ASSESSMENT OF RADAR-DERIVED TROPICAL CYCLONE STRUCTURE USING DIFFERENT QUALITY CONTROL METHODS

by

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(Under the Direction of Marshall Shepherd)

ABSTRACT

The Tail Doppler Radar (TDR) is a vertically-scanning radar found on the NOAA WP-3D and G-IV aircraft and is used for studying tropical cyclone structure and evolution. The quality control (QC) method applied to TDR data, NOAA-QC, has been shown to accurately identify non-meteorological data (NMD), but is aggressive at removing meteorological data (MD) especially in the lower and upper troposphere. The purpose of this study is to assess the benefits of reprocessing TDR data with a less aggressive QC method. We employ a recently-developed machine-learning quality control method, which has been shown to retain more MD than NOAA-QC, to reprocess a subset of cases. It is discovered that the machine-learning method is more accurate than NOAA-QC at retaining MD, especially within the lower and upper troposphere. Increased MD coverage with machine-learning is further demonstrated through increases in coverage within 3D wind analyses for each case.

INDEX WORDS: TDR, NOAA-QC, MLQC, machine learning, boundary layer, outflow, MD, NMD, tropical cyclone (TC)

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CHAPTER 1

INTRODUCTION

The exact history of the creation of the first radars is quite muddled; radars were a product of WWII engineering, and as a result, the countries involved (mainly Britain and the United States) wanted to keep their new technology a secret from the opposing side. The development of the first ever radar is usually credited to Scottish physicist and meteorologist Robert A. Watson-Watt. His idea of using electromagnetic waves to locate enemy aircraft led to the creation of the Chain Home radars, which ended up being a crucial factor in the victory at the Battle of Britain (Whiton et al. 1998). As these new radars were used more abundantly among some of the allied powers, it was soon realized that unfavorable weather conditions would obscure the targets of interest. Dr. J. W. Ryde of the British General Electric Corporation Research Laboratory was the first to relate the sensing of the meteorological clutter to Rayleigh scattering of water droplets. Soon after the war, the allied militaries released the new radar technology to several newly created meteorological radar labs for further research (Rogers and Smith 1983).

Through the next few decades, radars proved useful within meteorological operations and research. Analysis of radar data helped to improve our overall understanding of convective storms, and having real-time visualizations of storm systems improved operational nowcasting and warnings (Whiton et al. 1998). Within the world of tropical meteorology, radars increased observations and understanding of tropical mesoscale convective systems and tropical cyclones (TCs) while over land (Marks 1990). However, when it came to sensing tropical weather phenomena (especially TCs), radars were significantly disadvantaged, as they were unable to reach the ocean or remote land areas. In 1971, Roger Lhermitte proposed the idea of using airborne Doppler radars in order to improve sensing of convective systems and the vertical motion of hydrometeors (see Figure 1). Since the aircraft would be relatively close to its sensing target, he suggested the use of a shorter wavelength (such as Ku or X band). To limit the Doppler effects of the aircraft on the radar output, it was also recommended that the radar beam be positioned perpendicular to the flight path. (Lhermitte 1971).

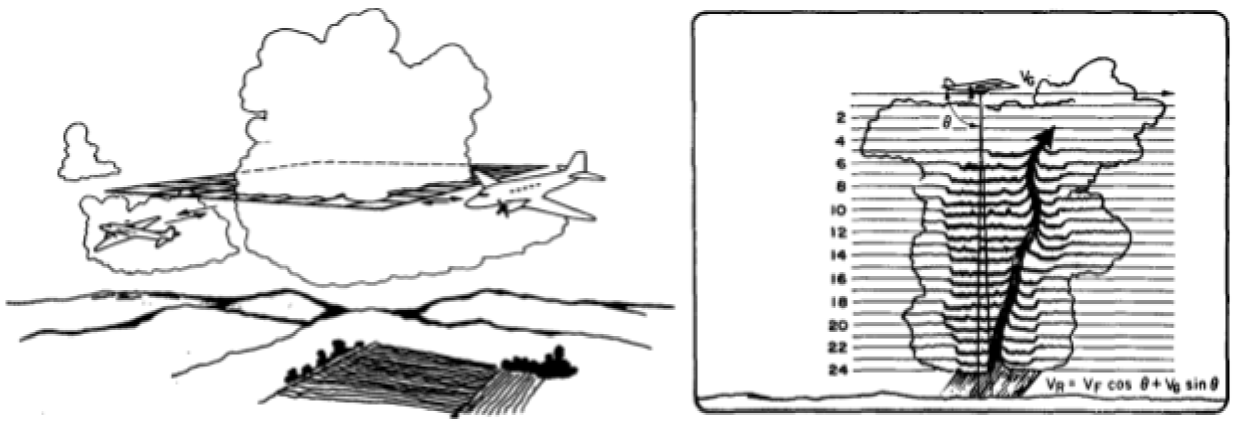


Figure 1: *Lhermitte's two proposed methods of using airborne radars, which served as the basis for NOAA's WP-3D airborne radars. The depiction on the left shows his proposed horizontal beam method using two radars scanning simultaneously to derive three-dimensional winds. The image on the left shows his vertical beam method scanning updraft velocities in a convective thunderstorm. Source: Lhermitte 1971*

Five years after Lhermitte's paper was published, NOAA obtained its first WP-3D aircraft (known as NOAA-42 or Kermit), equipped with an airborne Doppler radar (Lee et al. 2003). The X band radar (wavelength of 3.2 cm) found a place at the tail of the aircraft, hence its eventual name, the Tail Doppler Radar (TDR) (see Figure 2). It worked

Figure 2*: A current image of the TDR on the tail of NOAA's WP-3D N42 aircraft (Kermit). Source: AOML/NOAA*

similarly to a ground-based radar that was tilted on its side, as the antenna would scan for a full 360˚ rotation. The azimuth angle was constantly adjusted to ensure that the beam was always perpendicular to the flight path, as was proposed by Lhermitte (1971) (see Figure 3) (Jorgensen et al. 1983). The initial tests of the NOAA-42 TDR conducted between 1980-82, as summarized in Jorgensen et al. (1983), showed promising results when compared with ground-based radar output, although there were errors due to the constant shift in azimuth, temporal and spatial resolution, and a lack of quality control of velocity returns. They also discovered that a dual-Doppler analysis was possible by comparing data collected from different viewing angles.

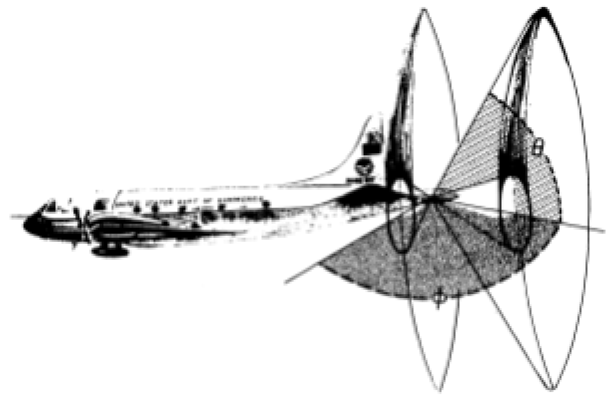


Figure 3: *The TDR's single beam scanning strategy. The elevation angle Θ is adjusted with the azimuth angle ϕ so that the beam is always normal to the flight path.*
Source: Jorgensen et al. 1983

Despite the errors, the first iteration of the NOAA-42 TDR was a success. In 1982, NOAA-42 probed Hurricane Debby and collected the first-ever Doppler winds in a TC (which then allowed for the researchers to create the first-ever horizontal map of winds in a TC). In addition, the TDR observed some mesoscale features within the hurricane that had not been measured prior, such as small scale eddies embedded in the flow and localized maxima of wind speed, divergence, and vorticity (Marks and Houze 1984). In 1983, the NOAA-42 TDR observed Hurricane Alicia, which led to the first ever mapping of three-dimensional winds (see Figure 4). This not only provided the first ever observations of TC structure and flow, but also led to the first ever quantification of TC water budget (Marks and Houze 1987). To help alleviate the resolution issues, a TDR of the same specifications was installed on NOAA-42's sister aircraft, NOAA-43 (also known as Ms. Piggy). Having the same instrumentation on both radars allowed for more continuous sensing of the TC. The first time the two aircraft were flown together was during Hurricane Norbert in 1984 (Marks et al. 1992), then again during record-breaking Hurricane Gilbert in 1988 (which reached a minimum sea level pressure below 900 mb) (Black and Willoughby 1992, Dodge et al. 1999, Lee et al. 2003).

