

1 **A New Framework for Evaluating Model Simulated**
2 **Inland Tropical Cyclone Wind Fields**

3 **Jie Chen¹, Kun Gao¹, Lucas Harris², Timothy Marchok², Linjiong Zhou¹,**
4 **Matthew Morin²**

5 ¹The Program in Atmospheric and Oceanic Sciences, Princeton University, Princeton, NJ

6 ²NOAA Geophysical Fluid Dynamics Laboratory (GFDL), Princeton, NJ

7 **Key Points:**

- 8 • We introduce a new framework for evaluating modeled inland tropical cyclone wind
9 fields with observation-based, theory-driven wind profiles.
10 • The theory-driven wind profile well represents the observed radial distribution of
11 inland tropical cyclone wind speeds.
12 • We propose simple indicators to summarize the model performance on inland wind
13 field predictions.

Corresponding author: Jie Chen, chenjie@princeton.edu

Abstract

Though tropical cyclone (TC) models have been routinely evaluated against track and intensity observations, little work has been performed to validate modeled TC wind fields over land. In this paper, we present a simple framework for evaluating simulated low-level inland winds with in-situ observations and existing TC structure theory. The Automated Surface Observing Systems, Florida Coastal Monitoring Program, and best track data are used to generate a theory-driven wind profile that reasonably represents the observed radial distribution of TC wind speeds. We quantitatively and qualitatively evaluated the modeled inland TC wind fields, and described the model performance with a set of simple indicators. The framework was used to examine the performance of a high-resolution two-way nested Geophysical Fluid Dynamics Laboratory model on recent U.S. landfalling TCs. Results demonstrate the capacity of using this framework to assess the modeled TC low-level wind field in the absence of dense inland observations.

Plain Language Summary

Some of the biggest human impacts of tropical cyclone (TC) winds come after the TC makes landfall. A skillful prediction of the radial distribution of winds is essential for forecasting TC-induced inland hazards. However, the forecast skill of numerical hurricane models on inland TC wind fields has rarely been evaluated since it is challenging to collect wind observations during landfall, and the network of regular weather observations is too spread out to capture the strongest winds associated with a TC. This inhibits the improvement of forecast models and limits our understanding of the TC's inland evolution. Our work combines available inland in-situ wind observations over the southeastern U.S. with existing TC structure theory, and presents a new "optimal" estimate of the post-landfall winds. Our framework is found to be useful for evaluating the post-landfall TC winds in hurricane forecast models. In addition, the new evaluation technique can intuitively demonstrate how well the model simulates TC intensity and structure.

1 Introduction

Landfalling tropical cyclones (TCs) bring significant hazards and cause enormous economic losses (Villarini et al., 2014; Rappaport, 2014). These impacts could be amplified in a changing climate, given the potential that landfalling TCs may move and decay more slowly in a warming climate (Kossin, 2018, 2019; Li & Chakraborty, 2020; Chan et al., 2022), and compound hazards may increase under climate change (Gori & Lin, 2022; Feng et al., 2022). Beyond that, research suggests that TCs may make landfall in unusual regions that are more vulnerable to TC hazards due to a shift in landfall location and to a possible poleward shift in the latitude of maximum intensity in a warmer future climate (Kossin et al., 2014; Knutson & Coauthors, 2020). Indeed, even without the effects of climate change, TC damage is likely to double in the future since there are more people and assets in harm's way (Mendelsohn et al., 2012). Therefore, it is urgent to evaluate the post-landfall performance of hurricane models, especially for predicting the low-level TC wind field, since inland hazards and weather extremes are intimately linked to the wind field structure (Zhai & Jiang, 2014).

Though in-situ observations are essential for evaluating the simulation of inland TC low-level wind fields (Nolan et al., 2021), our community lacks dense and systematic observations of the TC low-level wind field after landfall. As such, it is necessary to introduce alternative analyses for the evaluation of modeled inland TC winds. In this work, we form a framework assessing the model performance on predicting inland TC wind fields using observation-based, theory-driven wind profiles. This wind profile is generated from existing TC structure models given observable TC parameters obtained primarily from the available observations. Beyond the widely-used International Best Track Archive for Climate Stewardship (IBTrACS version 4, Knapp et al. (2010)) for TC intensity and track, the

64 minute-by-minute, near-surface observations provided by the Automated Surface Weather
 65 Observations (ASOS) and the Florida Coastal Monitoring Program (FCMP) are also used.
 66 The model evaluated in this work is the Tropical Atlantic version of Geophysical Fluid Dy-
 67 namics Laboratory (GFDL)’s System for High-resolution prediction on Earth-to-Local Do-
 68 mains (T-SHiELD hereafter), which will be introduced in the following section. T-SHiELD
 69 has shown skillful predictions of TC landfall track and intensity (Harris et al., 2020; Gao
 70 et al., 2021). Since T-SHiELD shares much of the code with the NOAA’s next-generation
 71 Hurricane Analysis and Forecast System (HAFS) and also includes advanced features devel-
 72 oped at GFDL for better hurricane predictions, it serves as a good representative model for
 73 the evaluation. Moreover, this work attempts to quantify the performance of the model on
 74 simulated wind fields via a set of time-dependent indicators that describe the characteristics
 75 of the forecast error. These evaluations can reveal the performance of model predictions for
 76 landfalling cases and quantify the improvement of forecast skills associated with the model
 77 development.

