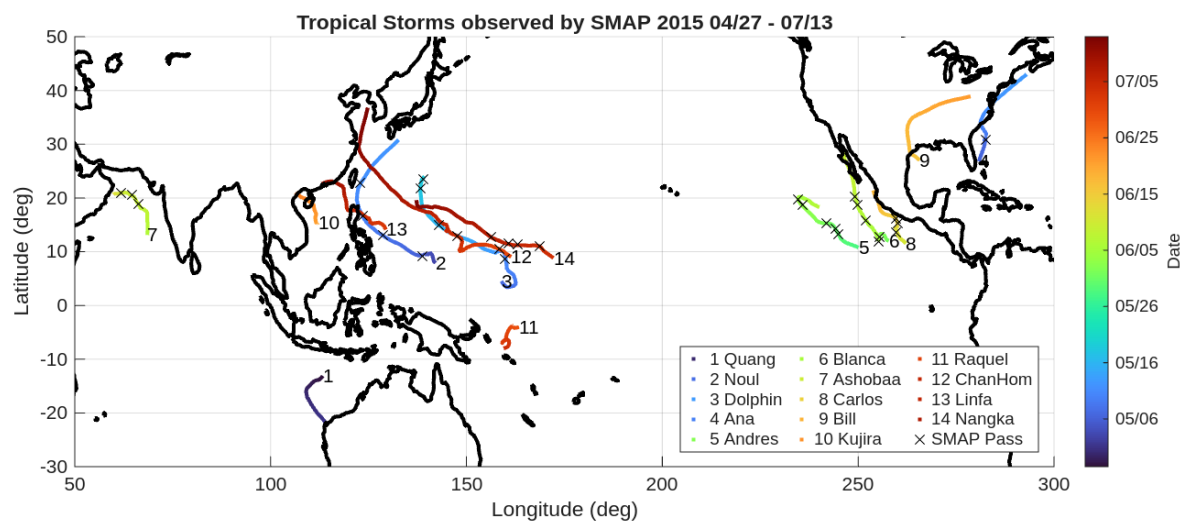


Figure 1. Best-Track locations of the 14 Tropical cyclones viewed by SMAP from 27 April 2015 to 13 July 2015, where the color of each Best-Track path indicates the date of the tropical cyclone. Crosses represent the highest-quality SMAP passes (See Section 2.2).

Table 1. Tropical cyclones observed by the SMAP radar.

#	Storm	Start Date	End Date	Speed Max (m/s)	Agency	Pass	Good Pass *
1	Quang	4/27	5/01	51.4	JTWC	0	0
2	Noul	5/02	5/12	55.9	JTWC	12	4
3	Dolphin	5/06	5/19	51.4	JTWC	14	5
4	Ana	5/06	5/12	26.8	NHC	8	1
5	Andres	5/28	6/07	64.8	NHC	13	5
6	Blanca	5/31	6/09	64.8	NHC	13	5
7	Ashobaa	6/06	6/12	22.3	JTWC	8	3
8	Carlos	6/10	6/18	40.2	NHC	11	3
9	Bill	6/16	6/21	26.8	JTWC	0	0
10	Kujira	6/20	6/24	22.3	JTWC	7	0
11	Raquel	6/28	7/04	17.9	JTWC	2	0
12	Chan-Hom	6/30	7/12	46.9	JTWC	9	1
13	Linfa	7/02	7/09	26.8	JTWC	9	0
14	Nangka	7/03	7/13	51.4	JTWC	7	4

* Good pass defined in Section 2.2.

Traditionally, scatterometers retrieve winds on a 25 km WVC grid, but UHR winds can be retrieved at a much finer spatial resolution. The UHR algorithm was originally developed in 2003 with QuikSCAT for tropical cyclone analysis [49] and has subsequently

been successfully used to enhance the spatial resolution of σ° measurements for many other scatterometers [50], but it has yet to be applied to SMAP wind retrieval. The UHR algorithm enhances the spatial resolution of scatterometer σ° separately by incidence and polarization. UHR reports σ° on a finer resolution grid (roughly 2.5 km), which now becomes the new WVC grid. Note that since the finer WVC is influenced by measurements in neighboring cells, the measurements in neighboring WVCs are statistically dependent (the noise is correlated).

The UHR algorithm calculates the σ° on a fine 2.5 km resolution grid. Forward-looking and aft-looking measurements are treated separately. At a given grid location (x, y are longitude and latitude), the σ° is determined by computing the weighted average of all measurements whose Measurement Response Function (MRF) at that location exceeds a -10 dB threshold. The measurements are weighted according to the value of their MRF at the location of interest (x, y) (Further discussion of the UHR algorithm and the Measurement MRF can be found in the literature [51,52]) per Equation (2). The MRF of slice measurements is shaped in range by the digital processing and is approximated as a rect function. In azimuth, the MRF is shaped by the antenna pattern, which is also approximated as a rect. The SMAP antenna is designed for a radiometer and so has much lower sidelobes than a traditional scatterometer. Through experimentation, it was found that more detailed approximations (e.g., a Gaussian) provided only marginal improvements over a rect [28,53]. Thus, for each grid element (UHR pixel), a weighted average of σ° measurements whose MRFs contain the UHR pixel is computed,

$$\sigma^\circ(x, y) = \frac{\sum_{s_i} A_{s_i}(x, y) \sigma_{s_i}^\circ}{\sum_{s_i} A_{s_i}(x, y)}, \quad (2)$$

where $A_{s_i}(x, y)$ is the MRF for the backscatter measurement ($\sigma_{s_i}^\circ$) at a longitude and latitude (x, y) [29]. Corresponding values are calculated for azimuth, incidence, and time. Theoretically, the summations in Equation (2) should be integrals, but in practice, the weighted averages are realized with discrete summations. Finally, the UHR algorithm generates AVE σ° images [53,54].

Tropical Cyclone Dolphin: L25km and UHR Comparison

There is a trade-off between spatial resolution and noise level for UHR σ° measurements. Figure 2 displays six different σ° measurements (HH-pol, VV-pol, and X-pol; fore and aft measurements) compared with conventional 25 km resolution (L25km (The designation “L25Km” mirrors common NASA level nomenclature (e.g., L1B and L2B) conveying the level of processing used to produce the data. “L25Km” highlights conventional wind retrieval at a WVC resolution of 25 km)) and UHR from Tropical Cyclone Dolphin on 14 May 2015. The first row displays conventional WVC 25 km resolution σ° measurements, and the second row displays UHR 2.5 km resolution σ° measurements.

The differences between the images highlight the characteristics of each σ° polarization and resolution. Comparing L25km and UHR panels, the same general features are present in both, although the UHR images contain finer details, which make it easier to identify meso-scale phenomena compared to L25km. For example, the eyewall is objectively clearer and more prominent in the UHR images compared to the L25km images. However, the enhanced resolution of UHR σ° images simultaneously increases the noise level present and may introduce some artifacts (wave pattern).

An example of the wind direction dependence of L-band σ° measurements is displayed in both the UHR and L25km images. However, the degree of wind direction dependence varies depending on the polarization. The HH- and VV-pol σ° response is significantly dependent on wind direction, while X-pol σ° images exhibit less directional dependence.

Since the absolute wind direction is unchanged between both fore and aft images (There is approximately a 15 min time difference between the fore and aft observations at a given location. Over this interval, wind direction is not expected to change appreciably), the difference in σ° response can be attributed to the unique response of the relative wind direction (Relative wind direction is the relative angle between the radar look direction and the absolute wind direction [7]), which highlights the wind direction dependence of σ° measurements. Notice that the HH- and VV-pol fore-looking measurements exhibit a larger σ° response along the east–west axis near the storm center, while aft-looking measurements exhibit a larger σ° response along the north–south axis near the storm center. In contrast, for X-pol σ° measurements, there is a relatively uniform response near the center of the storm independent of wind direction. This confirms that the HH- and VV-pol measurements have a non-negligible direction dependence, while the X-pol σ° response is relatively direction independent.