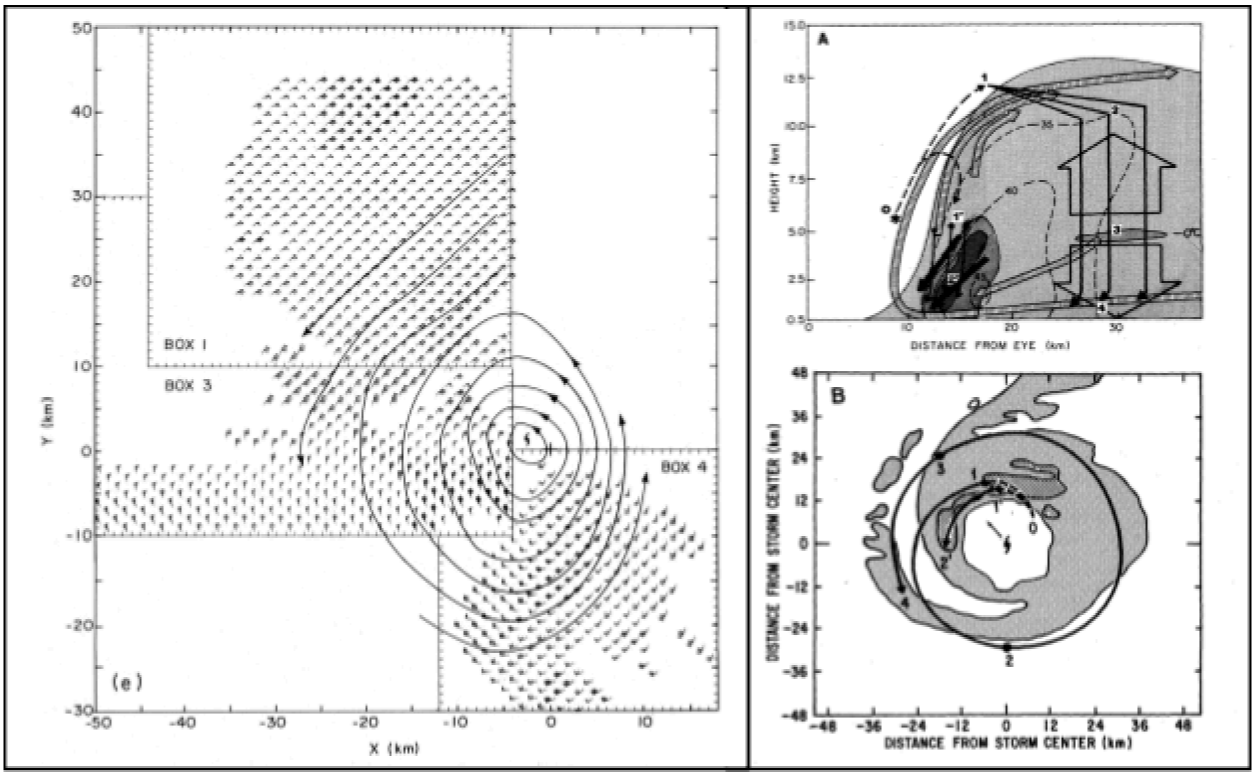


Figure 4:
Left image: The first-ever mapping of Doppler winds in a TC by a TDR in 1982 Hurricane Debby. Each of the boxes contain data collected by a pseudo-dual-Doppler analysis. Source: Marks and Houze 1984
Right image: A schematic of 1983 Hurricane Alicia's structure and flow, created with the first ever three-dimensional Doppler wind maps of a TC by a TDR. Source: Marks and Houze 1987

Up to this point, the main method of analyzing TDR data was the same method as outlined in Jorgensen et al. (1983): using different viewpoints from the same instrument to create a pseudo-dual-Doppler analysis. However, this method makes the inaccurate assumption that the TC has not developed or changed in between the two measurements being taken. For some cases, such as the Hurricane Alicia mission, the temporal gap between the two measurements can be

***Figure 5:** The dual-beam antenna of the TDR that's currently installed on NOAA's WP-3D and G-IV aircraft (as shown on the G-IV).*
Source: NOAA Hurricane Hunters Facebook Page

upwards of an hour (Marks and Houze 1984). As a result, the Fore/Aft Scanning Technique (FAST) was created. Originally proposed by Jorgensen and DuGranrut (1991), the FAST technique involves alternatingly sending two radar beams, one oriented towards the fore of the aircraft and the other towards the aft, both of which are at an angle approximately 20˚ from the normal to the aircraft path. After comparisons of different scanning techniques within different convective environments (e.g. an Oklahoma MCS and Hurricane Norbert), it was determined that FAST returns the most realistic data output when compared to ground-based radar and other ground-truth measurements, and, therefore, has been the TDR scanning strategy ever since (Gamache et al. 1995, Jorgensen et al. 1996). A French dual-beam antenna was installed on the WP-3D aircraft to allow for alternating scanning between the fore and aft directions (see Figure 5) (Roux and Viltard 1995). Beginning in 2017, the WP-3D TDRs were upgraded to permit dual transmission of the fore and aft beams (see Figure 6) (Jorgensen et al. 1996, Guy & Jorgensen 2014) further improving the temporal resolution of the measurements.

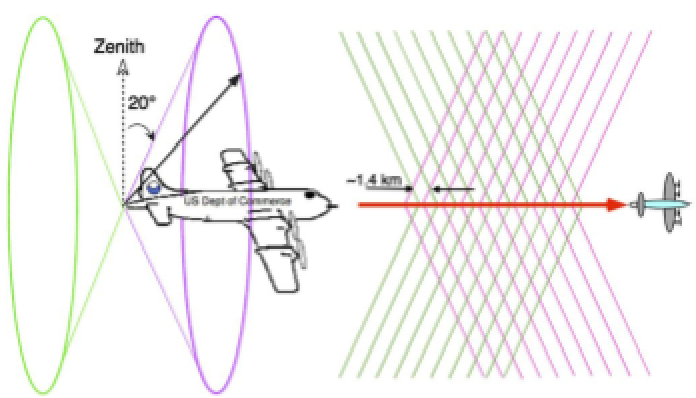


***Figure 6:** A schematic of the Fore/Aft Scanning Technique.*
Source: Guy and Jorgensen 2014

As TDR capabilities improved, case studies involving TDR data became more common, especially since the WP-3Ds have been regularly probing multiple TCs every year during the Atlantic hurricane season since the early 1980's (Marks 2003). Most of these case studies built on the previous observations of TC structure and dynamics. Some noteworthy case studies at this time include:

- Roux and Viltard (1995): In a case study of Hurricane Claudette (1991) probed by both WP-3D aircraft (one aircraft used the original single beam scanning strategy and the other used FAST), Roux and Viltard analyzed the mesoscale dynamics and flow evolution within 100 km of the storm center during a partial eyewall replacement cycle (ERC).
- Reasor et al. (2000): Through a true dual-Doppler analysis of Hurricane Olivia (1994) utilizing TDR data from both WP-3D aircraft, the inner-core asymmetric vorticity dynamics and evolution were analyzed as Olivia was weakening. This study was the first to evaluate previous symmetric and asymmetric vortex structure and intensity change theories.
- Black et al. (2002): This study also examined the Hurricane Olivia (1994) case of Reasor et al. (2000) but focused on the convective structure of the eyewall. By using vertical incidence data (i.e., nadir- and zenith-pointing TDR beams), Black et al. 2002 analyzed how (changes in) environmental shear affected the overall evolution of structure and flow of Hurricane Jimena (1991) and Hurricane Olivia (1994).

However, there was one major disadvantage to using TDR data that discouraged many researchers from using it in their studies: the quality control (QC) process. Due to the nature of the TDR (including bandwidth, scanning strategy, and being on a rapidly moving platform), the data contains non-meteorological data (NMD) that need to be filtered out before an analysis can be performed (see Figure 7). At this time, all QCing had to be done manually by a radar expert,

