PRECIPITATION EVALUATION OF THE REAL-TIME BASIN-SCALE HWRF IN 2017

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1. Introduction

Heavy precipitation is a major hazard in landfalling tropical cyclones (TCs). Historically, heavy rainfall has induced freshwater floods and mudslides during TC landfalls, accounting for 27% of deaths and devastating property (Rappaport 2014). The impacts of TC rainfall often cover a larger area and extend further inland than other TC hazards, including winds and storm surge. In addition, rainfall associated with TCs is dependent on factors other than maximum intensity. For example, a slow-moving TC can produce more rainfall than a fast-moving TC, regardless of maximum intensity. In other words, rainfall hazards may be higher in a tropical storm than in a major hurricane. In 2017, three hurricanes made landfall in the U.S. – Harvey, Irma, and Maria. Hurricane Harvey made landfall as a category four hurricane on the Saffir-Simpson scale and delivered over 60 inches of rainfall in parts of Texas. Harvey devastated Texas and Louisiana for 4 days, causing historical flooding and at least 68 deaths. This hurricane also caused the second highest economic loss in U.S. history (Blake and Zelinsky 2018).

Previous work has focused on quantitative precipitation forecasts (QPF) validation techniques to evaluate the utility of rainfall forecasts. Ebert (2003) verified QFP using bias score and equitable threat score (ETS; Stanski et al. 1989; Wilks 1995). Several models, including the National Centers for Environmental Prediction (NCEP) Eta model and the European Centre for Medium Range Forecasts (ECMWF) Integrated Forecasting System (IFS), were verified against satellites and rain gauge data in the regions of the United States, Germany, and Australia. Marchok (2006) developed a standard scheme for validating QPF of landfalling TCs. This scheme includes three parts: the pattern matching ability, mean rainfall and volume matching skill, and extreme amount capturing capability. Lonfat (2004) studied Tropical Rainfall Measuring Mission (TRMM) data and provided guidance of climatology rainfall features. Lonfat’s study also suggested the usage of a decibel rain rate (dBR) scale to provide validations of probability distribution functions (PDFs) or contoured frequency by radial distance (CFRD) methods. To validate rainfall from Hurricane Harvey, this study will utilize several methods from previous studies and will create new schemes to verifying QPF in numerical weather prediction model output.

The Hurricane Weather Research and Forecasting (HWRF) system is a customized hurricane/tropical storm model including the WRF model software infrastructure, and the Non-Hydrostatic Mesoscale Model on the E Grid (NMM-E) dynamic core (Biswas et al. 2017). HWRF is a nested model with a 18-km parent domain and 6- and 2-km movable nested domains. With support from the Hurricane Forecast Improvement Project (HFIP), the NOAA/AOML/HRD developed and maintained an experimental “Basin-Scale HWRF” model (HWRF-B; Zhang et al. 2016; Alaka et al. 2017), which produced low track forecast errors in 2017 when compared with other NOAA models. This study validated the 2017 real-time version of Basin-Scale HWRF (HB17). Due to the high dependence of precipitation on TC track, HB17 is leveraged as a rainfall research tool to evaluate precipitation performance on Harvey. The ultimate goals of this project are to evaluate TC rainfall performance in NWP and to create new probabilistic rainfall guidance for TC landfalls, thereby fulfilling HFIP objectives. Section 2 describes the methodology of this project, including the model, datasets, and forecasts of interest. Section 3 discusses the rainfall performance in HWRF-B forecasts and introduces NWP-based probabilistic guidance. Conclusions are provided in Section 4.