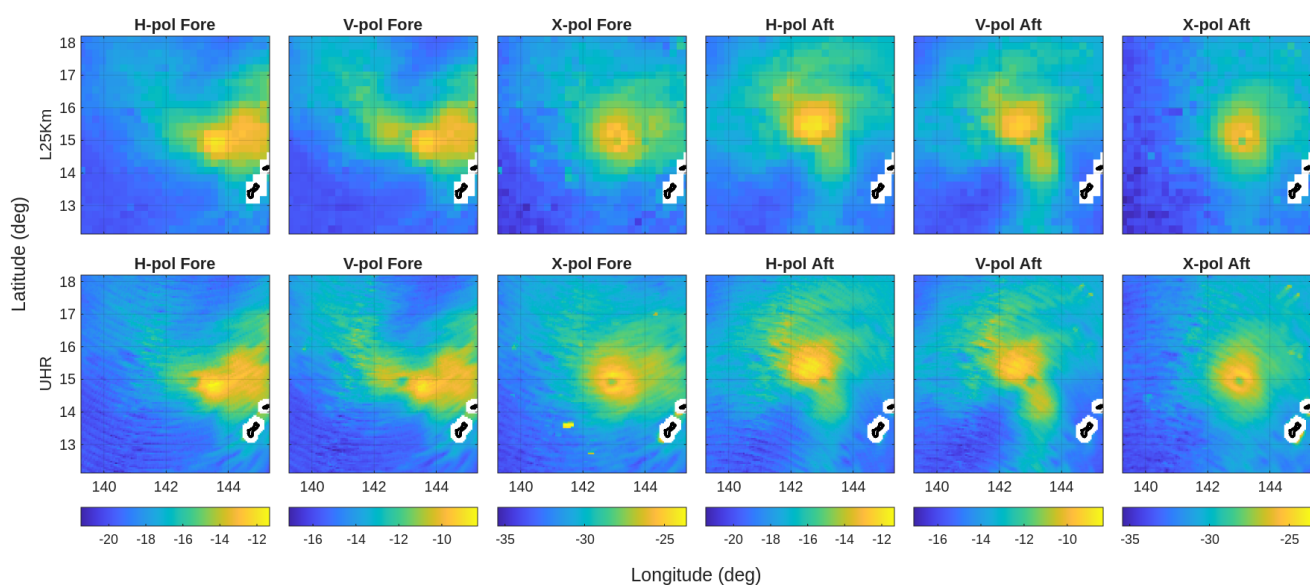


Figure 2. σ° measurements from Tropical Cyclone Dolphin on 14 May around 2045 UTC in WVC for L25km (top row), and UHR (bottom row), separated into fore (first three) and aft (last three) look directions, and polarizations.

2.2. A Tropical Cyclone-Tuned L-Band GMF

In prior work [14], an L-band GMF was created using SMAP σ° with Numerical Weather Prediction (NWP) winds as the reference dataset. Due to the limited number of high wind speed measurements reported by NWP, extrapolation of the GMF to high-to-severe wind speeds was performed based on trends at medium wind speeds. The GMF made from NWP winds experienced extreme limitations at high-to-severe wind speeds. This prompted the creation of a tropical cyclone-tuned GMF using an alternative vector wind reference dataset.

In this study, at high-to-severe wind speeds, HURDAT Best-Track data are used to model tropical cyclone winds. Since HURDAT reports only minimal information about the storm center (i.e., eye wall radius) and no wind values below 17 m/s, European Centre for Medium-Range Weather Forecasts (ECMWF) winds and scaled SMAP σ° measurements are used to augment the HURDAT wind data to create a new wind model. The new wind model is called the SMAP, HURDAT, and ECMWF (SHE) wind model (See Appendix B). The L-band tropical cyclone-tuned SO and SD GMFs are created using SHE model winds.

The SHE GMF

Collocated SHE winds and SMAP σ° measurements are used to create the GMF. Unfortunately, a limitation of the SHE wind model is that only high-quality passes can be used because the SHE model relies on SMAP σ° measurements to model winds near the storm center. Three criteria are used to determine whether the storm center is visible in the ground-swath of a SMAP pass (i.e., if a pass is high-quality):

1. The storm center in the swath of SMAP;
2. The storm center over the ocean;
3. Confidence in the visibility of the storm center.

The first two criteria are relatively objective, while the last criterion is subjective. It can be difficult to accurately identify the center locations of storms with low wind speeds. This has been a common problem for other scatterometers [36]. In this study, SMAP X-pol measurements are used to locate the storm centers despite their low SNR. Recall, the X-pol σ° response is not significantly dependent on wind direction and is relatively proportional to wind speed (See Section 2.1) [12].

The Best-Track HURDAT storm center can sometimes disagree with the SMAP σ° UHR storm centers. The identification of storm centers and estimation of storm size is difficult to automate [36], which means that the quality of a SMAP pass is subjectively determined. Only measurements where the storm center is visible in the swath over the ocean are used to make the SHE GMF.

The SHE SD GMF is created by performing harmonic decomposition on the UHR σ° measurements, which have been histogrammed into speed and direction bins using the SHE model winds. Using the A_0 coefficients (from Equation (1)) between 30 and 50 m/s, linear interpolation is used to extrapolate A_0 above 50 m/s. For A_1 through A_3 , the mean coefficient value between 30 and 50 m/s is used to extrapolate the coefficients above 50 m/s. The A_0 coefficient is used for the SO GMF shown in Figure 3. Separate GMFs are made for HH-pol, VV-pol, and X-pol.

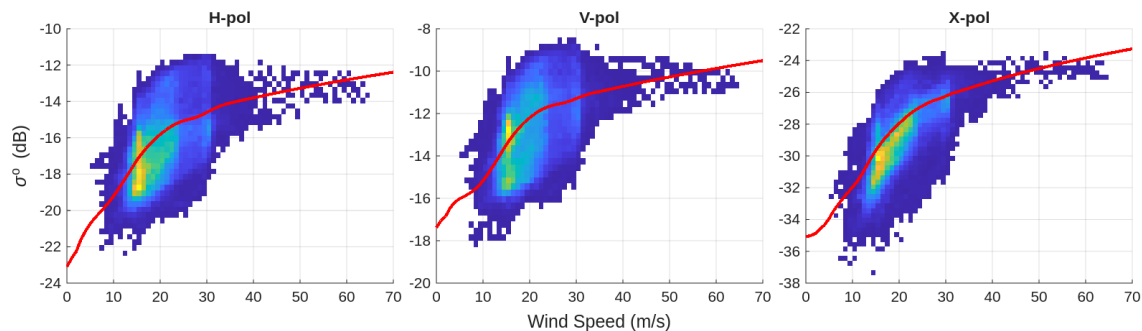


Figure 3. Joint distribution of σ° and SHE wind speeds with SHE GMF. The GMFs for HH-pol (left), VV-pol (center), and X-pol (right) are shown in dB. The red line shows the A_0 term of the SD GMF, which is also the SO GMF.

3. Results

3.1. Tropical Cyclone Wind Retrieval

Maximum likelihood wind retrieval [14] on SMAP measurements near tropical cyclones is performed using the SO and SD SHE GMFs. Wind estimates are generated from the 30 SMAP passes used to create the GMF. In the following, some passes are analyzed individually to compare with the ECMWF, HURDAT, and SHE reference datasets. The estimates are generated for UHR and L25km resolution to understand the improvements that UHR provides and the full capabilities of L-band wind retrieval near tropical cyclones.