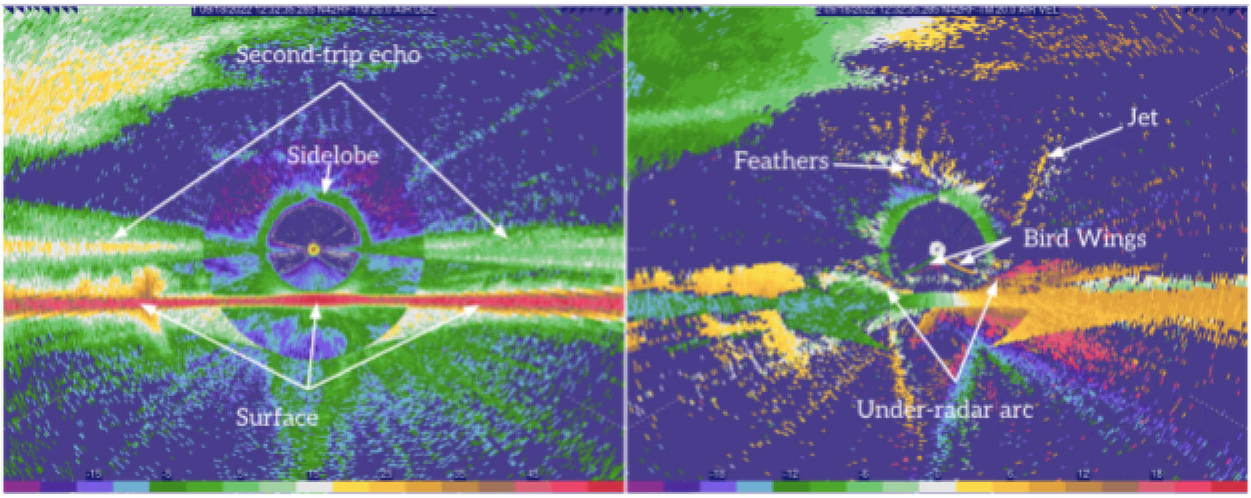


***Figure** 7: An image of unedited TDR data (reflectivity on the left, Doppler velocity on the right) from Hurricane Fiona. Arrows point to different types of NMD that gets removed during the QC process.*

which is a long and tedious process that can take months to complete for one case (Stern and Nolan 2009). Not only did this deter researchers from using the data, but it also inhibited the use of TDR data in operational forecasting. This all changed in 2005 when Gamache et al. (2005) created the current rules-based QC algorithm, NOAA-QC. Written in Fortran, NOAA-QC subtracts out the aircraft motion, removes sea surface contamination, applies a mask to the data to filter out noise, and uses Signal Quality Index (SQI) and Spectral Width metrics to discard any remaining NMD (Gamache et al. 2005). After the data is QC'd, it is run through NOAA-Synthesis, an analysis software (also created by Gamache et al.) that derives a three-dimensional wind field based on the Doppler velocities, similar to a dual-Doppler analysis. The processes behind NOAA-Synthesis are summarized in the appendix of Reasor et al. (2009). NOAA-QC went through extensive testing during the 2004 Atlantic Hurricane Season, and was put into operations on both the WP-3D aircraft the next year. As a result, in 2005, TDR-derived analyses were sent in real-time off the aircraft to the National Hurricane Center and were used in the forecasting of track and intensity of Atlantic TCs, such as Hurricane Katrina (Gamache et al. 2005 and Rogers et al. 2006). NOAA-QC also allowed for the assimilation of TDR data into TC forecasting models, such as the Hurricane Weather Research and Forecasting model (HWRF) and the current Hurricane Analysis and Forecast System (HAFS). Several studies have demonstrated that assimilating TDR data into these models has resulted in significant TC forecast improvements (Rogers et al. 2006, Aksoy et al. 2012, Knisely and Poterjoy 2023, Hazelton et al. 2022).

Once QC'd TDR data was more accessible to researchers in the late 2000's, TC studies began utilizing multiple cases in composite analyses. Earlier research utilized datasets comprised of fewer cases (compared to current times) to confirm and build on what has been previously learned by single case studies regarding topics such as tangential winds and the vertical structure of the radius of maximum winds (Stern and Nolan 2009), as well as vortex structure and dynamics (Rogers et al. 2012). As time passed and the TDR collected data on more cases, the datasets for composite studies grew (for example, Fischer et al. (2022) utilized 66 different cases), which allowed for the intercomparison of TCs. A popular area of interest has involved comparing structure and dynamics (such as inner-core, vortex, and TC boundary layer (BL) kinematics) among TCs of different intensification stages (Rogers et al. 2013, Fischer et al. 2022, Zhang et al. 2023).

The latest significant update regarding TDR data is the creation of the Tropical Cyclone Radar Archive of Doppler Analyses with Re-centering (TC-RADAR) by Fischer et al. (2022 & 2024). TC-RADAR is a publicly available, user-friendly dataset of TDR analyses that "comprises over 900 analyses from 273 flights into TCs in the North Atlantic, eastern North Pacific, and central North Pacific basins between 1997 and 2020," (Fischer et al. 2022, p. 2255). Fischer et al. (2022) does note that all TDR data in TC-RADAR that was collected prior to 2010 should not be used due to errors in the processing software (this issue still exists to date). The overall goal of TC-RADAR is to increase the usage of TDR data in TC research.

CHAPTER 2

BACKGROUND

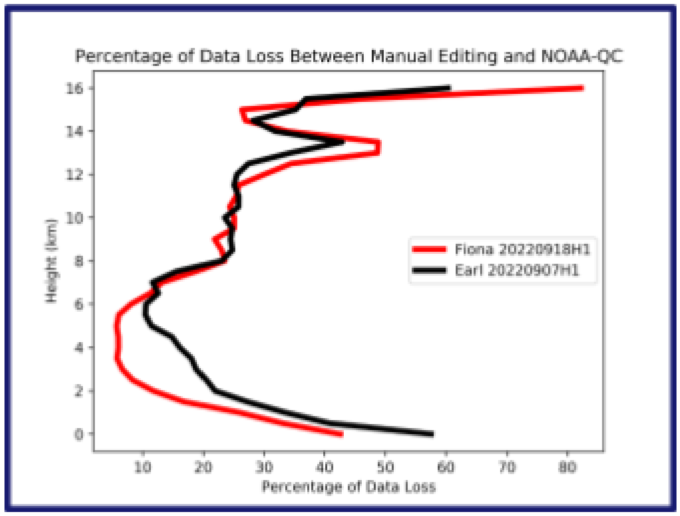


Figure 8: *The percentage of MD data loss with height due to NOAA-QC for 2022 Hurricanes Earl (flight 20220907H1) and Fiona (20220918H1). Source: Neighbour et al. 2024*

Within the past 50 years, TDR data has proven itself to be a crucial piece in improving both our overall understanding of TC processes and our ability to forecast TCs. The addition of NOAA-QC and TC-RADAR have made QC'd TDR data and TDR-derived analyses more accessible to TC researchers. Even though NOAA-QC is around 20 years old, Neighbour et al. (2024) was the first quantitative assessment of its performance and accuracy. Through case studies of 2022 Hurricanes Fiona and Earl, Neighbour et al. (2024) shows that NOAA-QC is accurate in filtering out NMD (with a 99.5% NMD removal rate), but is fairly aggressive, as it only retains around 70% of meteorological data (MD) in the process. The authors also discover that NOAA-QC removes the most amount of MD in the boundary layer (TCBL) and outflow layer (see Figure 8). Knowledge of the TCBL and the TC outflow layer are crucial for improving understanding of TC structure, evolution, and impacts.

Machine learning is a subset of artificial intelligence where a computer model can effectively use a knowledgebase of data to solve a problem and/or complete a task without being explicitly programmed to do so step-by-step (Kühl et al. 2022). Currently, there is a team at

Colorado State University that is using machine learning to create a new QC method for TDR data. Their machine learning QC (MLQC) model, known as the Random forest Optimized Non-meteorological IdentificatioN (RONIN), runs on Julia and uses a random forest technique (Breiman 2001) to filter out NMD. The RONIN methodology is similar to that of DesRosiers and Bell (2024) and has thus far shown to retain more MD than NOAA-QC.

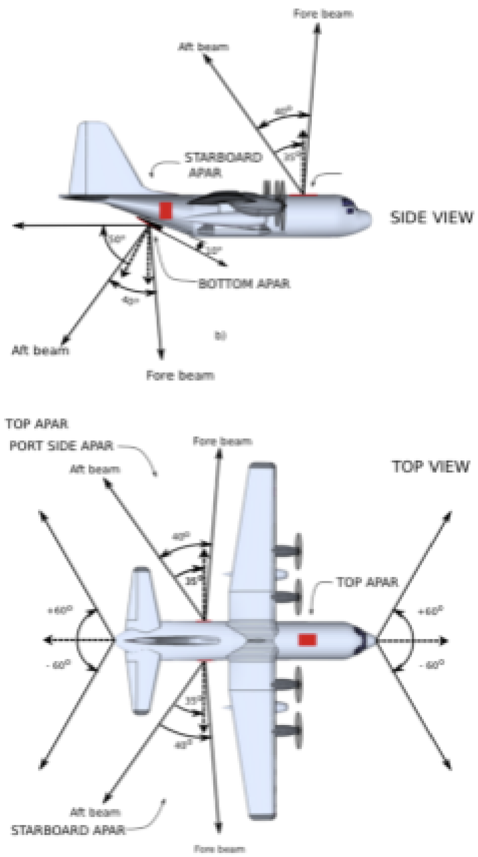


Figure 9: *A proposed APAR configuration on a C-130 for NSF/NCAR to replace the ELDORA radar. Source: Vivekanandan et al. 2014*

There are two main motivations for the creation of a new and improved QC method. The first, which is currently the main priority, is to improve the accuracy of TDR QC by retaining more MD in the final output while maintaining the current NMD detection accuracy. The secondary motivation is to prepare for a future without TDRs. Since the NOAA WP-3D aircraft are approaching 50 years of operations, NOAA is planning to replace them with new C-130 aircraft by 2030. However, TDRs cannot be used on C-130s due to the aircraft structure, so the entire airborne radar system will have to change. While the exact replacement for the TDR hasn't been decided yet, researchers have mainly been looking to airborne Phased Array radars (APARs) as a solution (see Figure 9). APARs provide many benefits, including improved functionality and temporal/spatial resolution. The main asset of APARs is their dual polarization capabilities, which would provide additional information about the shape, size, variability, and orientation of targets within a tropical cyclone (Vivekanandan et al. 2014). Due to the rules-based nature of NOAA-QC, it cannot be applied to the new radar. Switching to a new MLQC method would hopefully ease the transition between new radars due to the adaptability of machine learning.