78 In this paper, we first introduce the datasets, the GFDL T-SHiELD model, and the
 79 assessment framework (Section 2). Then we analyze the performance of the simulated T-
 80 SHiELD inland wind fields via the evaluation framework and the performance indicators
 81 (Section 3). We end with a summary and discussion (Section 4).

82 2 Data and Methods

83 2.1 Observation and model data

84 We use TC track and intensity data from IBTrACS version 4 for selected 2020–2022
 85 landfalling storms in the contiguous United States. Recent studies suggest that the data ac-
 86 curacy has been improved through years with advanced technology (Landsea, 2007; Landsea
 87 & Frankin, 2013; Zhu & Collins, 2021). Therefore, this work considers the IBTrACS reports
 88 as a baseline reference for the inland TC track and intensity change. The representative
 89 landfalling cases are the storms during the 2020-2022 hurricane seasons to strike along the
 90 coastlines of the Gulf of Mexico and the Florida peninsula: Laura (2020), Sally (2020),
 91 Delta (2020), Fred (2021), Ida (2021), and Ian (2022) (Figure 1). Except for Fred, which
 92 represents a low-intensity landfalling TC, selection of landfall cases is defined following the
 93 criteria used in Zhu and Collins (2021), but with a few modifications, including that the
 94 TC intensity upon first U.S. inland point must be Category 1 or higher (maximum wind
 95 speed ≥ 64 *kts*), and the intensity remains higher than 34 *kts* for at least 12 hours before
 96 dissipation or extratropical transition. This criteria enables a close and sufficiently lengthy
 97 examination after landfall while excluding the influences on TC intensity and structure from
 98 extratropical transition at higher latitudes (Evans & Hart, 2003).

99 We use several in-situ datasets for wind observations in addition to the IBTrACS: 1)
 100 ASOS wind data at each 5-min interval across 11 southeastern states obtained from the Na-
 101 tional Centers for Environmental Information (NCEI) and processed by Iowa Environmental
 102 Mesonet at Iowa State University (Figure 2a). Due to the destructive power of TC winds,
 103 ASOS sites near the eyewall may be missing validated wind records during the landfall. 2)
 104 the FCMP mobile tower observations (Masters et al., 2010; Balderrama et al., 2011). The
 105 FCMP 10-m mobile towers, T1 (29.44N,90.26W) and T5 (29.76N,90.56W) (Figure 1) are
 106 deployed to record Hurricane Ida’s wind speed every 0.1s, which are applied for additional
 107 analyses (Supplementary Figure 5).

108 The dynamical model to be evaluated is the GFDL T-SHiELD that is initialized by
 109 six-hourly National Centers for Environmental Prediction (NCEP) Global Forecast System
 110 (GFS) analyses, which is used to provide near real-time forecasts during recent hurricane
 111 season (Harris et al., 2020; Gao et al., 2021). The model applies the non-hydrostatic Finite-
 112 Volume Cubed-Sphere Dynamical Core (FV3) with a 3-km-resolution nested domain cover-
 113 ing the southeast U.S. and western Atlantic and 75 vertical levels (Chen et al., 2019; Zhou