Specific passes of Tropical Cyclone Dolphin on 14 May 2015, Andres on 2 June 2015, and Blanca on 5 June 2015 are shown in Figure 4. For each tropical storm, HURDAT wind regimes, SHE model winds, ECMWF winds, L25km, and UHR wind estimates are presented. These passes highlight the improvements that the UHR has compared to L25km, where the storm eye is easily distinguishable in every UHR image, while the eye is only sometimes visible for L25km images. For example, the eyewall is visible for the L25km image of tropical cyclone Blanca, but for the other tropical cyclones it is difficult to clearly distinguish the eyewall using the L25km image. The eyewall is substantially more visible using UHR speed estimates. Another result is that the wind direction retrieval near tropical cyclones is relatively good.

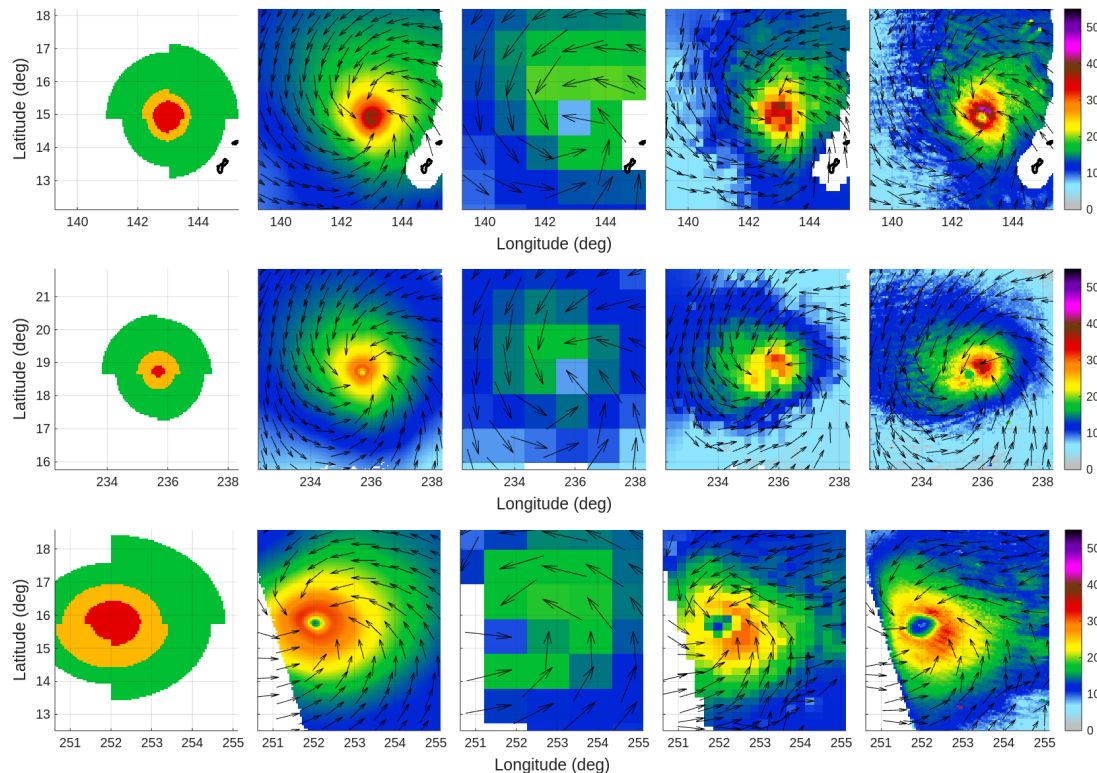


Figure 4. The near-surface vector winds for **(Top)** Tropical Cyclone Dolphin 14 May 2015, **(Middle)** Tropical Cyclone Andres 2 June 2015, and **(Bottom)** Tropical Cyclone Blanca 5 June 2015. Columns: **(Left)** HURDAT wind speed regimes, **(Left Center)** SHE wind model, **(Center)** ECMWF near-surface winds, **(Right Center)** L25km-retrieved winds, and **(Right)** UHR-retrieved winds. The heat map shows the wind speed, while the arrows demonstrate the wind directions.

3.1.1. Cumulative Wind Retrieval Statistics Analysis

The error statistics calculated to evaluate the wind estimate accuracy with respect to the SHE wind model from the 30 high-quality SMAP passes are Root Mean Square Error (RMSE), Mean Error (ME), and Standard Deviation (STD) error. Quality control is performed to mitigate the influence of errors from low wind speed measurements and measurements with Radio Frequency Interference (RFI), which is often present in L-band [55]. To restrict analysis to high-to-severe winds, wind retrieval is limited to only winds located between the storm center and the outermost HURDAT wind speed regime. Additionally, RFI is mitigated by analyzing σ° as a function of distance from the storm center. The mean and Standard Deviation of σ° measurements in each bin are calculated, and measurements that are more than two Standard Deviations from the mean in the radial bin are omitted from analysis.

Wind retrieval at a particular location can be performed with up to six σ° measurements for each UHR pixel (Fore-looking: HH-pol, VV-pol, and X-pol. Aft-looking: HH-pol, VV-pol, and X-pol). Three combinations are used to evaluate the wind retrieval capabilities of L-band scatterometers at high-to-severe wind speeds (See Table 2): Multiple-look directions with X-pol (MLwX), Multiple-look directions without X-pol (MLwoX), and Multiple-look directions only using X-pol (MLoX). Using these three σ° combinations, two experiments are used to evaluate L-band tropical cyclone wind retrieval: polarization sensitivity to wind speed, and a comparison between SO and SD GMF retrieval.

Table 2. Names of the σ° combinations used for wind retrieval comparison.

σ° Combination Names	Acronym	HH-pol Fore	VV-pol V Fore	X-pol Fore	HH-pol Aft	VV-pol Aft	X-pol Aft
Multiple look w/ X-pol	MLwX	✓	✓	✓	✓	✓	✓
Multiple look w/o X-pol	MLwoX	✓	✓		✓	✓	
Multiple look only X-pol	MLoX			✓			✓

The sensitivity of the three σ° polarizations (HH-, VV-, X-pol) at severe winds is tested. HH- and VV-pol σ° measurements exhibit a tendency to generate wind speed estimates that are clipped at the highest value of the GMF, a phenomenon referred to as saturation. Conversely, X-pol σ° measurements do not saturate. They exhibit a stronger correlation between wind intensity and σ° measurements [12] compared to HH- and VV-pol σ° measurements.

The second experiment compares error statistics between SO and SD estimates to evaluate the directional dependence of L-band σ° at high-to-severe wind speeds. This experiment determines if L-band measurements have a wind direction dependence at high wind speeds because the SD GMF models a wind direction dependence, whereas the SO GMF does not account for wind direction.

3.1.2. Wind Retrieval Distributions

The SO and SD GMFs are used to retrieve the winds. The joint distributions between the estimated and reference vector wind dataset for the three σ° combinations are shown in Figure 5. The wind distributions for SO and SD (the rows of Figure 5) have minor differences, while generally the same trends are shared between the estimates from the two GMFs (Recall the SD GMF assumes that σ° measurements exhibit a directional response while the SO GMF does not). Since the differences at higher wind speeds are minimal, it suggests the σ° response has minimal direction dependence at higher wind speeds. The only combination of σ° measurements that exhibits a significant difference between the SO- and SD-derived estimates is the MLoX combination. The SD-MLoX combination has fewer measurements that become saturated than the SO counterpart, suggesting that the SD algorithm is superior at handling measurements with higher noise levels.