With this in mind, there are currently two major proposals for future research in the works at NOAA's Atlantic Oceanographic Meteorological Laboratory (AOML). The first takes the MLQC efforts one step further by proposing a completely new processing methodology for the NOAA airborne radars. The proposed methodology includes using Colorado State University's (CSU) RONIN for QCing the data, a novel machine learning model to de-alias Doppler velocities, and finally a new wind synthesis software coded in Julia. This proposal hopes to improve the numerical accuracy of airborne radar-derived three-dimensional wind analyses for both TC research and operations, as well as to ease the future transition between the airborne radars. The second proposal aims to investigate how the new TDR MLQC method will impact TC forecasts in the HAFS model. The proposed study will create three sets of TDR data collected within 2022-24, two of which are QC'd by either MLQC or NOAA-QC, and one set that includes no TDR data at all (to serve as a control). The researchers plan to assimilate each dataset separately into the HAFS model and assess how the forecast and model error changes.

CHAPTER 3

MOTIVATION AND RESEARCH QUESTIONS

It has been noted that the numerical output of the TDR-derived analyses does not align with that of other measurements taken (such as dropsonde or scaled TDR data). Specifically, the wind speeds are often smaller in magnitude than expected. A good example of this is comparing how the data in Fischer et al. 2022 (which uses solely TDR data) doesn't completely match with that from Zhang et al. 2023 (which scales TDR wind speeds from higher altitudes to the TCBL), especially around the TCBL (see Figures 10 & 11). Researchers point towards the scanning limits of the TDR and/or the automated processing of TDR data, including NOAA-QC and NOAA- Synthesis, as a possible cause (Reasor et al. 2009, Stern and Nolan 2009, Rogers et al. 2012, Fischer et al. 2022). However, there has not yet been any attempt to understand how the

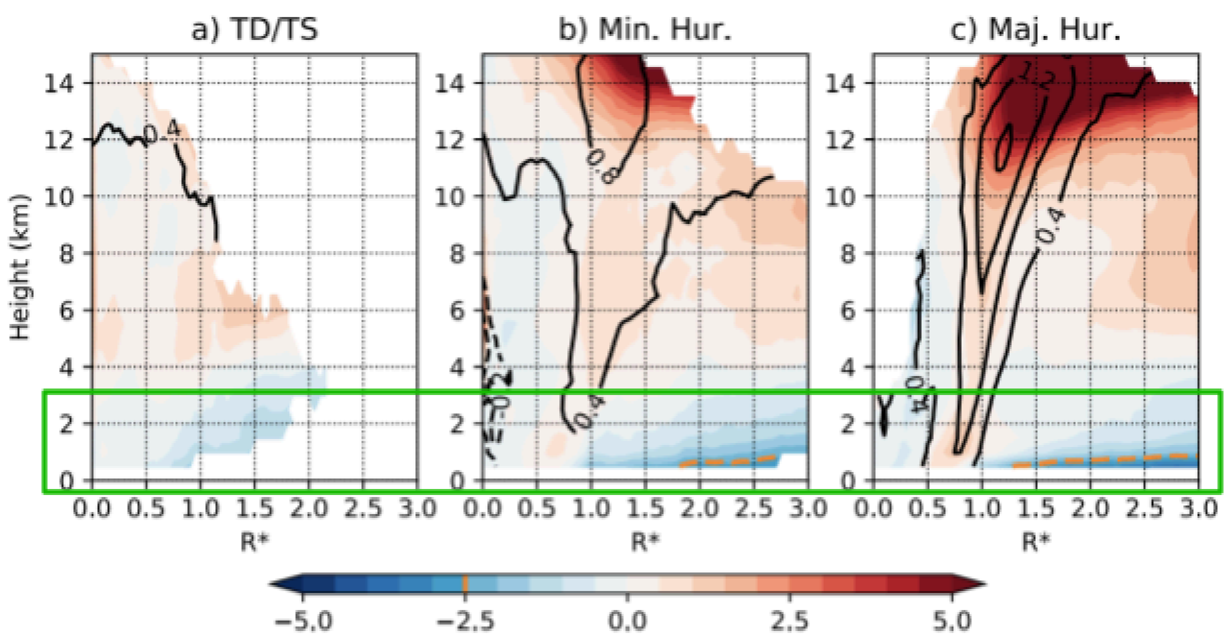


Figure 10: *Composite mean azimuthally averaged radial wind in m/s from Fischer et al. 2022. The green box highlights the TCBL, which is the area of focus for Zhang et al. 2023.*

processing of TDR data, especially QC, affects the output of analyses and structural diagnostics. This is especially important now since TDR data is being utilized more in TC research, thanks to the data (which has been QC'd by NOAA-QC) being publicly available through TC-RADAR. It's also been noted that despite NOAA-QC's accuracy in removing NMD, some TDR-derived analyses still contain NMD. The consensus before Neighbour et al. (2024) has been to blame the current QC method, but since we discovered that NOAA-QC is accurate in its filtering of NMD, this raises the question: what could be causing this discrepancy between TDR and other measurements to occur? This is especially crucial for operations because the inclusion of NMD in analyses can inhibit TC forecasting.

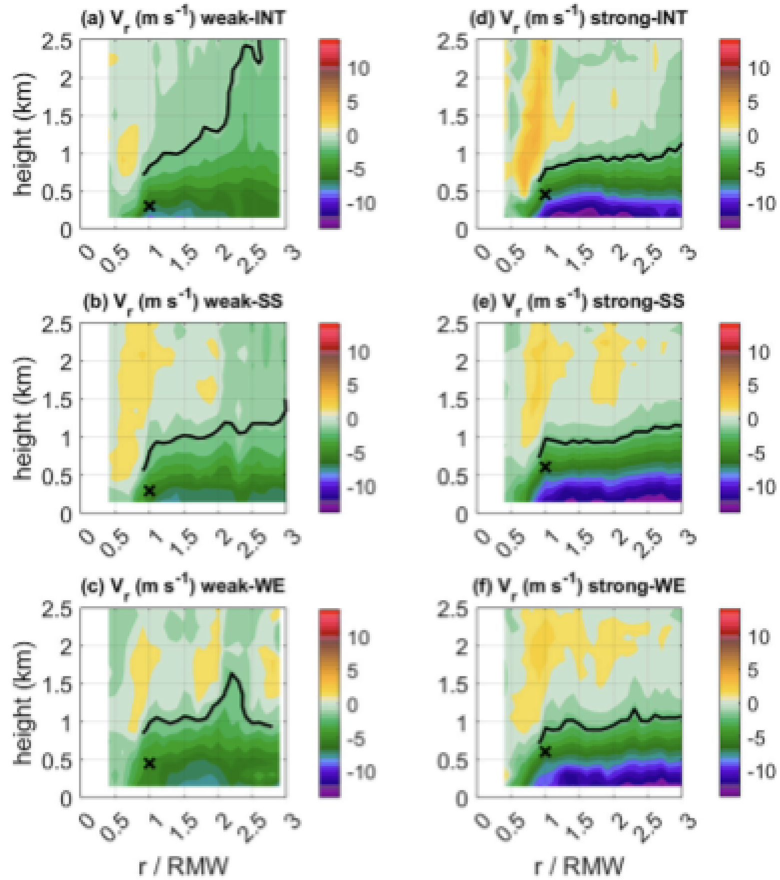


Figure 11: *Composite-mean azimuthally averaged winds in m/s for the TCBL from Zhang et al. 2023.*

Therefore, as an extension of Neighbour et al. (2024), this project aims to investigate how different QC methods affect TC structure derived from TDR analyses and structural diagnostics, specifically within the TCBL and outflow layer. Specifically, we want to know how the incorporation of a new and improved MLQC method will affect/advance TC research and forecasting operations, and whether the TDR data in TC-RADAR should be reprocessed with a new QC method. Our specific research questions are as follows:

1. How does RONIN's performance compare to that of NOAA-QC?
   a. Specifically, how do their MD retention and NMD filtering rates compare?
   b. Where are the differences in MD retention and NMD filtering (within each radar sweep and by height)?
   c. Does the performance of RONIN and NOAA-QC vary by case?
2. How does using RONIN to QC TDR data affect TDR-derived analyses when compared to analyses from data QC'd by NOAA-QC?
   a. In cases where NMD contamination is present in the real-time, NOAA-QC'ed analyses, how does using RONIN to QC TDR data affect the amount of NMD contamination within RONIN-derived analyses?
   b. How does coverage and data quality vary between the two analyses? Do different QC methods yield fundamentally different TC structures?