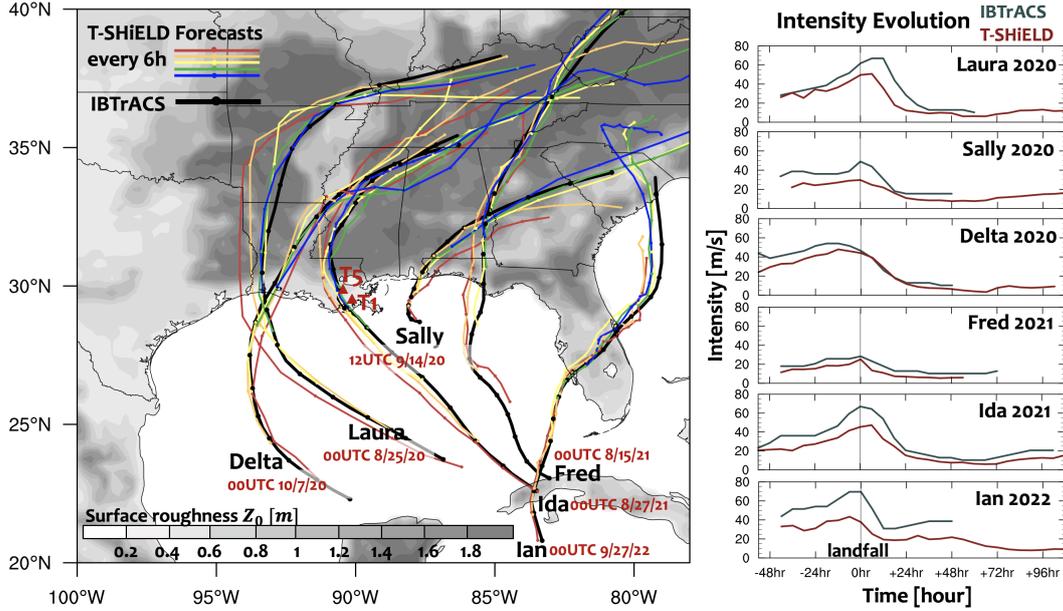


Figure 1. T-SHiELD tracks of six selected 2020-2022 U.S. landfalling hurricanes, initialized every six hours starting from the labeled time (colored tracks), and the corresponding IBTrACS tracks (thick black track). The evolution of the predicted mean intensity averaged over the successive T-SHiELD forecasts (red) is compared to the IBTrACS intensity (black) in the right panel. The evolution time shown in the X-axis is referenced by each landfall time reported by the IBTrACS. The two FCMP mobile towers T1 (29.44N,90.26W) and T5 (29.76N,90.56W) for Hurricane Ida (2021) are marked on the map with red triangles. The surface roughness (Z_0) obtained from the Fifth generation of ECMWF atmospheric reanalyses of the global climate (ERA5) will be used to calculate the surface drag coefficient in this work (see Appendix A).

114 et al., 2019; Gao et al., 2021; Harris et al., 2021). For representative cases in this work,
 115 forecasts initialized from different times before landfall show consistent intensity and track
 116 prediction. To avoid a weakening of the wind field characteristics when using the mean wind
 117 field averaged over the successive T-SHiELD forecasts (Figure 1 left), we pick the T-SHiELD
 118 forecast initialized 12 hours prior to the observed landfall time for each case. That is, the
 119 T-SHiELD forecast time since the landfall is 12 hours plus the observation time in this work.
 120 We produce model output every 15 minutes for comparison to high-frequency ASOS data.

121 **2.2 The evaluation framework**

122 **2.2.1 Wind speed radial distribution**

123 ASOS sites are unevenly distributed and sparse. To alleviate this problem, we produce
 124 radial wind speed distributions from ASOS sites in each TC quadrant. The four earth-
 125 relative quadrants are identified by the observed, time-dependent TC center (Figure 2a-b,
 126 blue). Given that IBTrACS provides TC location every 3 or 6 hours, the ASOS radial
 127 wind distribution is also generated every 3 or 6 hours. Correspondingly, the nearest T-
 128 SHIELD grid points to each ASOS site are selected and formed into the radial wind speed
 129 distributions based on simulated TC locations at each observed time (Figure 2a-b, red).
 130 Adjacent ASOS sites may have the same corresponding T-SHiELD grid point due to the
 131 site sparsity in some areas. For a more consistent comparison, the maximum wind speed
 132 recorded by each ASOS site during the analyzed observation hour will be selected from its

133 twelve records at each 5-minute interval to represent the hourly wind speed, and similarly,
 134 the T-SHiELD modeled wind speed maxima during the same hourly period are selected
 135 from the outputs.

136 *2.2.2 The observation-based, theory-driven wind profile*

137 In addition to the direct site-by-site wind comparison between ASOS and T-SHiELD as
 138 shown in Fig.2b, we introduce an observation-based, theory-driven inland TC wind profile
 139 for further quantitative assessments. The Chavas et al. (2015) wind field model (referred
 140 to as C15 hereafter) is a simple theoretical model formed by mathematically merging the
 141 Emanuel and Rotunno (2011) inner wind field model and Emanuel (2004) outer wind field
 142 model. With a small number of physical parameters, C15 captures the structure of the
 143 observed TC wind field over the ocean, and has been applied in TC surge risk simulations
 144 and analysis (Xi et al., 2020; Lin et al., 2020; Wang et al., 2022). For post-landfall TC
 145 evolution, the C15 model well-reproduces the simulated wind field in response to idealized
 146 landfalls (Chen & Chavas, 2023). Using the observed parameters to generate a theoretical
 147 post-landfall wind field is a natural attempt to link the theoretical understanding to the
 148 real-world applications. The full solutions of using the C15, including how environmental
 149 approximations are calculated are provided in the Appendix A. Essential parameters re-
 150 quired to generate the radial wind profile are the TC intensity (v_m) and any wind radius
 151 (e.g., radius of 10 ms^{-1} wind, referred to as r_{10} hereafter).