The saturation of σ° measurements at high-to-severe wind speeds is analyzed by comparing differences among estimate distributions for the different polarizations (the columns of Figure 5). The results suggest that HH-pol and VV-pol measurements tend to saturate around 20 m/s. This happens for both SO and SD GMFs. Contrarily, the X-pol-derived wind estimates suggest that X-pol measurements have a stronger correlation with the SHE-modeled winds above 20 m/s. X-pol-derived wind estimates can saturate, but the amount depends heavily on which GMF is considered. SD wind estimates are less sensitive to saturation than SO estimates (These results are a representative sample. More σ° polarization combinations are possible, including single-look estimates. Unfortunately, the single-look estimates tend to saturate more often than multiple-look estimates, so they are not shown).

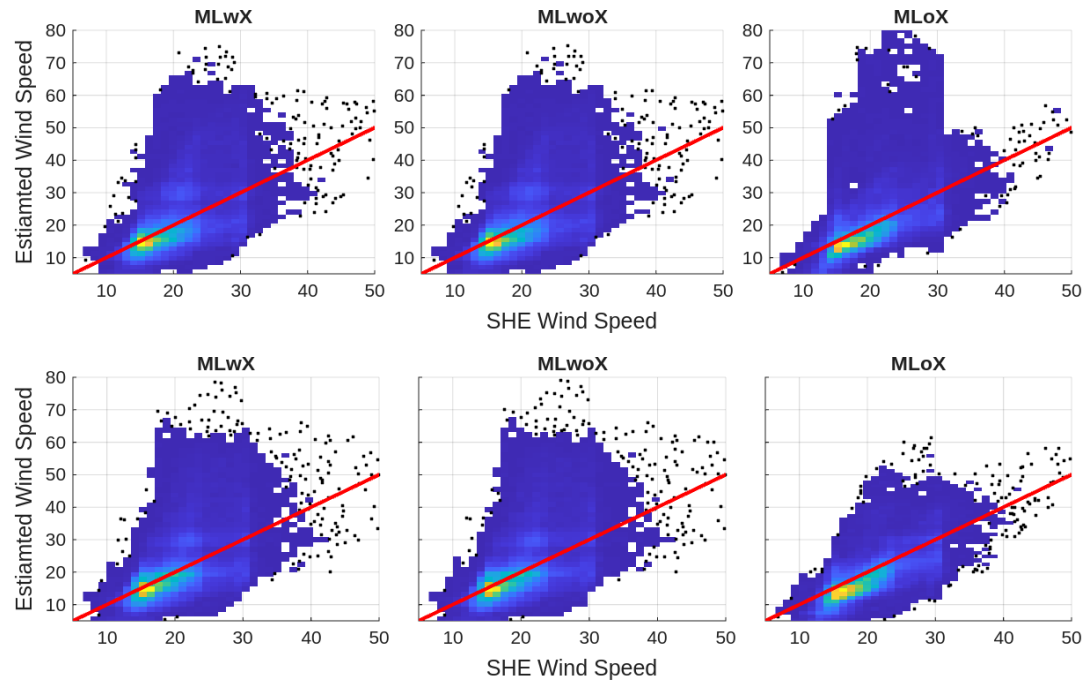


Figure 5. Joint distribution of multi-look direction-estimated wind speed with SHE wind speed for the three σ° measurement combinations used for wind retrieval with the (Top) SO and (Bottom) SD GMFs. Columns: (Left) HH-pol, VV-pol and X-pol, (Center) HH-pol and VV-pol, and (Right) Only X-pol. The red line denotes the ideal $y = x$ relationship between the estimate and SHE wind speeds. The wind speed estimate RMSE, ME, and STD are shown in Figure 6. Comparison of MLwX and MLwoX with MLoX using the SO algorithm demonstrates the improvement achievable using only X-pol without HH- and VV-pol.

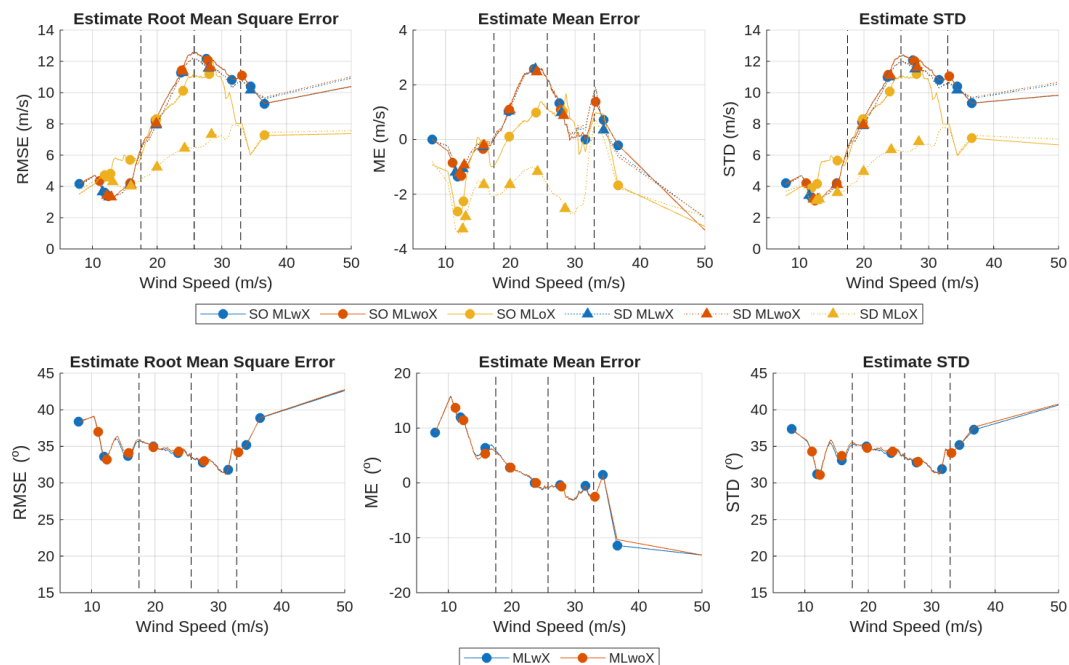


Figure 6. (Top) Speed and (Bottom) Direction Estimates (Left Column) RMSE, (Center Column) ME, and (Right Column) STD for the combinations of σ° using SO and SD retrieval. MLwX, MLwoX, and MLoX are shown in blue, orange, and yellow, respectively. Triangle markers denote SD retrieval, while circular markers denote SO retrieval. Dashed black lines show the HURDAT wind speed regimes 34, 50, and 64 kts [17, 25, and 32 m/s].

The wind direction distributions are shown in Figure 7. The distribution of MLwX and MLwoX demonstrates that the wind estimates that are produced are generally clustered around four estimates of 45° , 135° , 225° , and 315° . This suggests that MLwX and MLwoX estimates cause certain wind directions to be estimated regardless of the actual wind direction (i.e., wind direction retrieval is not possible for estimates depending on HH- and VV-pol measurements).