CHAPTER 4

DATA AND SOURCES

To meet both the goals of this thesis and to assist the objectives of further studies, we will be focusing on TDR data collected during 2022-24. It is important to note that all TDR data, regardless of QC method, has been thinned by ⅔, as is the operational standard. Raw TDR data was downloaded from the NOAA Aircraft Operation Center's public server. All NOAA-QC and manually edited datasets to be used in this research were downloaded from a shared Google folder. The analyses derived from NOAA-QC'd TDR data for the 2024 cases are the analyses that were created in real-time during NOAA Hurricane Reconnaissance Missions, and these were downloaded from AOML Hurricane Research Division's (HRD) public server. Running CSU's RONIN requires Julia to be installed. In addition, we used NCAR's LROSE RadX to convert the TDR data to different formats as necessary, as well as LROSE SOLO3 to view the individual TDR sweeps. To create TDR-derived structural diagnostics of the MLQC'd data, we used NOAA-Synthesis, a software created by John Gamache that will de-alias the data and create three-dimensional winds (similar to that of Gamache et al. 2005 and Reasor et al. 2009 with the QC code removed). NOAA-Synthesis requires jobfiles, backdoor files that provide necessary case-specific information, in order to run. To use NOAA-Synthesis for the RONIN-QC'd data, we downloaded the jobfiles used in real time from NOAA AOC's public server and edited them using the AOML Jobfile Editing software. Finally, to view the analyses created by NOAA-Synthesis, we utilized NASA's Panoply visualization software.

- NOAA AOC public server of raw TDR data: https://seb.omao.noaa.gov/pub/acdata/

- NOAA AOML HRD's public server of real-time TDR analysis graphics: https://www.aoml.noaa.gov/ftp/pub/hrd/data/RTradar/
- NOAA AOC's public server of real-time TDR analyses and jobfiles: https://seb.omao.noaa.gov/pub/flight/radar/
- RONIN: https://github.com/irslushy/Ronin.jl
- NCAR LROSE: https://www.eol.ucar.edu/content/lidar-radar-open-software-environment
- AOML Jobfile Editing Software (requires Java Web Start): https://seb.omao.noaa.gov/tdrjob/
- NASA Panoply: https://www.earthdata.nasa.gov/data/tools/panoply
    - Note: due to the current status of NASA GISS, this website may no longer work. I unfortunately could not find a replacement.

CHAPTER 5

QUALITY CONTROL METHODOLOGIES

NOAA-QC

NOAA-QC is a rules-based QC method written in Fortran and created by Gamache et al. (2005). The methodology for NOAA-QC hasn't changed drastically over the years other than to account for new masks and changes in the TDR scanning strategy. Prior to every hurricane season, the mask used in NOAA-QC is created through multiple test flights over perturbed sea surface and clear air. The data collected from these flights is then averaged together to find the mean reflectivity values for each radar-relative azimuth and range (which are all stored in the mask). In operations, in order for a gate to be kept as MD, the reflectivity value of this gate must be greater than a specific reflectivity threshold above the mask's value for that range and azimuth.

In addition to the mask, NOAA-QC subtracts out the aircraft motion from the raw Doppler velocity. Then, it removes the surface by looking for high reflectivity gradients (around 5-10 dBz per gate) around the area where the surface is usually located on the radar. Next, it uses several rules-based thresholds to further filter the data, such as signal-to-noise (to despeckle), Spectral Width (to remove known NMD sources, such as the side lobe and second trip echoes), and SQI (to remove NMD with sources that are not easily identified). Finally, NOAA-QC dealiases the data with multiple passes through a Bargen-Brown de-aliasing technique (Gamache et al. 2005).

RONIN

RONIN is a machine learning quality control method written in Julia version 1.10.5. The untrained RONIN code is available to the public on Github to be used in other applications, such as ELDORA data. For this study, we are using a RONIN model trained using data from four cases: Hurricane Earl (flight 20220907H1), Tropical Storm Fiona (flight 20220918H1), Hurricane Lee (20230912I1), and Tropical Storm Beryl (20240705H1). Eighty percent of this data was randomly selected to be used in training of the model, while the other twenty percent was set aside for testing purposes. In the training process, each sweep in the training dataset is given to the model in its raw and manually edited form to show the computer how a human would go about editing the raw data. The training of the RONIN model used in this study was previously done by AOML and Colorado State University.

The RONIN methodology is based on that of DesRosiers and Bell (2024). The version of RONIN used for this study is a two-pass model that utilizes a 90% agreement threshold for its decision trees. Figure 12 shows the classification scheme of RONIN. During the first pass, the

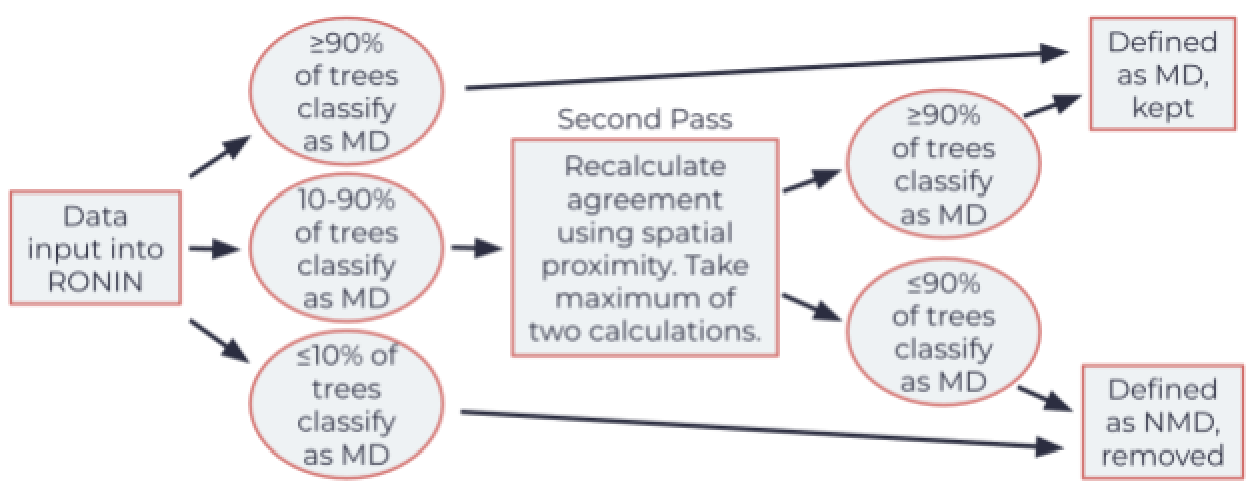


Figure 12: *A schematic of the workings of RONIN (Random forest Optimized Nonmeteorological IdentificatioN), which is a two-pass random forest ML method with a 90% agreement threshold and spatial awareness. It was trained on manually edited data from 2022097H1 (Earl), 20220918H1 (Fiona), 20230912I1 (Lee), and 20240705H1 (Beryl).*

agreement level amongst all decision trees for each gate is calculated. The gates where at least 90% of decision trees have determined the data to be meteorological are automatically classified as MD. On the flip side, the gates that at most 10% of trees have found to be meteorological are automatically determined NMD and removed. The majority of the gates will lie between the 10-90% range and move to the second pass. During the second pass, the decision trees conduct a reassessment of the data, and the agreement level amongst all trees for each gate is recalculated. During this process, the decision trees utilize a gate's spatial proximity to other gates that have already been classified during the first pass to influence their final assessment. After the recalculation, RONIN takes the highest agreement level of the two passes for each gate. The gates where at least 90% of the decision trees agree the data is meteorological for the second pass are classified as MD and retained. For all other gates, since neither pass generated a meteorological classification agreement level of at least 90%, they are deemed NMD and removed from the final QC'd sweep. This process repeats for every sweep included in the dataset fed to RONIN until the model has seen all of the sweeps included.

CHAPTER 6

RESEARCH METHODOLOGY

Research Question #1

How does RONIN's performance compare to that of NOAA-QC?

The methodology here will be very similar to the analysis methodology of Neighbour et al. (2024). Here, we will be focusing on four cases: 2022 Hurricane Earl, 2022 Hurricane Fiona, 2023 Hurricane Lee, and 2024 Hurricane Beryl.