2. Methodology

2.1 Dataset

The purpose of this study is to evaluate rainfall performance of HB17 in real time. HRD maintains this experimental dynamic model and has operated it as an HFIP real-time demo for the past several hurricane seasons. The HB17 model resolution is 18-6-2 km and uses Ferrier-Aligo (FA) scheme for microphysics parameterization. This scheme is designed for improving deep convective cloud simulations, especially in 1-4 km high-resolution models (Biswas et al. 2017). In this study, we retrieved 3-hourly data with 2-km spatial resolution for azimuthal analyses and swath data for pattern analysis. To consider a model useful, model prediction needs to outperform climate model and persistence forecasts (Ebert 2003). R-CLIPER (RCLP) is a Rainfall Climatology and Persistence Model provided by HRD. This climatology-based model predicts rain rate for every 0.1 hour (6 min) based on storm location and intensity. The resolution of RCLP is 0.25 degree.

To evaluate model performance, two state-of-the-art observational datasets are considered as true rainfalls here. National Stage IV QPE product (ST4) is radar and rain gauge precipitation analyses from NCEP. This product provides hourly observational rainfall with 4 km resolution. The other dataset is Integrated Multi-Satellite Retrievals for GPM (IMERG). This is a product from NASA's Global Precipitation Measurement (GPM). This mission utilizes available rainfall-related satellites and estimates from their passive microwave to produce 3-stage IMERG datasets - Early, Late, and Final. In this study, we only consider final versions of IMERG as it has the highest accuracy among these three datasets due to an adjustment of ground-based rain gauge data. Rain gauge data is considered as the most accurate observation of rainfall and provides the the best estimation especially where gauge density is reasonable (Ebert 2003). IMERG resolution is 0.1 degree and output frequency is 0.5 hour. Besides these two observational datasets, HURDAT2 is used to determine storm centers and tracks for observations. HURDAT2 is also known as Best Track data provided by NOAA/National Hurricane Center.

2.2 Selected Cycles

There are three cycles of Hurricane Harvey selected for this study based on HB17's track performance – 00 UTC 24 Aug 2017, 18 UTC 24 Aug 2017, 00 UTC 25 Aug 2017. As hurricane precipitation is highly concentrated along the track, an outstanding track performance is the first requirement of precipitation analyses. The left panel of Figure 1 highlights how the selected cycles' forecasts produced better track than the others. In addition to three deterministic forecasts, this study also discusses the probabilistic prediction of HB17. For probabilistic rainfall, we use 21 members of an ensemble run at 00 UTC 25 Aug 2017, shown as the right panel of Figure 1.

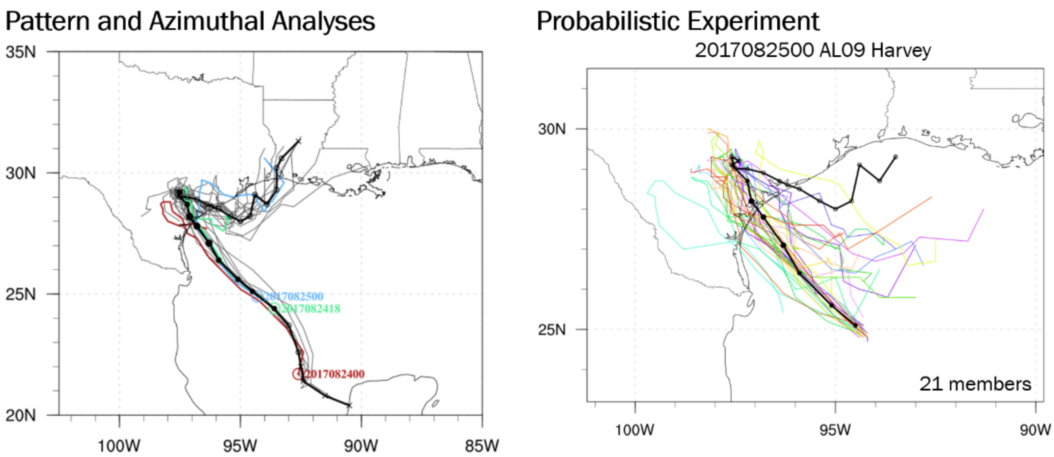

Fig. 1. Selected cycles of this study. Left panel: HB17 Harvey track forecasts in Gulf of Mexico. Colored tracks are selected cycles of this study. Red line is the track forecast at 00 UTC 24 Aug 2017; green one is at 18 UTC 24 Aug 2017; blue one is at 00 UTC 25 Aug 2017. Right Panel: HB17 ensemble track distribution of Harvey cycle 00 UTC 25 Aug 2017.