152 Here we use our observed wind profiles to generate the required input parameters for
 153 the C15 wind profile. Given the ASOS wind speed radial distribution, we first fit a cubic
 154 spline to identify the representative $r_{10}(\tau)$, or $r_5(\tau)$ when $r_{10}(\tau)$ is not applicable, for the
 155 wind field in each quadrant (Figure 2c, dash line), where τ is the time since TC landfall.
 156 For the TC intensity after landfall, $v_m(\tau)$, which is not reliably captured by the ASOS
 157 or FCMP, we use the widely-applied sustained maximum wind speed from IBTrACS. We
 158 call this theoretical inland TC wind profile in each quadrant the *observation-based, theory-*
 159 *driven wind profile* (Obs-Theo hereafter). For further quantitative assessment, the Obs-Theo
 160 wind profile will be used to verify the T-SHiELD wind profile as in Figure 2d, as long as
 161 the required parameters are available from the observational datasets. In the quantitative
 162 evaluation, the T-SHiELD wind profile is azimuthally-averaged based on all model grid
 163 points in each quadrant, and smoothed by averaging over every several points along each
 164 selected arc to reduce noise from various maxima and minima in the wind data, which is
 165 necessary for a high-resolution model.

166 Notably, with just size parameters from the cubic spline fit, the Obs-Theo wind profile
 167 well represents the observed wind speed distribution in the outer region ($r = 200 - 600 km$)
 168 with a small root-mean-square error ($2-3 ms^{-1}$) that slightly increases with the forecast
 169 time in selected landfall case (Supplementary Figure 1). For the inner region, where we
 170 lack a dense network of ASOS observations, the Obs-Theo profile is primarily determined
 171 by the IBTrACS v_m . As shown in Supplementary Figure 2a, at 1800UTC 29 Aug 2021, the
 172 Obs-Theo inner wind profile can vary remarkably given IBTrACS v_m or FCMP-recorded v_m
 173 that differ significantly (Supplementary Figure 2b). In the absence of dense observations, it
 174 is challenging to verify the Obs-Theo inner wind profile. FCMP along the landfall track is
 175 not routinely provided for every landfall TC. Future work could explore using an alternative
 176 v_m other than that from IBTrACS, or testing the Obs-Theo profile against specific cases
 177 with dense inner region observations.