1. Download, install, and configure Julia and RONIN on my Linux Desktop. Install any necessary dependencies before compiling, and create necessary subdirectories.
2. Download the manual-QC, NOAA-QC, and raw TDR data for all four cases. Also download all Correction Factor (CFAC) files for 2022, 2023, and 2024.
    a. Raw TDR data will download as a zipped file in sigmet format. NOAA-QC data is provided by Paul Reasor and John Gamache.
    b. Unzip all files and use RadxConvert to convert the data to dorade format (this way, the data can be read into SOLO3). Then, thin the data by ⅔ to match the manually edited data.
    c. Export the CFAC files to dorade datasets for all QC methods and all four cases.
3. Convert all dorade data to CfRadial format using RadxConvert so the data can be read by RONIN and the Python scripts (see below).
4. Use RONIN to QC the raw TDR data for each case.
    a. Copy the raw TDR CfRadial data into the necessary RONIN subdirectory.

b. In the RONIN directory, run Julia version 1.10.5, load dependencies, jld2 files, and the model configuration structure. Next, clean the individual sweeps in the RONIN subdirectory. Once complete, move the cleaned data out of the RONIN subdirectory to a secure location.

c. Each case should now have three similar datasets of individual TDR sweeps, with each dataset having been QC'd by a different method (manual, NOAA-QC, and RONIN).

5. Calculate and analyze performance statistics for both RONIN and NOAA-QC.

a. Neighbour et al. (2024) created Python scripts to generate statistics (specifically, NMD filtering rate and MD retention rate) on the performance of NOAA-QC as a comparison to manual-QC. This assumes that the manually edited data is "ground-truth" and that there was no human error in the QC process.

b. Using the list of training sweeps from Colorado State University, remove the sweeps used to train the model from all datasets. This way, RONIN will be evaluated solely on how it QC's data it has not yet seen.

c. Match the NOAA-QC and RONIN sweeps to ensure a direct comparison for each case.

d. Using these Python scripts, generate performance statistics for both NOAA-QC and RONIN, for each case and for all cases combined. These statistics are found using the following equations:

$$hit\,rate = 100 * \frac{TP}{NMD_{tot}}$$

$$miss\,rate = 100 * \frac{FN}{NMD_{tot}}$$

$$false\,positive\ =\ 100\ *\ \frac{FP}{MD_{tot}}$$

where tot_NMD (tot_MD) is the total amount of NMD (MD) in the sweep (defined by the manually edited data), TP is true positive (NMD correctly removed by the QC method), FN is false negative (NMD incorrectly kept by QC), and FP is false positive (MD incorrectly removed by QC).

i. Note that in this study, hit rate is referred to as NMD removal rate and false positive is referred to as MD removal rate for clarity. Miss rate is not discussed as it is equal to one hundred minus the hit rate.

e. Use these statistics to assess how RONIN quantitatively performs in comparison to NOAA-QC on a case-by-case basis.

6. Use SOLO3 to view the individual TDR sweeps from both the RONIN and NOAA-QC datasets for each case. Qualitatively compare how RONIN and NOAA-QC perform on an individual sweep by sweep basis, documenting areas of importance or significant contrast.

Research Question #2

How does using RONIN to QC TDR data affect TDR-derived analyses when compared to analyses from data QC'd by NOAA-QC?

Here, we will be focusing on all TC cases during 2022-24 where TDR data was collected.

1. Download John Gamache's 3D wind analysis software (NOAA-Synthesis), NASA's Panoply, AOML's jobfile editing software, and all necessary dependencies. Install and compile software.

2. Using flight paths from Tropical Atlantic and the Level 2 processing log from Paul Reasor, investigate all 2024 cases and select a group of cases with different reprocessing needs and intensity (tropical storm, minor hurricane, and major hurricane).
3. Download the raw TDR data for the selected 2024 cases and prepare the data to be QC'd by RONIN by following steps 2a to 3 from Research Question #1. Also download the matching operational jobfiles for each case.
4. Use RONIN to QC the data for each case by following steps 4a-b from Research Question #1. This will create a dataset of selected 2024 TCs that have been QC'd by RONIN. Move the data to the model run subdirectory of NOAA-Synthesis.
5. Use the jobfile editing software to adjust the start and end times of each case to be within the time range of its matching RONIN dataset. Also remove 0.5 from the azimuth angle corrections. Export each zipped jobfile to the case-specific model run subdirectory of NOAA-Synthesis, then unzip.
6. Create a text file within the NOAA-Synthesis run subdirectory that will direct the software to the location of the RONIN-QC'd CfRadials.
7. Run the RONIN 2024 dataset through NOAA-Synthesis.
8. Download the TDR-derived real-time (NOAA-QC'd) analyses for each case from the AOC public server.
9. Use Panoply to map both QC methods for each individual case on an earth-relative frame of reference at different heights above sea level.
10. Compare the RONIN TDR analyses to the real-time analyses for each case, and document in detail the similarities and differences. Pay extra attention to the cases that had NMD contamination in the real-time analyses. If needed, use SOLO3 to view the

QC'd Dorade files for each QC method to determine performance regarding NMD removal and MD retention.

11. Graph the NMD filtering and MD retention rates as a function of height (as in Neighbour et al. (2024)) for each case to compare how RONIN and NOAA-QC perform at different height levels within the TCs of interest.

The Cases Used in this Study

The cases we chose to answer Research Question #1 were selected because we had the manually edited data accessible from earlier research, they contained NMD in the 3D wind analyses or presented problems during Level 2 reprocessing, and they provided a variety in terms of intensity and environment. These four cases are:

- Earl (flight 20220907H1, leg 125303-132518 UTC): At the time of this flight, Earl was classified as a Category 1 Hurricane and was located over the Atlantic Ocean east of The Bahamas. The leg in question traverses from the northeast to the southwest and crosses through the center of rotation around 1307 UTC.
- Fiona (flight 20220918H1, leg 123041-125227 UTC): During this flight, Fiona was classified as a Tropical Storm, and will therefore be represented as Tropical Storm Fiona in this research. At this time, Fiona was located in the Caribbean Sea just south of Puerto Rico. The leg in question is outbound from the center heading northwest.
- Lee (flight 20230912I1, leg 124223-132940 UTC): At the time of this flight, Lee was classified as a Category 3 Hurricane and was located over the Atlantic Ocean east of The Bahamas. The leg in question traverses from east northeast to west southwest and crosses through the center of rotation at around 1309 UTC.

- Beryl (flight 20240705H1, leg 222200-224400 UTC): During this flight, Beryl was classified as a Tropical Storm, and will therefore be represented as Tropical Storm Beryl in this research. At this time, Beryl was just entering the Gulf of Mexico after crossing through the Yucatan Peninsula. The leg in question is outbound from the center and traverses over land through clear air (where NOAA-QC particularly struggles) heading south.

The cases selected for Research Question #2 were guided by the National Hurricane Center (NHC), as they wanted to see RONIN applied to several recent (2024) cases with a variety of intensities and reprocessing needs. We selected six cases from 2024 to be used to answer Research Question #2.

- Debby (flight 20240804H1, leg 123558-135709 UTC): Debby was classified as a Tropical Storm during this flight, and was located in the Gulf of Mexico west of Florida. The leg heads west for the downwind, then turns and goes southeast for the inbound/outbound, crossing the center of rotation at 1329 UTC. This case did not need any additional reprocessing for Level 2.
- Ernesto (flight 20240813H1, leg 214515-225419 UTC): At the time of this flight, Ernesto was classified as a Tropical Storm and was located over the Virgin Islands. The leg in question traverses towards the southeast, then turns and heads north for the inbound/outbound, crossing the center of rotation at 2231 UTC. Because the aircraft flew right over multiple islands during this leg, the data needed some reprocessing for Level 2. This also involved the removal of the downwind leg, which was problematic in the reprocessing process.

- Helene (flight 20240925H1, leg 242800-253640 UTC): During this flight, Helene was a Category 1 Hurricane and was located in the Gulf of Mexico northeast of the Yucatan and west of Cuba. The leg traverses towards the south southeast for the downwind, then turns towards the northeast for the inbound/outbound, crossing the center of rotation at 2511 UTC. This case did not need any reprocessing for Level 2.
- Rafael (flight 20241106H2, leg 212500-222345 UTC): Rafael was classified as a Category 2 Hurricane during the time of this flight and was located over northwestern Cuba. The leg traverses south directly over mainland Cuba and La Isla de Juventud, crossing the center of rotation at 2152 UTC. Because the aircraft flew directly over land, the data needed reprocessing and an adjustment to the end time to fix the resulting noise for Level 2.
- Beryl (flight 20240702H1, leg 250640-263700 UTC): At the time of this flight, Beryl was classified as a Category 4 Hurricane and was located in the Caribbean Sea south of Hispaniola. The leg in question heads downwind towards the west southwest, then turns and goes southeast for the inbound/outbound, crossing the center of rotation at 2558 UTC. This case did not need any reprocessing for Level 2.
- Helene (flight 20240926I1, leg 095214-111021 UTC): During this flight, Helene was a Category 1 Hurricane located in the Gulf of Mexico northwest of Cuba and west of the Florida Keys. The leg heads downwind towards the south, then turns and traverses west for the inbound/outbound, crossing the center of rotation at 1042 UTC. This case needed some reprocessing due to some noise in reflectivity, and the downwind leg was removed for Level 2.