3. Discussions

3.1 Pattern Analysis

The precipitation pattern analysis helps understand model performance on accumulated rainfall distribution. Figure 2 shows Hurricane Harvey's precipitation swath of available lead time. In the 00 UTC 24 Aug 2017 cycle, ST4 data was only available from forecast hour 15. Thus, the rainfall is accumulated from forecast hour 15 to 126 for this cycle. For the other two cycles, it is accumulated from forecast hour 0 to 126. In Figure 2, all results show concentrated rainfall along its track in general. Observational data indicates that the heaviest rainfall occurred over Houston due to Hurricane Harvey's strong outer rainband. Moreover, IMERG shows heavy rainfall barely occurs over the ocean in this case. However, it is important to recall that observational precipitation values over ocean are estimated only from passive microwave without any ground-based observation adjustments (i.e. rain gauge data cannot correct rainfall over ocean). Nevertheless, satellite microwave data is the best resource as of now to estimate precipitation upon oceans. Stage IV, a ground-based rainfall dataset, provides more pattern details due to higher resolution than IMERG. Stage IV and IMERG here show similar rainfall patterns over land, yet Stage IV got stronger peak rainfall over Houston. The climatology model, RCLIPER, only shows a main rainfall pattern along the track without predicting the heavy rainfall pattern over Houston. Compared to RCLIPER, HB17's pattern is more similar to the observations. In the first two selected cycles, HB17 predicted heavy rainfall occurring not only over Houston, but also over Austin and San Antonio. This second-peak-rainfall false alarm was not present in the 00 UTC 25 Aug 2017 cycle. However, the peak value of Houston heavy rainfall slightly dropped, and the center moved towards the west as the second landfall occurred at Louisiana in this cycle. HB17 also slightly overestimated certain amount of rainfall along its path over the ocean compared to IMERG. Nonetheless, HB17 predicts a peak rainfall over Houston and more realistic rainfall patterns than RCLIPER. The general patterns from HB17 actually match well to the observational data.