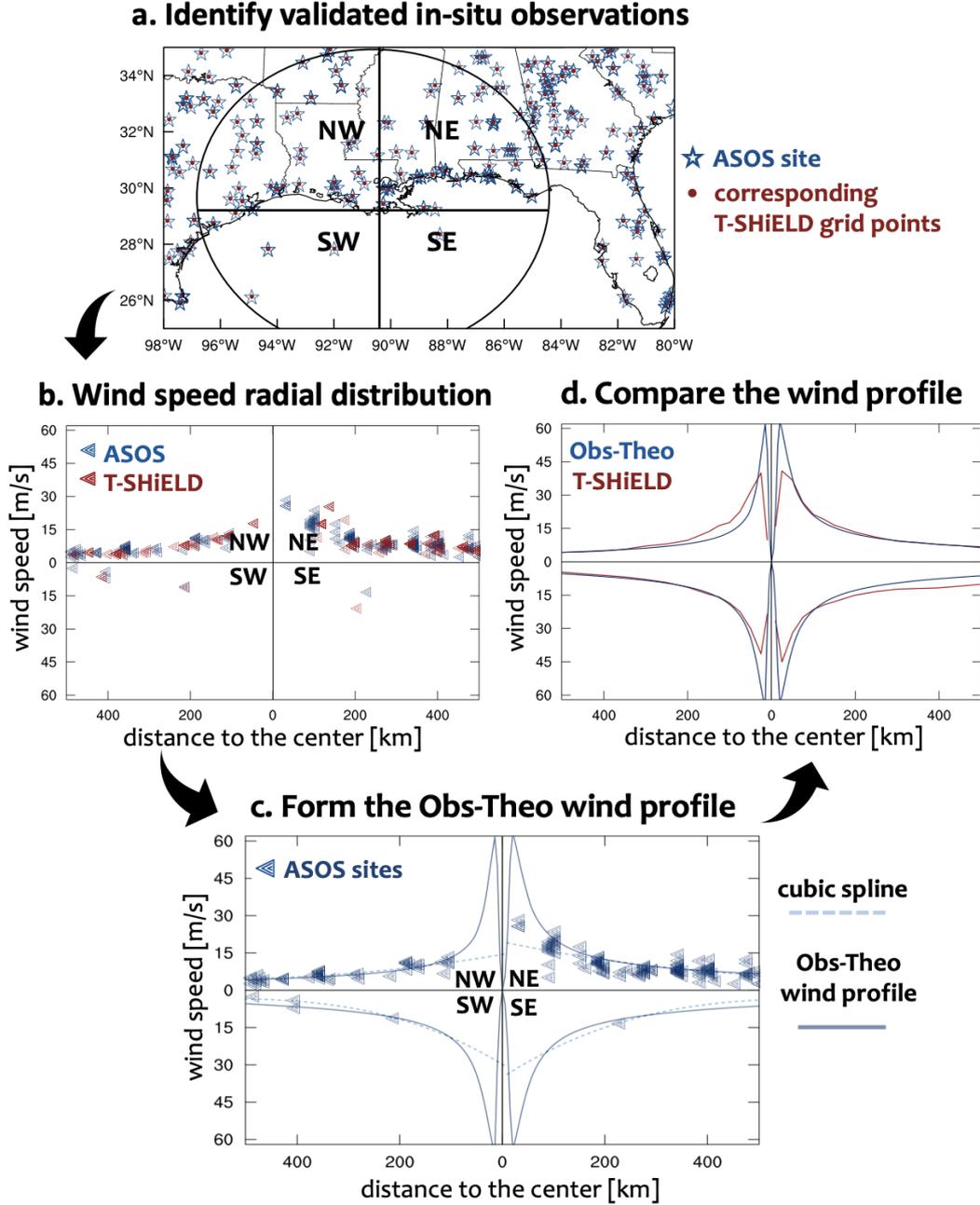


Figure 2. Schematic for the evaluation framework using Hurricane Ida at 1800UTC 29 Aug 2021 as an example. (a) The locations of the validated ASOS sites and their corresponding nearest T-SHiELD grid points. The analyzed area ($r \leq 600$ km) from the observed TC center is divided into four earth-relative quadrants. (b) In each quadrant of (a), the hourly-maximum wind speed values of all the ASOS sites and T-SHiELD grid points are lined into a wind speed radial distribution based on their distance to the observed or simulated TC center, respectively. (c) The observation-based, theory-driven (Obs-Theo) wind profile (solid curve) for Ida at this time, where the maximum wind speed v_m is obtained from IBTrACS, the representative radius r_{10} for the wind field in each quadrant is obtained from the cubic spline (dash curve) of the ASOS wind speed radial distribution. The average root-mean-square deviation of ASOS observations from the Obs-Theo wind profile is 2 ms^{-1} . (d) A comparison of the Obs-Theo and the T-SHiELD wind profiles in each quadrant at this time for Ida. The T-SHiELD wind profile is generated based on all model grid points in each quadrant.

3 Assessing the T-SHiELD performance on inland TC wind field

Hurricane Ida (2021), a destructive Category 4 hurricane, is the second most-damaging hurricane to hit Louisiana in history (Beven et al., 2021). The post-landfall remnants of Ida also caused catastrophic damages from flooding and thunderstorms across the Northeastern states (Smith et al., 2023). Here we use Ida as an example to show the evaluation framework.

The direct comparison of the Ida inland wind speed radial distributions between ASOS observations and T-SHiELD forecast, similar to Figure 2b, are provided in the supplementary materials, along with the results of other representative cases (Supplementary Figure 3-5). Overall, the T-SHiELD forecast reproduces the observed post-landfall structural change of the wind speed radial distribution. However, the direct comparison of the wind speed radial distribution cannot quantitatively show the performance of the T-SHiELD forecast, especially when ASOS lacks validated data near the eyewall or over the ocean. Therefore, we evaluate the T-SHiELD wind profile with the Obs-Theo wind profile for further quantitative assessments as introduced in Figure 2c-d.

3.1 Wind profile comparison: using model performance indicators

To ensure a uniform comparison across cases with varying storm structures and sizes, characteristic wind profiles, $\tilde{v}(\tilde{r})$, are used here (Chavas & Knaff, 2022; Klotzbach et al., 2022), where the wind speed is normalized by the observed maximum wind speed v_m from IBTrACS as $\tilde{v} = v/v_m$, and radius is normalized by the radius of maximum wind speed r_m identified by the Obs-Theo wind profile as $\tilde{r} = r/r_m$. We only assess the wind field outside r_m ($\tilde{r} > 1$) since neither the theory nor the forecast model can well describe or simulate the wind field inside r_m . We divide the wind field into inner region ($1 < \tilde{r} < 3$) and outer region ($\tilde{r} > 3$) for more in-depth analysis.

Using Hurricane Ida at 1800UTC 29 Aug 2021 as an example, the characteristic wind profiles of Obs-Theo and T-SHiELD are compared in each quadrant, respectively (Figure 3). The wind speed difference $\Delta\tilde{v}$ between the T-SHiELD forecast and Obs-Theo along the characteristic radius \tilde{r} is defined as the error profile, $\Delta\tilde{v}(\tilde{r})$. In this way, the shape of the error profile explains the performance of T-SHiELD on the inland wind field simulation. We use a simple linear fit to the error profile in each region, as

$$\Delta\tilde{v} = \begin{cases} \beta(\tilde{r} - 1) + \alpha, & 1 < \tilde{r} < 3 \\ \beta(\tilde{r} - 3) + \alpha, & \tilde{r} > 3 \end{cases} \quad (1)$$

where the two indicators, α and β together describe characteristics of the error profile—the performance of the T-SHiELD wind field forecast—at a single time for a selected storm.