CHAPTER 7

RESULTS

All Cases

	% NMD removed	% MD removed
NOAA-QC	98.70%	27.10%
MLQC	99.05%	9.11%

		% NMD removed	% MD removed
Earl 20220907H1	NOAA-QC	99.72%	31.25%
	MLQC	99.26%	11.81%
Fiona 20220918H1	NOAA-QC	99.66%	26.25%
	MLQC	98.63%	6.24%
Lee 20230912I1	NOAA-QC	99.49%	23.73%
	MLQC	98.52%	8.73%
Beryl 20240705H1	NOAA-QC	96.17%	36.76%
	MLQC	99.72%	15.86%

Figure 13: *Performance statistics for both NOAA-QC and RONIN (MLQC), calculated on the non-training sweeps for Hurricane Earl (2022), Tropical Storm Fiona (2022), Hurricane Lee (2023), and Tropical Storm Beryl (2024).*

The performance statistics for both NOAA-QC and RONIN were calculated for each case individually and for all four cases combined (see Figure 13). Since Lee, Fiona, and Earl were average cases for NOAA-QC, it performed as expected with around a 99.6% NMD removal rate and over a quarter of MD removed as well. For these three cases, RONIN significantly increased the amount of MD retained, from 11.81% MD removal with Earl down to 6.84% for Fiona. However, RONIN was slightly less accurate in removing NMD for Earl, Fiona, and Lee, having an average NMD removal rate of just under 99%.

On the other hand, Beryl is a different story. Beryl was specifically included because we were curious to see how RONIN would perform in a situation where NOAA-QC is known to fail: clear air over land. As was expected, NOAA-QC was the least effective for Beryl out of all four cases, with an NMD removal rate of 96.17% and an MD removal rate of almost 37%. Unlike NOAA-QC, RONIN was able to adapt to the significant change in environment and was quite successful. As a result, using RONIN on the Beryl case caused an increase in both NMD removal and MD retention. Therefore, the combined statistics for all four cases illustrate that using RONIN leads to improved overall accuracy in removing NMD and retaining MD. Obviously, this is not true for all four cases individually, and will likely not be true for the majority of TDR data. However, RONIN's ability to pivot on a case-by-case basis demonstrates that nearly all cases will likely see an increase in MD retention when RONIN is the QC method.

We also compared individual sweeps QC'd with NOAA-QC and RONIN to determine where the main differences are located on a radar-relative frame of reference. Figure 14 shows a comparison of a sweep from Lee QC'd with NOAA-QC (top) and RONIN (bottom). In a

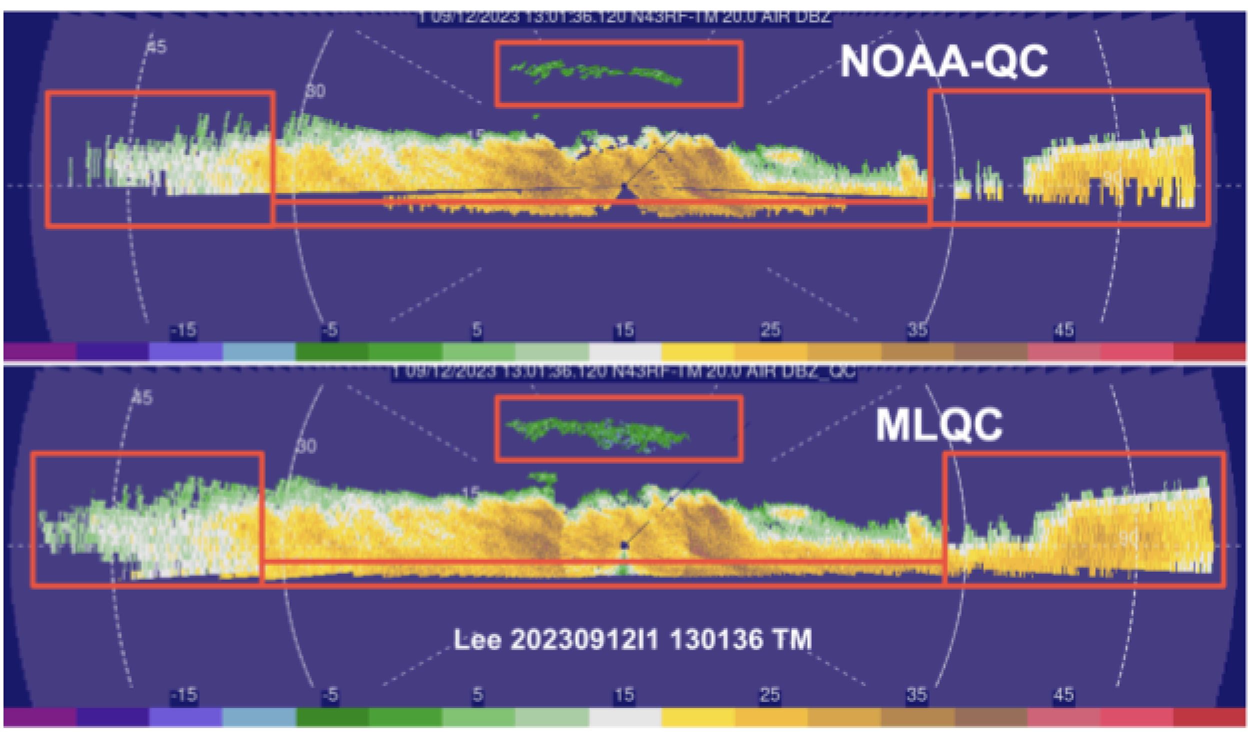


Figure 14: A comparison of a fore sweep from Lee 20230912I1, QC'd by both NOAA-QC (top) and RONIN (MLQC, bottom). The data is shown as a vertical radar scan on a polar coordinate system with the TDR as the center. The red boxes show the areas with the greatest changes: the TCBL, outflow, and areas further from the radar.

comparison between the two, there doesn't seem to be a significant difference in NMD retained. The main improvement with RONIN, on the other hand, is the significant increase in MD. The main additions of MD are located in the TCBL (bottom box), TC outflow (top box), and areas further away from the radar (two side boxes). There are also improvements in the filling of gaps within the MD left by NOAA-QC when QC'ing with RONIN.

The most crucial aspect of this research is how a difference in QC will affect the TDR-derived analyses and structure. As a sanity check, we created the 3D wind analyses using NOAA-Synthesis for all four cases used to answer Research Question #1. While the results were positive in terms of more MD retention (see Figure 15), because it is impossible to create the analyses without the sweeps used to train RONIN, we are unable to use these results to make any definitive conclusions on how RONIN using RONIN to QC TDR data will affect TC structure. Therefore, in collaboration with NHC, we selected six new cases, all from 2024, to answer Research Question #2. For simplicity, we will only be presenting the analyses at four height levels: TCBL (0.5-5 km), flight level (3 km), midlevel (7 km), and outflow (12-14 km).