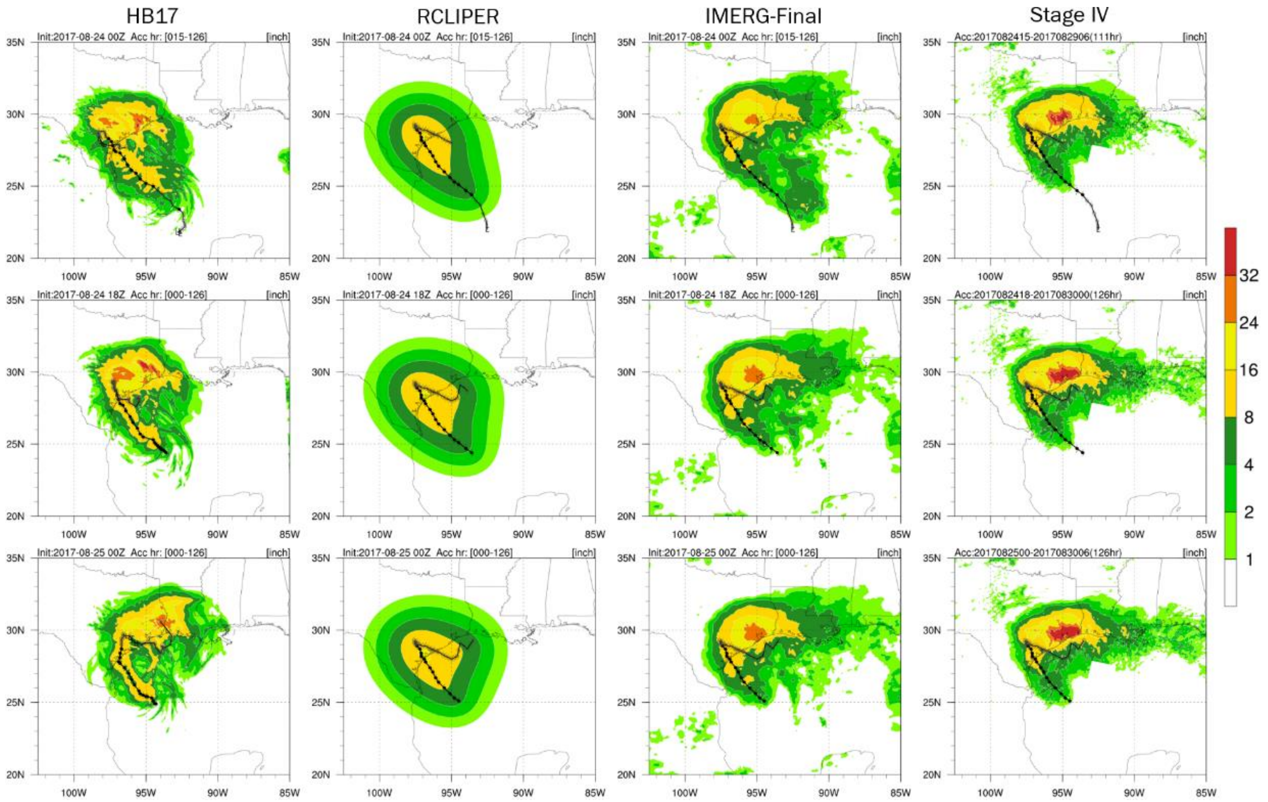

Fig 2. Rain swath of HB17, RCLIPER, IMERG, and Stage IV. First row is at 00 UTC 24 Aug 2017, second row is at 18 UTC 24 Aug 2017, and third row is at 00 UTC 25 Aug 2017. Black lines are the forecasted/best tracks of models/observations.

3.2 Azimuthal Analyses

Azimuthal analyses examine precipitation structure from center to outer rainband in order to further assess the performance on peak, overall, and distribution of rainfall. Figure 3 shows radial distribution of averaged rain rate. RCLIPER (green) got slightly steeper slope than the other datasets. It had the highest averaged rain rate at 100 km and the lowest at 300 km. HB17's prediction (red) was very close to observational values (blue and purple), especially in the outer rainband from 100 km to 300 km. Due to its high resolution (2 km), HB17 captured eye structure well, although the peak value was greater than observations. As both resolution and overestimation can contribute to this high peak value, it is necessary to consider the impact of resolution difference between datasets.. Rain flux is a function of rain rate and resolution which indicates total amount of rain within each 10 km radius intervals from 0 km to 300 km. Figure 4 shows rain flux radial distribution. HB17 is consistent with observational data from 100 to 300 km but overestimate rain amount in the core region. RCLIPER rain volume decreased from 150 to 300 km which differed from all other datasets. In radial distribution analysis, HB17 has a proven skill on producing reasonable values in the outer rainband, but slightly overestimates the core region.

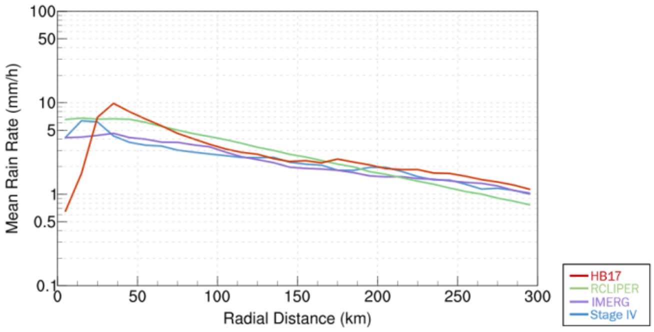

Fig. 3. Radial distribution of averaged rain rate for selected cycles of Hurricane Harvey. HB17's distribution is the red line, RCLIPER is green, IMERG is purple, and Stage IV is blue. The radial distance is from 0 to 300 km.