We name α , the y-intercept, as the wind field *bias indicator*, the value of which reflects the normalized T-SHiELD forecast bias at $\tilde{r} = 1$ or 3. Negative α indicates a weaker wind field forecast at the starting point of inner or outer wind region. β , the slope of $\Delta\tilde{v}(\tilde{r})$, describes how the forecast error changes along the radius from the starting point of each region, and is defined as the wind profile *shape indicator*. For both α and β , lower magnitudes suggest better wind field simulations, as $(\alpha, \beta = 0)$ indicates the modeled wind profile exactly matching the observed one. In this work, "best forecast" is defined by both indicators that have a magnitude smaller than $O(10^{-2})$. For example, the near-zero α and β in the outer regions suggest a T-SHiELD simulation comparable to the corresponding Obs-Theo wind profiles in the NE, SE, and NW quadrants (Figure 3a, b and d, purple fit curves). However, in the SW quadrant, the higher magnitude of α ($\sim -10^{-1}$) and the near-zero β indicates a uniform weaker wind field simulation among the outer region (Figure 3c). In contrast to the well-simulated outer region, T-SHiELD shows a weaker forecast bias gradually increasing towards the r_m within the inner region (Figure 3, yellow fit curve). In this Ida example, the IBTrACS $v_m = 64.3 \text{ ms}^{-1}$ at 1800UTC, thus the value of inner-region α can be translated into a weaker intensity bias up to tens of ms^{-1} at $\tilde{r} = 1$. More examples interpreting the values of α and β are shown in Supplementary Figure 6.

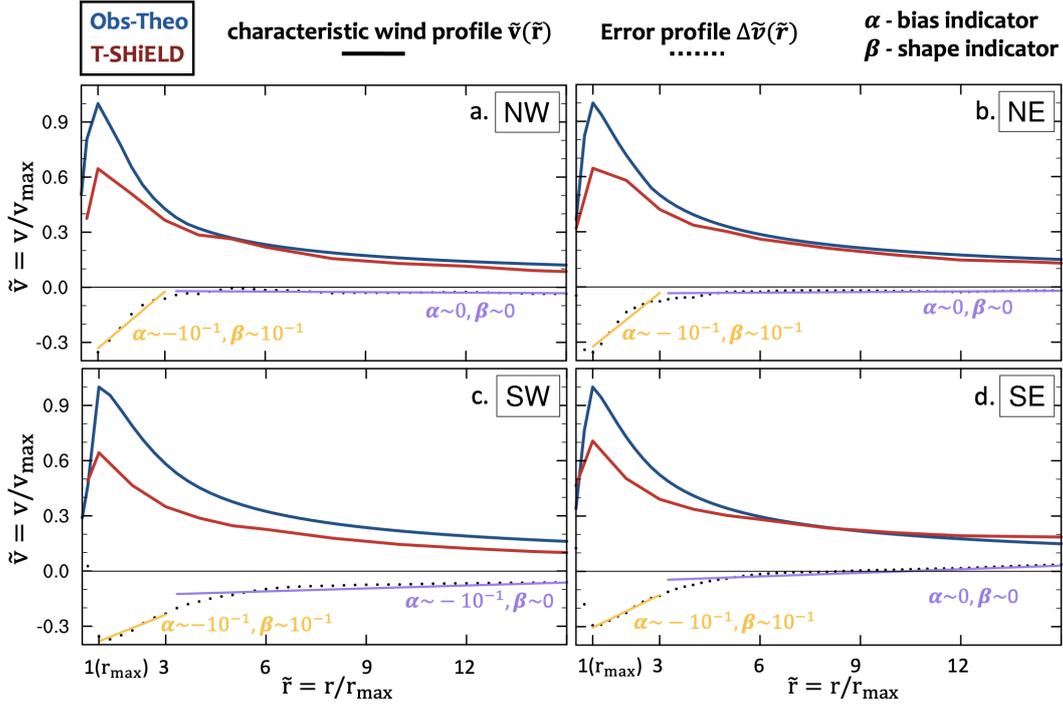


Figure 3. The comparison of characteristic wind profile $\tilde{v}(\tilde{r})$ between the Obs-Theo profile (blue line) and the T-SHiELD wind profile (red line) for Hurricane Ida at 1800UTC 29 Aug 2021. The error profile $\Delta\tilde{v}(\tilde{r})$ (dash curve) is linearly fitted among the inner region (yellow line, $1 < \tilde{r} < 3$) and outer region (purple line, $\tilde{r} > 3$), respectively. α is defined as the wind field bias and β is defined as the wind profile shape indicator. $v_m = 64.3 \text{ ms}^{-1}$ is obtained from the IBTrACS.