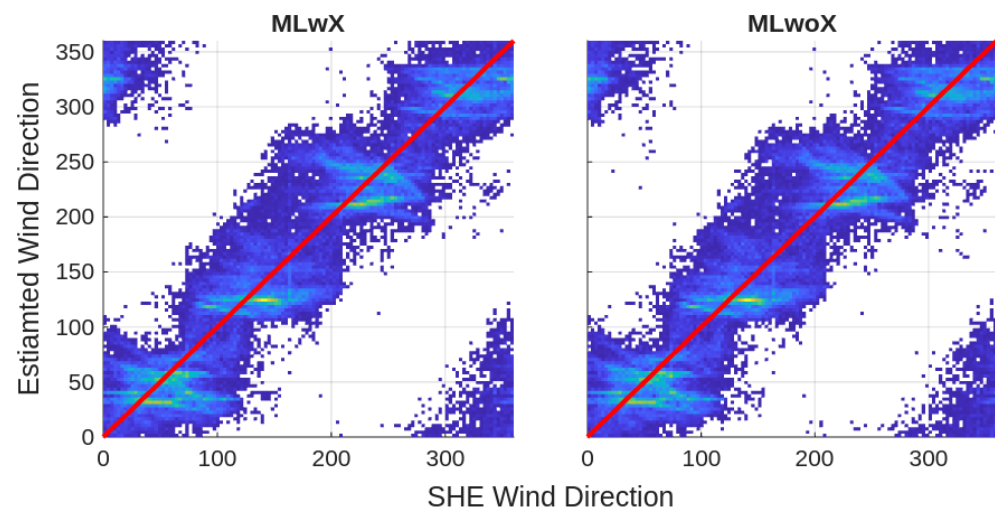


Figure 7. Joint distribution of multi-look direction-estimated wind direction with SHE wind direction for the three σ° measurement combinations used for wind retrieval. Columns: (Left) HH-pol, VV-pol and X-pol, (Right) HH-pol and VV-pol. The red line denotes the ideal $y = x$ relationship between the estimate and SHE wind directions. The wind direction estimate RMSE, ME, and STD are shown in Figure 6.

To validate the usage of the SHE model, the Remote Sensing System Tropical Cyclone (RSS TC) SMAP radiometer wind product [56] is compared to the wind estimates. The RSS TC SMAP radiometer wind product is collocated with the SMAP radiometer UHR data, and the comparison of the wind estimates is shown in Figure 8. The ideal $y = x$ relationship is shown for each comparison. The SMAP scatterometer UHR estimates align well with the RSS TC SMAP radiometer wind product. The deviations from the ideal at high wind speeds are due at least in part to the finer spatial resolution offered by the UHR product compared to the lower resolution (25 km) of the radiometer-derived winds; see Figure 9. A comparison between the SHE model and the RSS TC SMAP radiometer wind product is also shown. This comparison confirms the utility of the SHE wind model as a useful wind reference for tropical cyclones.

3.1.3. Wind Speed Estimates

The wind speed estimate error statistics using the SO and SD GMFs are shown in the top row of Figure 6. The RMSE, ME, and STD of the estimates are calculated for the three σ° combinations in non-uniform wind speed bins. The size of wind speed bins is chosen so that each bin contains the same number of measurements.

Analyzing the RMSE of Figure 6, some trends are shared between the various estimates. At low wind speeds (below 12 m/s), all estimates have roughly 4 m/s RMSE. The RMSE increases for all the estimates in the first HURDAT regime (17 m/s to 25 m/s), although the rate of increase is different for each estimate type. In the second HURDAT regime (25 m/s to 32 m/s), the RMSE decreases for most estimates. There are insufficient estimates in the third HURDAT wind speed regime to draw any substantial conclusions about error statistic trends. Overall, the SD MLoX produces the most accurate wind estimates. The STD results tend to follow RMSE trends. The ME trends show that SD MLoX has a bias of almost 2 m/s

in the first and second HURDAT wind regimes. All other estimates have larger biases due to wind speed saturation.

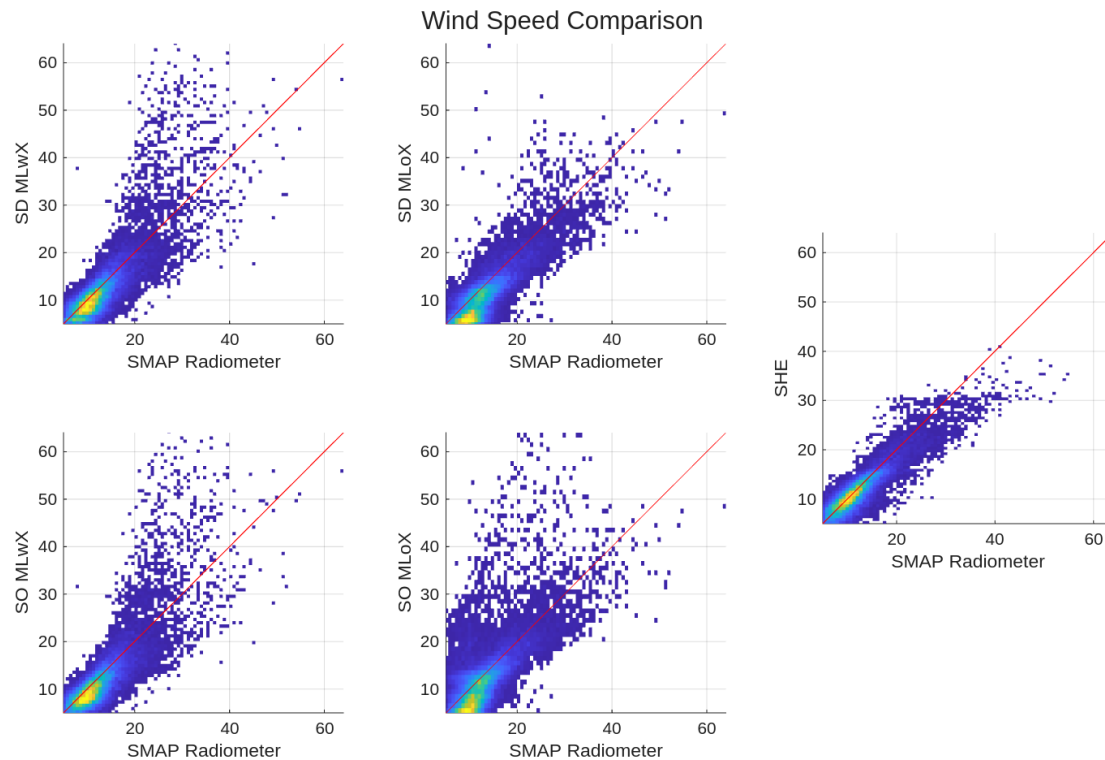


Figure 8. Validation of the SHE wind speed model using the Remote Sensing System Tropical Cyclone (RSS TC) SMAP Radiometer wind product. The RSS TC wind speed estimate closest to each UHR wind estimate is compared with SD MLwX, SD MLoX, SO MLwX, SO MLoX, and the SHE wind model wind speeds. The red line shows the ideal $y = x$ relationship.

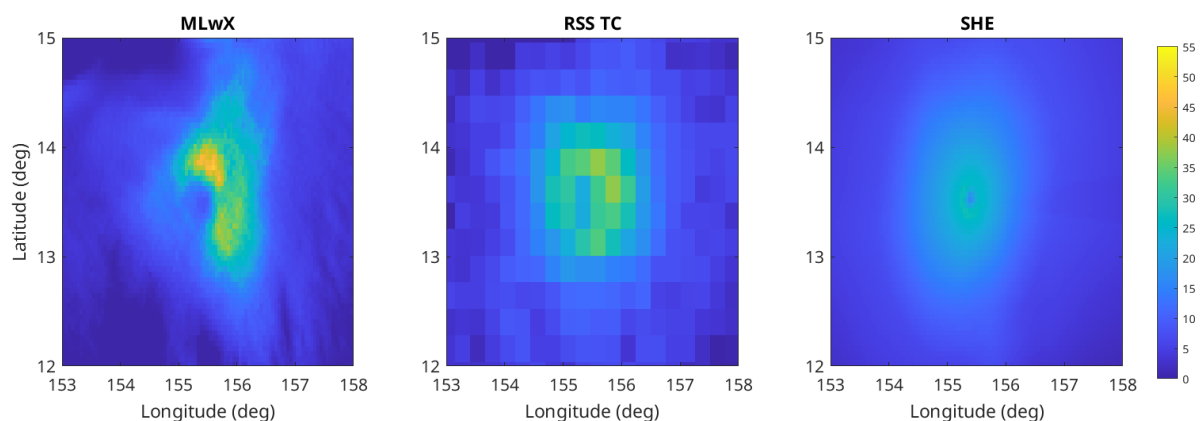


Figure 9. Wind speed map from Tropical Cyclone Nangka on 6 July about 2300 UTC for UHR (left), RSS TC (center), SHE model (right). Note the finer resolution of the UHR wind speeds compared to the RSS TC winds, which resolve areas of higher wind speed. In this case, the SHE model under-predicts the highest wind speeds.