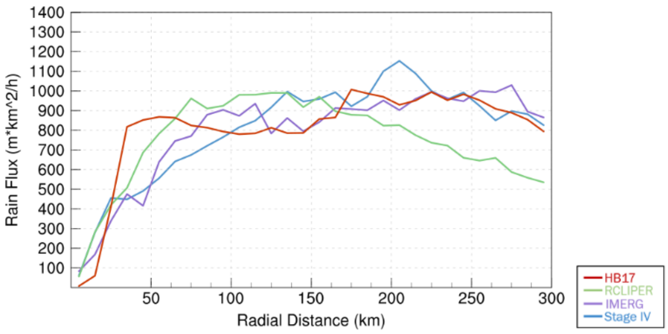

Fig. 4. Similar to Fig. 3, but for rain flux.

Probability distribution functions (PDFs) and cumulative distribution functions (CDFs) of decibel rain rate (dBR) in Figure 5 analyze how the model produces light/heavy precipitation compared to observations.

$$dBR=10\ \log10(\textit{precipitation\_rate})$$

PDF and CDF were calculated in 2dBR threshold from 0 dBR (1 mm/h) to 27 dBR (approximately 500 mm/h). In the figure below, it only shows up to 200 mm/h as no prediction exceeds this. The results show HB17's 50th percentile of CDF (yellow dot) is 2.9 mm/h, RCLIPER is 1.5 mm/h, IMERG is 2.7 mm/h, and Stage IV is 2.5 mm/h. Accordingly, HB17 predicts a reasonable proportion of both lighter and heavier rainfall, but RCLIPER produces a significant amount of lighter rainfall, resulting in a low value of 50th percentile. On the other hand, HB17's 75th percentile (green dot) is 6.8 mm/h while IMERG is 4.4 mm/h and Stage IV is 5.2 mm/h. This indicates that HB17 generates a greater amount of extreme rainfall than observational data indicates. PDF reveal similar information. HB17's PDF shows this model produces about 2% of rainfall above 50 mm/h, IMERG has roughly 0%, and Stage IV has less than 1%. PDF and CDF suggests that HB17 generally produces representative dBR/rain rate with slightly higher frequency on extreme rainfall (> 50 mm/h). Besides, it is also worth noting that IMERG's PDF demonstrates higher frequency in 2 - 6 mm/h comparing to Stage IV.

Contoured frequency by radial distance (CFRD) plots are shown in Figure 6. These depict the PDFs of each 10 km interval from 0 to 300 km. CFRD shows how PDF varies from center to outer rainband and helps locate where the overestimation of extreme rainfall (>50 mm/h) happened. RCLIPER's CFRD shows rain rate gradually decreased from the center to outer region. At the center, the rain rate mostly varies from 3 mm/h to 10 mm/h. All rain rates are below 5 mm/h from 150 km to 300 km. Compared to observational datasets, RCLIPER doesn't produce realistic radial rain rate frequency. Shown in the top-right panel of Figure 6, IMERG's estimation from microwave trends on high frequency of 2-8 mm/h. Rain rate generally drops down from core to 150 km and then Harvey's heavy rainfall located at outer rainband rises the rain rate back up around 250 km. Stage IV also shows rain rate risen at 200 km due to the outer rainband precipitation. HB17 matches Stage IV observations for the most part, except within 50 km, where its rain rate is greater. In the core, HB17 has about 8% frequency above 50 mm/h while Stage IV only captures around 4%. Therefore, HB17's slight overestimation of extreme rain rate happened in the core region where rainfall is mostly driven by convection.