3.2 Composite results of 2020-2022 selected Hurricanes

Given the value of averaged $\alpha(\tau)$ and $\beta(\tau)$ in each quadrant of all representative TCs, where τ indicates the time since the observed landfall, we can examine the overall performance of T-SHiELD simulated inland wind field for the 2020-2022 selected hurricanes.

For inner regions, α and β do not fall in the “best forecast” interval (Figure 4a-d, grey shaded area). The values of α and β indicate that T-SHiELD underestimates the maximum wind speed v_m , leading to a weaker wind field forecast where the forecast error increases towards the r_m (Similar to Figure 3a). There is no clear trend for $\alpha(\tau)$ and $\beta(\tau)$ in each quadrant after landfall, suggesting that the T-SHiELD performance on the inner wind field does not change significantly after landfall. However, for the outer region, T-SHiELD wind profiles are comparable to the Obs-Theo in each quadrant (Figure 4e-h). Despite the NW quadrant (Figure 4e), both α and β largely fall in the “best forecast” interval after the landfall, indicating a -forecast outer wind field across different cases.

To summarize, the value of indicators $\alpha(\tau)$ and $\beta(\tau)$ suggests that T-SHiELD mostly struggles with representing the inner-core wind structure of landfalling TCs. The relatively large negative $\alpha(\tau)$ values (Fig. 4a-d) suggest the structural biases are related to the negative model intensity biases (Figure 1). Therefore, improving the T-SHiELD intensity forecasts, for example, through a vortex-specific initialization technique, may significantly improve its performance on the overall wind field forecast.

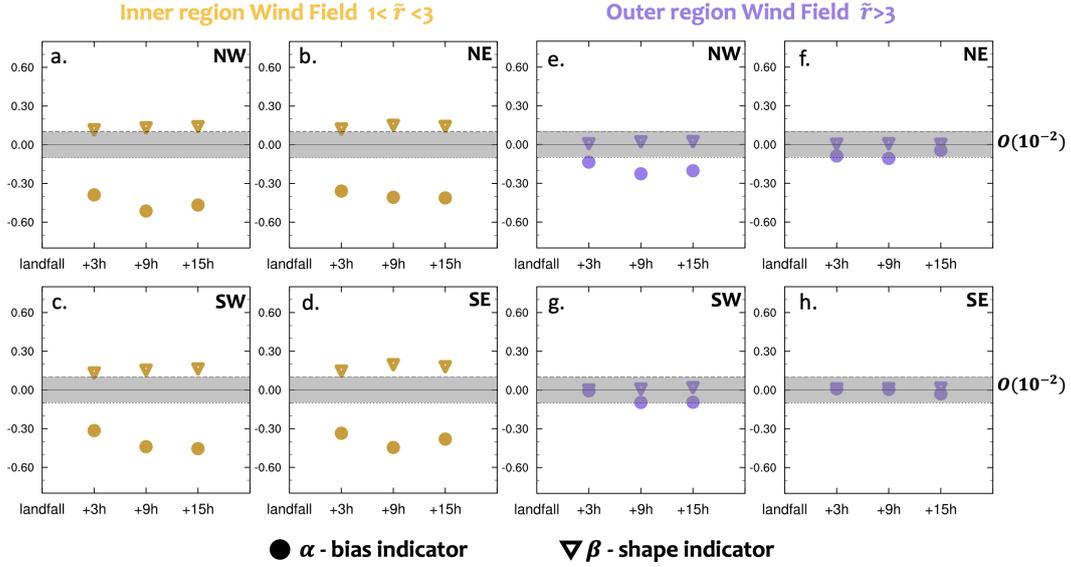


Figure 4. The averaged $\alpha(\tau)$ and $\beta(\tau)$ of six 2020-2022 major hurricanes at discrete lead times after their corresponding landfalls, which describe the T-SHiELD performance on predicting the inland low-level wind field. Left panels show the inner region wind field ($1 < \tilde{r} < 3$), and right panels for the outer wind field ($\tilde{r} > 3$). α indicates the normalized intensity bias of the T-SHiELD forecasts compared to the observations at $\tilde{r} = 1$ or 3, while β indicates the shape similarity between the observed and T-SHiELD wind profiles. The indicator magnitudes ranging from -0.1 to 0.1 are shaded, where 0 indicates a perfect simulation (no forecast error). Indicators falling in the shaded interval suggest a "best forecast" in this work.