Comparing the wind estimate error statistics by the σ° combinations used for each estimate confirms that HH-pol and VV-pol derived estimates are more likely to become saturated than solely X-pol derived estimates. These results align with results from Section 3.1.2. The results show that despite consistently underestimating the wind speed, the MLoX is the most accurate speed estimate. This suggests that X-pol σ° measurements have the strongest

correlation with high-to-severe wind speeds. This is especially true when comparing to HH- and VV-pol derived wind estimates, which saturate at high wind speeds.

Most of the σ° combinations produce the same error statistics independent of GMF except for the MLoX. For MLoX, the SD estimate has a lower RMSE than the SO counterpart. This result suggests that X-pol σ° exhibits a non-negligible wind direction dependence (although its dependence is small). Also, the SD wind retrieval is more resistant to saturation than SO retrieval for X-pol measurements.

3.1.4. Wind Direction Estimates

Summary error statistics are calculated and shown in Figure 6 for the retrieved wind directions using the three combinations of σ° measurements. Since SO retrieval does not generate wind direction estimates, no direction comparisons can be made between SO and SD estimates. The MLwX and MLwoX have relatively similar wind direction estimate statistics for RMSE, ME, and STD. The RMSE and STD are relatively constant around 35° for all wind speeds. The ME is relatively small near 0° for all wind speeds between 0 and 35 m/s.

4. Conclusions

The UHR algorithm is applied to SMAP scatterometer radar measurements, improving the spatial resolution over conventional scatterometer SMAP L25km wind estimates. The improved spatial resolution enables the visualization of meso-scale tropical cyclone features like the eyewall. These details are difficult to distinguish with the standard resolution product but have become clearer with the increased resolution provided by the UHR algorithm. While SMAP SAR images have finer resolution, SMAP collected very few measurements over the ocean (only within 1000 km of the coast on ascending passes). Further, SAR images lack multi-azimuth observations to support wind direction retrieval.

In this study, SMAP σ° measurements and tropical cyclone Best-Track data are used to create a tropical cyclone-tuned GMF. The SHE wind model is developed from HURDAT Best-Track data, ECMWF winds, and SMAP σ° measurements. The SHE wind model is used as the vector wind reference dataset to create the SMAP tropical cyclone-tuned GMF. Wind retrieval near tropical cyclones using L-band UHR σ° measurements is performed using three combinations of σ° values. The distributions of wind estimates are compared for different combinations of σ° measurements. HH- and VV-pol are more likely to result in saturated wind speed estimates than wind estimates produced solely from X-pol measurements. The distributions also suggest that the SO algorithm produces estimates that are more likely to saturate than the SD algorithm.

Three estimate error statistics are calculated with the SHE model as the wind vector reference dataset. The error statistics are compared to determine which algorithm performs better, SD or SO. This comparison is meant to quantify the L-band σ° measurement wind direction dependence. The error statistics are also compared to determine which σ° polarizations cause the wind estimates to saturate.

The X-pol σ° measurements generate the best wind estimates at high-to-severe wind speeds. It is not unreasonable to assume that if the SNR is improved, the wind speed estimate accuracy from X-pol measurements could also increase. Analyzing HH- and VV-pol derived wind estimates (MLwX and MLwoX) suggests that as the wind speed saturation occurs above 20 m/s, the directional accuracy also degrades and is unusable.

Our conclusions are nuanced. The number of measurements available for this study is constrained by the duration of the SMAP radar mission, and the number of SMAP passes over tropical cyclones. This means that the same measurements used to develop the GMF were also used to assess its wind retrieval performance. Unfortunately, no independent

validation dataset is available for these study conditions. Additionally, the SHE wind model is an experimental model that uses HURDAT as the primary data source. HURDAT has some notable and widely acknowledged limitations (i.e., the data being estimates in lieu of actual measurements). More L-band scatterometer measurements of tropical cyclones are required to better develop wind retrieval techniques. For example, a future mission, the Global L-band Observatory for Water Cycle Studies (GLOWS) [57], is a follow-on mission for SMAP and will include an L-band scatterometer.

Author Contributions: Conceptualization, B.J.F. and D.G.L.; methodology, B.J.F. and D.G.L.; validation, B.J.F.; formal analysis, B.J.F. and D.G.L.; investigation, B.J.F. and D.G.L.; resources, D.G.L.; data curation, B.J.F. and D.G.L.; writing—original draft preparation, B.J.F.; writing—review and editing, B.J.F. and D.G.L.; visualization, B.J.F. and D.G.L.; supervision, D.G.L.; project administration, D.G.L.; funding acquisition, D.G.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was internally funded by Brigham Young University.

Data Availability Statement: The original data presented in the study are openly available from the following sources: SMAP used in this study is available from the National Snow and Ice Data Center (NSIDC) Distributed Active Archive Center (DAAC, <https://nsidc.org>, accessed 15 July 2026) The Best-Track data is distributed from the National Hurricane Center (NHC, <https://www.aoml.noaa.gov/hrd/hurdat/>, accessed 15 July 2026) and the Joint Typhoon Warning Center (JTWC, <https://www.metoc.navy.mil/jtwc/jtwc.html?best-tracks>, accessed 15 July 2026). The SMAP radiometer tropical cyclone sea surface wind data were produced by Remote Sensing Systems (RSS, <https://www.remss.com/tropical-cyclones/tc-winds/>, accessed 3 October 2026). The derived GMF data presented in this study are freely available at <https://www.scp.byu.edu/LbandGMF> (accessed 3 October 2026).

Acknowledgments: The authors did not use generative artificial intelligence (AI) tools in the preparation of this manuscript.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Justification for the Use of a Non-Traditional Reference Vector Wind Dataset

The limited number of SMAP σ° measurements observed near tropical cyclone level winds precludes the use of most commonly used reference vector wind datasets. NWP or buoys have traditionally been used as a reference dataset for scatterometer studies but are limited to non-tropical cyclone level winds. For studies centering on tropical cyclone winds, airborne sensors, and H*Winds have been used for validation but were not be used in this study due to lack of availability.

Since buoys, NWP, airborne sensors, and H*Winds are not practical reference wind vector wind datasets for this study, another source for tropical cyclone winds is required. To address this problem, we develop a Best-Track-derived wind model, called the SHE model. The SHE model uses HURDAT, ECMWF, and SMAP data. Development of the SHE model is discussed in Appendix B. Figure A1 shows a comparison between the SHE and ECMWF winds as an example of why the new wind model near tropical cyclones was created.