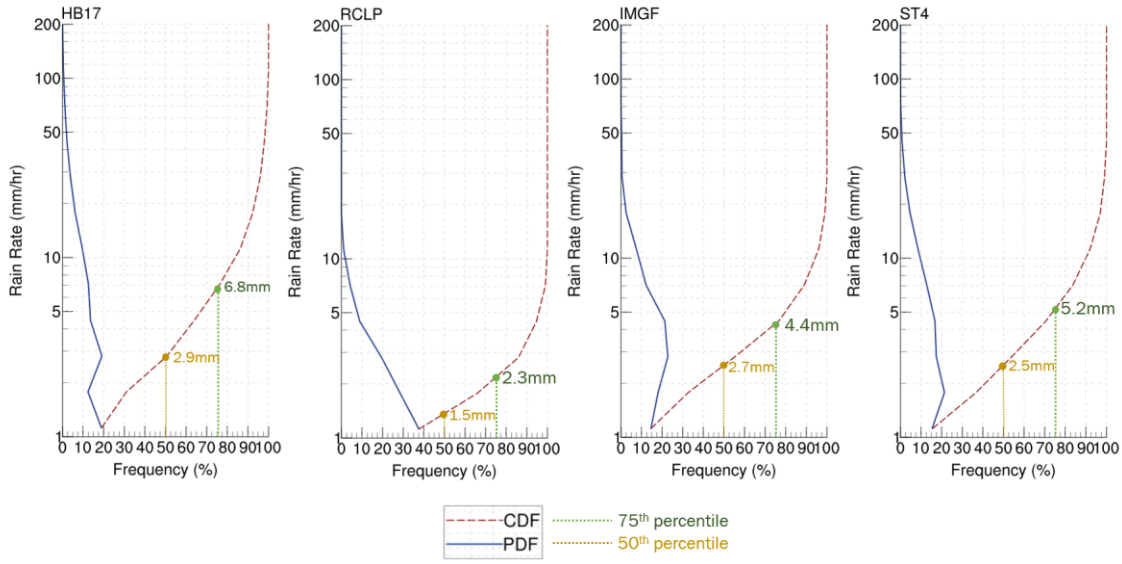

Fig. 5. PDF and CDF of dBR. Blue line is PDF and dashed red line is CDF. 50th percentile of CDF is indicated via yellow points and 75th percentile via green points. From left to right panel, the results are from HB17, RCLIPER, IMERG, and Stage IV sequentially.

3.3 Precipitation Probabilities

In order to minimize uncertainty of current deterministic forecasting, this study also demonstrates an experiment of probabilistic precipitation forecasting using an HWRF ensemble. Figure 7 shows probabilistic precipitation of 1, 4, 8, 16 inches at 00 UTC Aug 25 2017 generated by a 21-member ensemble run. The upper-left panel of Figure 7 shows 1-inch-rain probability; it corresponds to the outline of rain patterns in Figure 1. In general, the 90% of 1-inch probability caught the rain pattern outline really well but missed part of Louisiana and southern Mississippi. The figures of 4 and 8 inch probability predicted less rainfall over the ocean, which is more realistic compared to the deterministic forecasts and observational data in Figure 1. Especially in the 8 inch probability panel, the predictions shows rainfall above 8 inch most likely happens in land and a spot at 20N and 95W. The observational datasets in Figure 1 show that heavy rainfall over the ocean occurred around 22N and 94W. Moreover, peak rainfall of 16 inches in the probabilistic forecast occurs around Houston. This matches observations better than deterministic run, which got a peak rainfall closer to Louisiana. Therefore, this experiment shows that probabilistic rainfall prediction, considering several track possibilities, can deliver more rational results to professionals and to the general public.