4 Summary

This work presents a novel framework for assessing the model performance on predicting the inland TC low-level wind using the observation-based, theory-driven wind profile that combines the ASOS observations and the existing theoretical TC wind field model. Although the evaluation in this paper only focuses on the performance of the GFDL T-SHiELD on six major landfalling hurricanes in the continental U.S. along the Gulf of Mexico coast from 2020 to 2022, the evaluation framework can be generalized to other model evaluations emphasizing the TC wind field.

In our framework, we introduce several observation-based evaluation approaches into the wind field assessment. The ASOS wind speed radial distribution, which generally depicts the TC asymmetric structural change shortly after landfall, can directly be used to qualitatively evaluate the model overall forecast of the inland TC wind field. Then, the wind profile in each quadrant generated by the theoretical wind field model given observable TC parameters (r_{10} , v_m) obtained from ASOS and IBTrACS enables further quantitative evaluations for the simulated inland wind field. This Obs-Theo wind profile well represents the observed wind speed distribution in the outer region. Finally, the forecast error along the radius (i.e., error profile) is linearly fitted among the inner and outer regions, described by the wind field bias indicator and wind profile shape indicator of the fitted lines. These indicators quantitatively reveal the performance of the model on inland TCs, and can also be used in future work to reveal the improvement in wind field forecast skill associated with the model development.

260 Compared to TC track and intensity, the post-landfall evolution of the TC low-level
 261 wind field has not received much attention in previous model evaluation studies due to the
 262 complexity of the TC structural change and the lack of in-situ inland wind field observations.
 263 This wind field evaluation framework provides an alternative approach assessing the model
 264 directly with in-situ observations taking advantage of existing TC structure theory. However,
 265 our community still needs to advance the post-landfall TC observations, especially among
 266 the eyewall region, and provide reliable routinely-used TC datasets to strengthen our studies
 267 on inland TC hazards and their evolution.

268 5 Open Research

269 The GFDL T-SHiELD outputs, processed ASOS data, and the observation-based,
 270 theory-driven wind profile data used in this work are available on Zenodo (DOI 10.5281/zen-
 271 odo.7937697). The IBTrACS data is available at [https://climatedataguide.ucar.edu/
 272 climate-data/ibtracs-tropical-cyclone-best-track-data](https://climatedataguide.ucar.edu/climate-data/ibtracs-tropical-cyclone-best-track-data). The ASOS data applied
 273 in this work is available at Iowa State University ([https://mesonet.agron.iastate.edu/
 274 ASOS/](https://mesonet.agron.iastate.edu/ASOS/)). The FCMP data of hurricane Ida is available by contacting Prof. David Nolan
 275 at University of Miami. The C15 wind structure model is available at [https://doi.org/
 276 doi:10.4231/CZ4P-D448](https://doi.org/doi:10.4231/CZ4P-D448).

277 Appendix A C15 wind field model

278 The C15 model mathematically merged the Emanuel and Rotunno (2011) inner wind
 279 field model (Eq.36 therein) and Emanuel (2004) outer wind field model (Eq.31-33 therein)
 280 solution to produce a model for the complete azimuthal wind profile. This merging yields a
 281 unique solution; the process is described in C15 (Eq.2-10 therein). Using C15, parameters
 282 required to solve the differential equations for the wind profile are: storm intensity v_m ,
 283 radius of maximum wind speed r_m for the inner region, the intensity and radius of the
 284 merge point connecting the inner and outer region, v_a and r_a , and a specified radius input
 285 r_{fit} , χ and Coriolis parameter f for the environmental conditions where $\chi = \frac{2C_d}{W_{cool}}$. C_d
 286 is the exchange coefficients of momentum, W_{cool} is the free tropospheric subsidence rate.
 287 The value of W_{cool} is constrained by the thermodynamics of the free troposphere and can be
 288 estimated from the ambient stratification and radiative cooling rate via radiative-subsidence
 289 balance. Given the environmental parameters χ and f , one only needs to know two storm
 290 parameters – the intensity v_m and any wind radius (e.g. r_m , r_{17} , or r_{10}) – to specify the
 291 model solution.

292 In this work, v_m and r_{10} are primarily obtained from IBTrACS and ASOS observations.
 293 f is calculated by the TC location provided by IBTrACS; C_d is calculated from the Fifth
 294 generation of ECMWF atmospheric reanalyses of the global climate (ERA5) surface rough-
 295 ness (Hersbach, 2010) and then averaged within $r = 0 - 600$ km to yield a single value within
 296 each of the four earth-relative quadrants (Figure 1). Previous work testing C15 against ide-
 297 alized landfall suggests that, the wind field solution is not very sensitive to W_{cool} except
 298 for at large radii. Thus, the radiative-subsidence rate W_{cool} is set to 0.002 ms^{-1} , which is
 299 the median of the best-fit value for observed storms (Chavas et al., 2015) and identical to
 300 idealized experiments in Chen and Chavas (2023) and related studies.

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