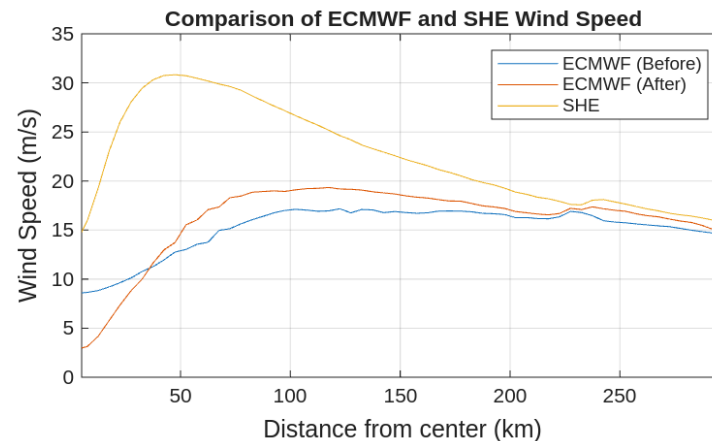


Figure A1. Comparison of SHE and ECMWF winds speeds from Tropical Cyclone Blanca 5 June 2015 as a function of distance from the storm center. The re-centered ECMWF winds from the file before and after the storm are plotted in red and blue while the SHE model winds are plotted in yellow.

Appendix B. The SHE Model

Appendix B.1. Wind Speed

The SHE model is created primarily with HURDAT Best-Track wind extent radii, and is augmented with ECMWF winds and scaled SMAP σ° measurements. First, the three HURDAT wind speed regimes of the radii of maximum wind extent are used to model the winds between 34 and 64 knots. Second, the ECMWF winds are used to model distant vector winds from the storm center (outside the farthest HURDAT radius). Lastly, SMAP σ° measurements are used to model winds near the storm center including the eyewall of the tropical cyclone and the location of maximum sustained wind speed.

We begin the discussion of the SHE model by focusing on the application of HURDAT data. Recall, HURDAT reports the radii of maximum wind extent (radius for 64, 50, and 34 kts) and each radius has up to 4 values (While sometimes a radius value can be missing from a Best-Track entry, the storms analyzed in this study are well developed and have all of the radii values for all of the quadrants) for each quadrant around the storm center (i.e., northeast, southeast, southwest, and northwest). These radii are used to model the winds between 64 and 34 kts. A curve of continuous radii values around the storm center is determined by blending between the radii of the 4 quadrants using a cosine function and weights. The weights are calculated by,

$$\tilde{w}_i(\theta) = \max(0, \cos(\Delta\theta_i))^n, \quad (\text{A1})$$

where θ is the direction around the storm center, and n determines the sharpness of the transition between quadrants (3 was used). The weights are then normalized (w_i) and are used to create the continuous HURDAT radii values $R(\theta)$,

$$R(\theta) = \sum_{i=1}^4 w_i(\theta) R_i. \quad (\text{A2})$$

This is performed for the three wind speed regimes (64, 50, and 34 kts), generating a smooth radii for in all azimuth directions around the storm center. Finally, the winds speeds for locations between the HURDAT maximum wind speed radii are computed using linearly extrapolation using the wind speed regime (64, 50 or 34 kts) and the corresponding radii in each direction around the storm center. This creates the HURDAT wind field (V_{HURDAT}).

The ECMWF wind field (V_{ECMWF}) is used for winds outside the furthest HURDAT wind speed radius. Weights are calculated to transition between the V_{HURDAT} and V_{ECMWF} ,

$$\tilde{W}_e = 1 - \exp\left[-S\left(\frac{R}{R_{\text{outer}}}\right)^2\right], \quad (\text{A3})$$

where $\tilde{W}_e$ is the weight, S is a tune-able sharpness factor, R is the distance to the storm center, and R_{outer} is the transition radius between ECMWF and HURDAT data. The transition radius is set to be twice the largest radii reported by HURDAT.

SMAP σ° measurements are used to model wind speeds near the storm center. First, the radius of maximum wind (RMW) is determined from analyzing X-pol σ° measurements surrounding the storm center. The X-pol σ° measurements are used because they exhibit the smallest wind direction modulation (See Section 2.1). The corresponding RMW σ° values ($\sigma_{\text{RMW}}^\circ(\theta)$) as a function of azimuth (θ) around the storm center. The wind speeds corresponding to the RMW ($V_{\text{RMW}}(\theta)$) are calculated by scaling the σ° values by the HURDAT maximum sustained wind speed (V_{max}) using,

$$V_{\text{RMW}}(\theta) = V_{\text{max}} \frac{\sigma_{\text{RMW}}^\circ(\theta)}{\max(\sigma_{\text{RMW}}^\circ(\theta))}, \quad (\text{A4})$$

where V_{max} is the HURDAT maximum sustained wind speed. Second, the wind speed at the storm center (Wind speeds at the tropical storm center are theoretically near zero but due to the low spatial resolution of SMAP scatterometer/UHR σ° measurements, the observed wind speed in the eye, the “effective wind speed” is non-zero) is calculated using SMAP X-pol σ° measurement. The effective storm center wind speed (V_{center}) is calculated using,

$$V_{\text{center}} = V_{\text{max}} \frac{\sigma_{\text{center}}^\circ}{\max(\sigma_{\text{RMW}}^\circ(\theta))}, \quad (\text{A5})$$

where $\sigma_{\text{center}}^\circ$ is the SMAP σ° nearest the storm center. A linear extrapolation of wind speeds is performed for locations between the storm center and the RMW, and between the RMW and the either the closest HURDAT, or (if no HURDAT regimes are available because the storm is in early stages of development) the ECMWF at twice the RMW. This creates an initial SMAP-derived wind function (V_{SMAP}). Figure A2 shows an example of how the SMAP σ° measurements are scaled to model the wind speeds near the storm center. A SMAP weight ($\tilde{W}_s$) is created to blend between the V_{SMAP} and V_{HURDAT} derived winds,

$$\tilde{W}_s = \exp\left[-S\left(\frac{R}{R_{\text{inner}}}\right)^2\right], \quad (\text{A6})$$

where R_{inner} is the transition radius between HURDAT and SMAP derived winds.

A HURDAT weight is created to blend between V_{HURDAT} , V_{ECMWF} , and V_{SMAP} ,

$$\tilde{W}_h = 1 - \tilde{W}_s - \tilde{W}_e, \quad (\text{A7})$$

and the weights are normalized. The total SHE wind speed function is created by

$$V_{\text{SHE}} = W_h V_{\text{HURDAT}} + W_e V_{\text{ECMWF}} + W_s V_{\text{SMAP}}, \quad (\text{A8})$$

where W_h , W_e , W_s are the normalized weights. An example of the creation of the SHE wind speed is shown in Figure A3.

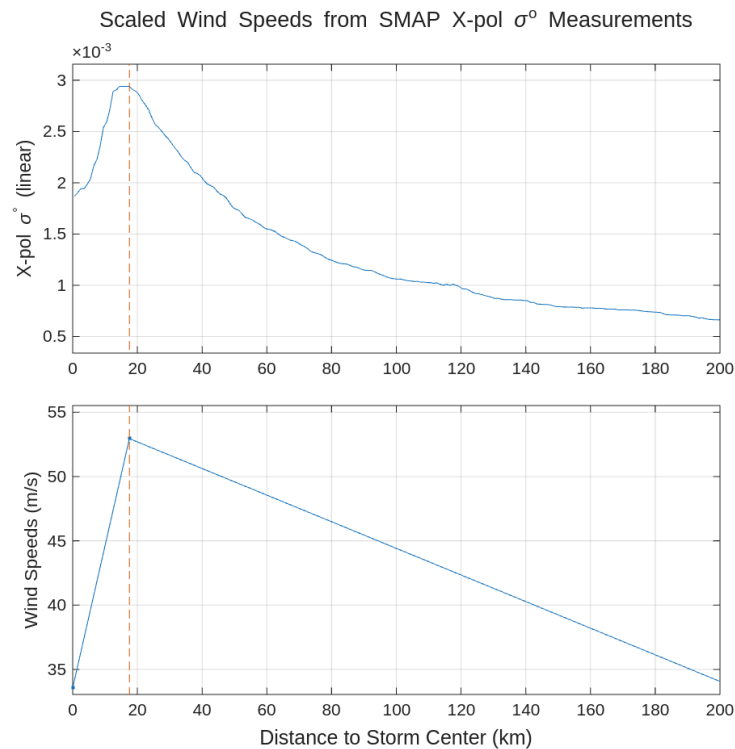


Figure A2. Data from Tropical Cyclone Dolphin on 14 May 2015 around 2045 UTC. **(Top)** Average σ^0 as a function of distance from the storm center. **(Bottom)** Scaled wind speeds from SMAP X-pol σ^0 measurements as described in Equations (A4) and (A5). The dashed line denotes the mean RMW.