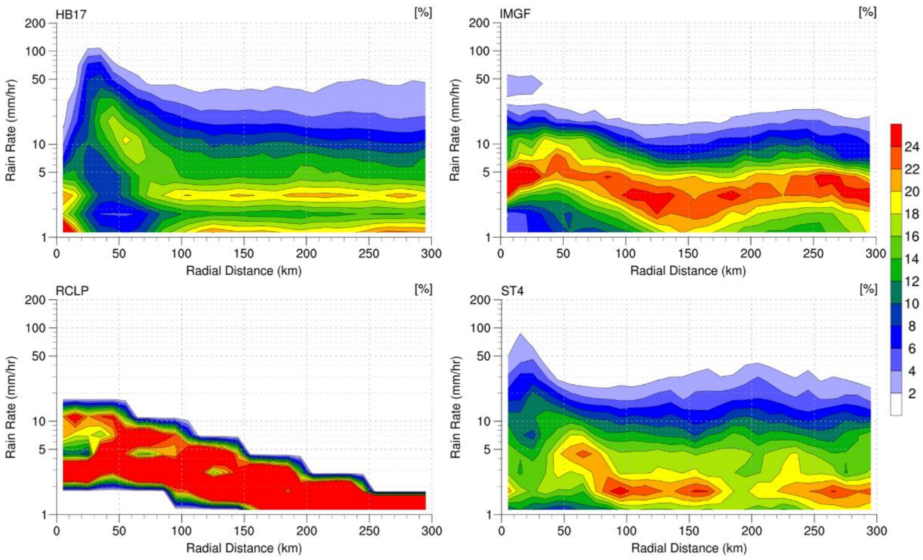

Fig. 6. Contoured frequency by radial distance (CFRD). Distance interval is 10 km starting from 0 km to 300 km and rain rate interval is 2 dBR. Upper-left panel is HB17; Upper-right is IMERG; Lower-left is RCLIPER; Lower-right is Stage IV.

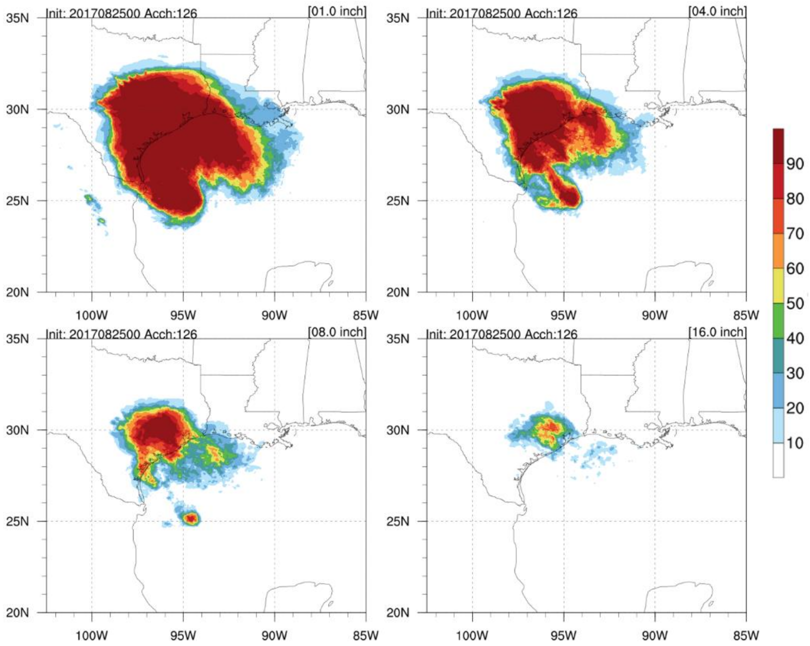

Fig. 7. 126-hour probabilistic rainfall for Harvey cycle 00 UTC 25 Aug 2017. Thresholds are 1, 4, 8, and 16 inches for panels from left to right and top to bottom.

4. Conclusions

This case study of Hurricane Harvey for HB17 shows that HB17 produces realistic precipitation, in terms of patterns, amount of rainfall, and rain rate radial and frequency distribution. Overall, it captured outer rainband heavy precipitation successfully. However, the core convection is slightly stronger than reality, inducing higher precipitation rate around the eye. Moreover, using the more computationally expensive probabilistic forecasting methodology, more realistic rainfall results were obtained.

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