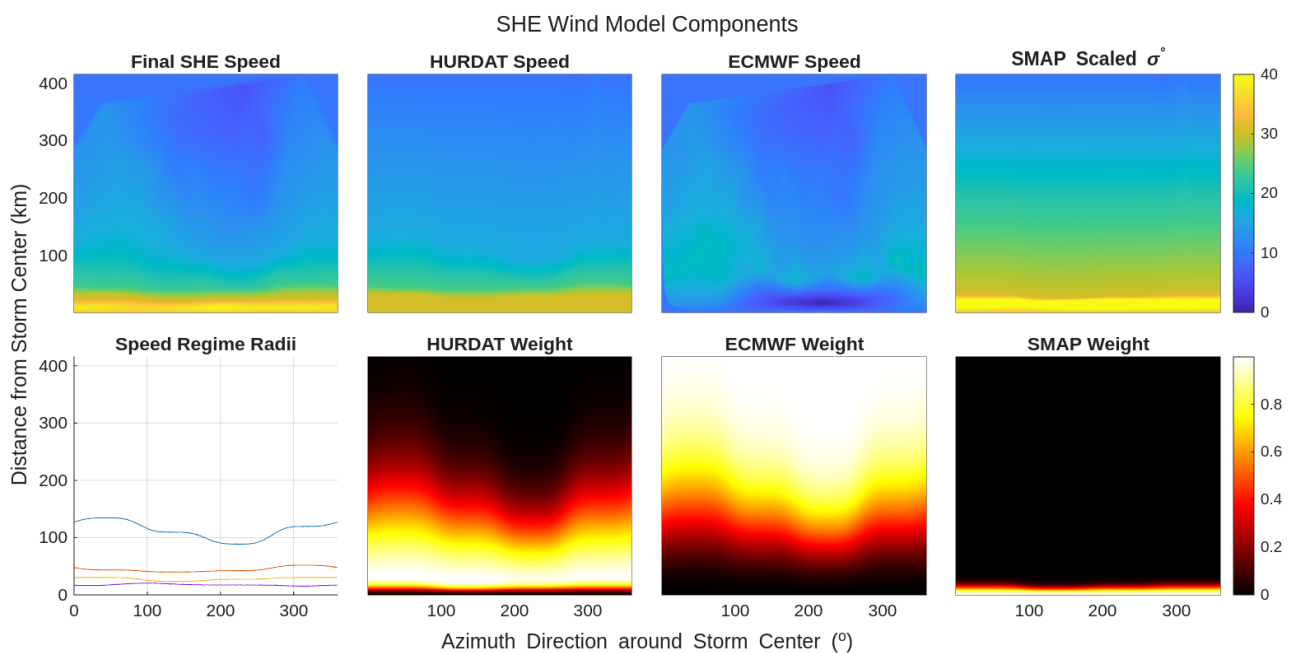


Figure A3. Data from Tropical Cyclone Dolphin on 14 May 2015 around 2045 UTC. **(Top Left)** The final SHE speed model. **(Top Left Center)** Wind speed modeled by HURDAT. **(Top Right Center)** Wind speed modeled by ECMWF. **(Top Right)** Wind speed near the storm center modeled by SMAP. The weights are shown for **(Bottom Right)** the storm center, **(Bottom Right)** ECMWF, and **(Bottom Center Right)** HURDAT. **(Bottom Left)** Wind speed regime radii where the blue, orange, and yellow lines show the HURDAT 34 kts, 50 kts, and 64 kts radii, respectively, and the purple line shows the RMW determined by X-pol SMAP σ^0 measurements.

Appendix B.2. Wind Direction

HURDAT has no information about wind direction around tropical cyclones. However, tropical cyclone wind directions have a circular structure curling around the storm center. The wind direction of tropical storms can be crudely modeled by calculating the vector from the center ($c_{x,y}$) of the tropical cyclone to a point of interest ($p_{x,y}$) and subtracting an offset (θ_o). The crude wind direction model is calculated using the longitudinal-component ($L_x = \cos[p_{x,y} - c_{x,y}]$) and latitudinal-component ($L_y = \sin[p_{x,y} - c_{x,y}]$) between the storm center and the point of interest. The crude wind direction estimate is calculated using the arc-tangent ($\theta_c = \arctan(L_y, L_x)$). The SHE wind direction is calculated by subtracting the offset ($\theta_w = \theta_c - \theta_o$). The θ_o is 72° and is empirically determined from calculating the difference between crude estimate wind direction and ECMWF wind direction near tropical cyclones.

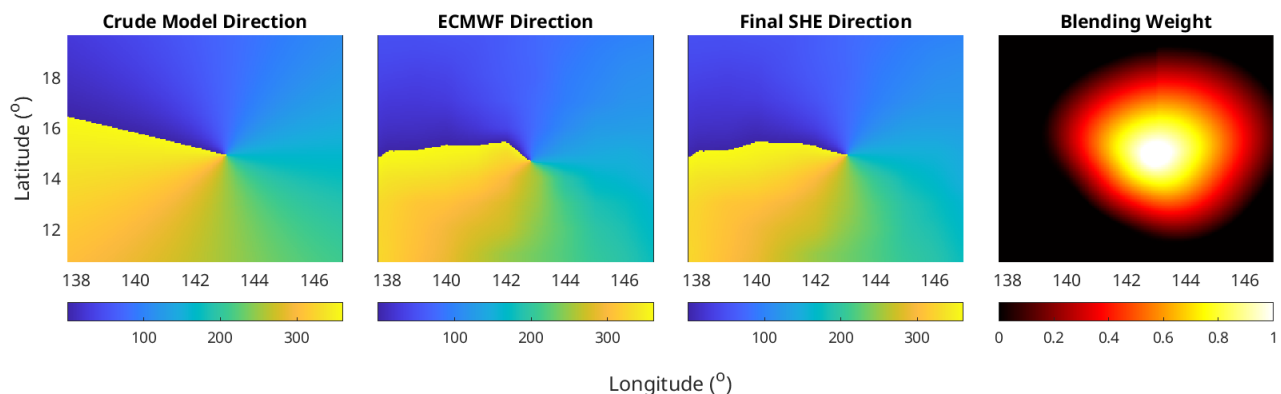


Figure A4. Wind direction data for the SHE model from Tropical Cyclone Dolphin on 14 May 2015 around 2045 UTC. **(Left)** The crude direction model. **(Left Center)** ECMWF wind direction. **(Right Center)** Weights for the crude wind direction. **(Right)** Total wind direction of the SHE model.

As with the wind speed modeling, a blending of the crude wind direction model and ECMWF wind direction is performed. A transition radius of twice the largest HURDAT radius is chosen to blend from the crude wind approximation to the ECMWF wind direction. A sigmoid function transitions from 1 to 0 at the transition radius. An example of the SHE wind direction modeling is presented in Figure A4.

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