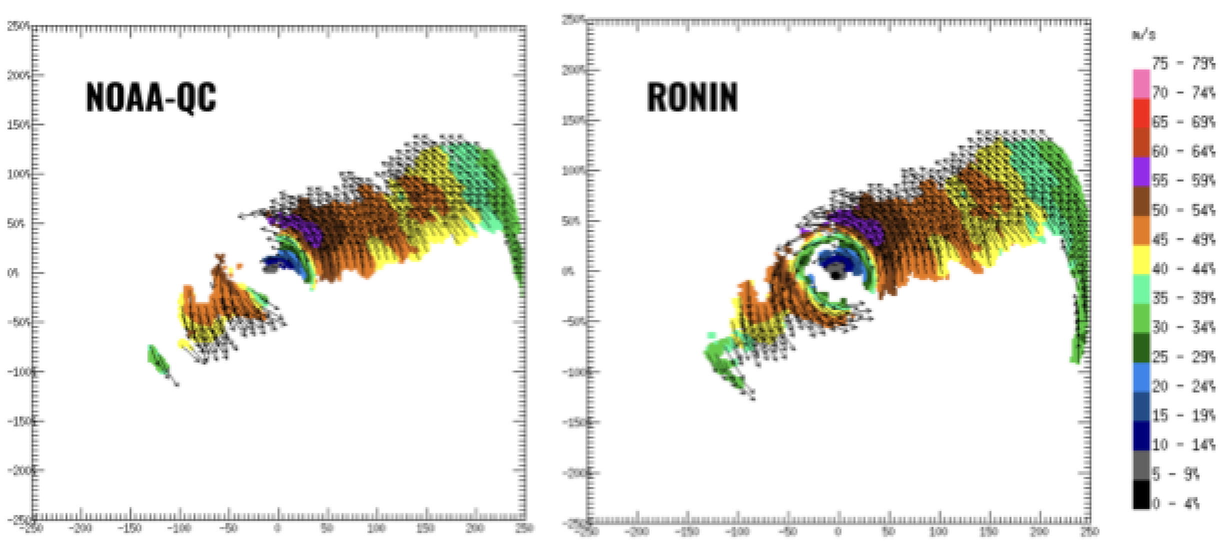


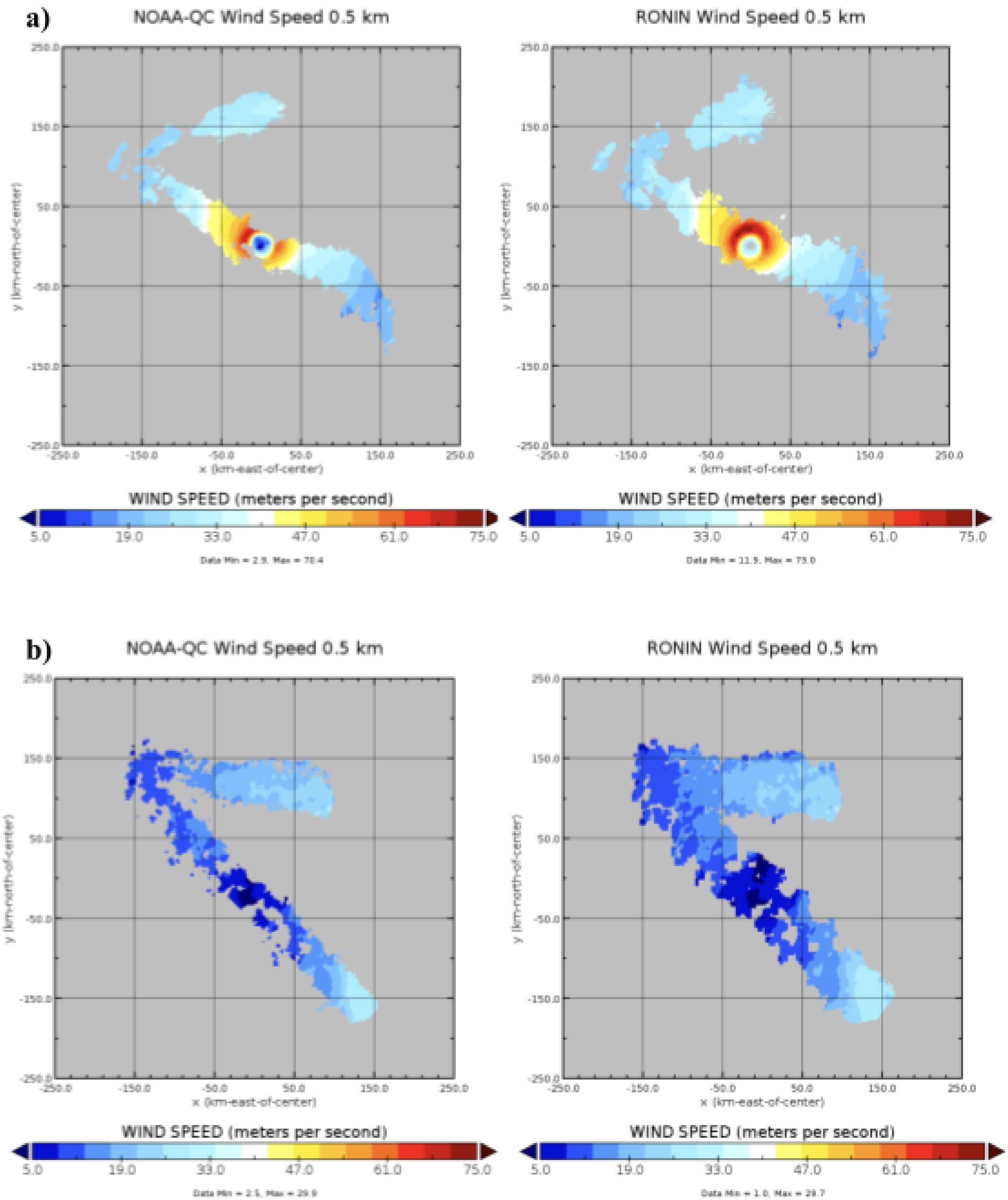
Figure 15: *A comparison of 1 km winds from analyses created from NOAA-QC'd and RONIN-QC'd data for Lee (2023091211). RONIN shows significantly more of Lee's eyewall. However, since RONIN has seen some of this data already, we cannot use this to make any conclusions.*

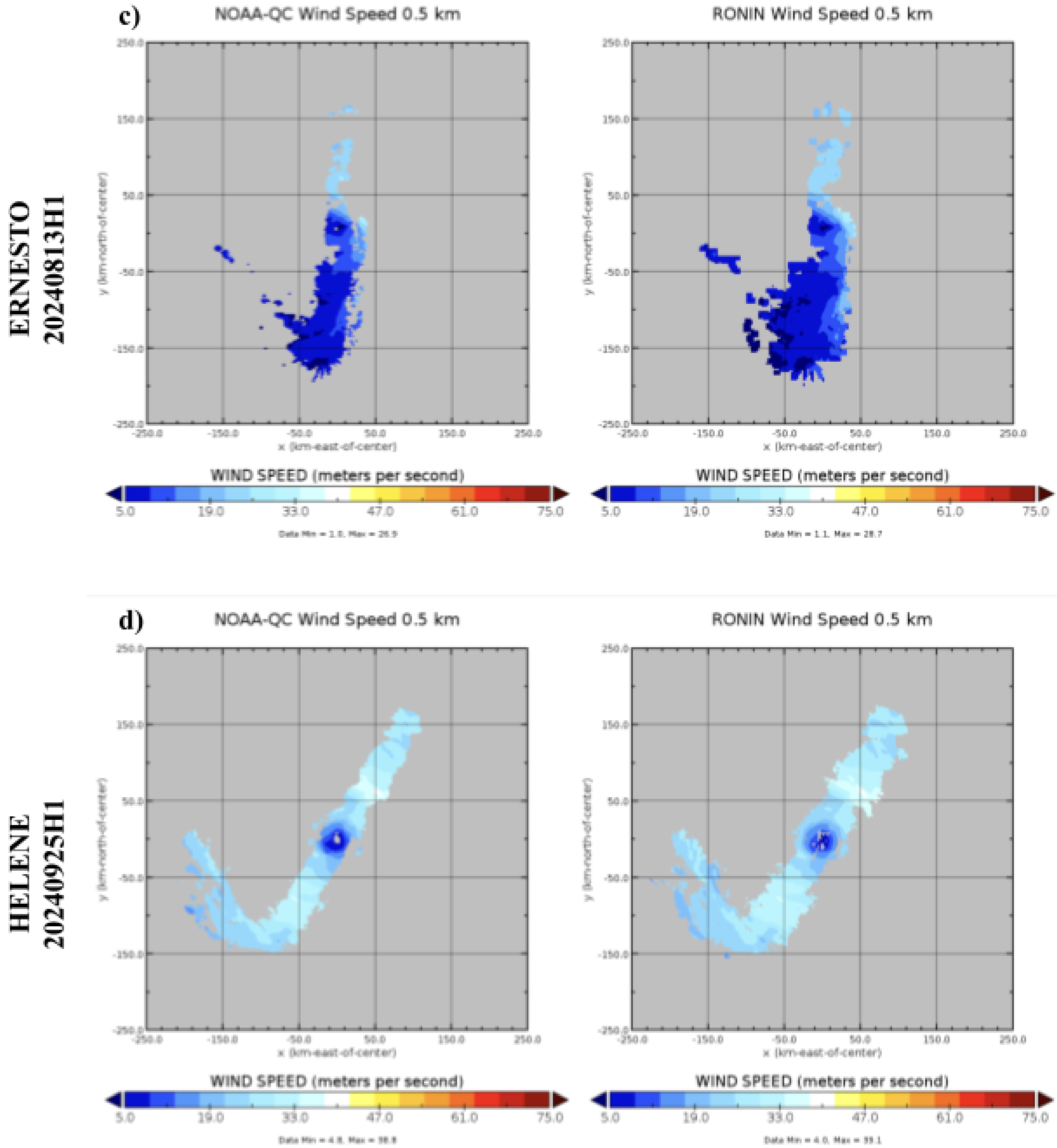
As expected from looking at the individual sweeps, some of the greatest differences between NOAA-QC and RONIN in the analyses are within the TCBL (see Figure 16). The main improvement with RONIN is the significant increase in coverage of MD. This is shown through the closure of gaps within the MD and the increase in data further away from the flight track. More importantly, we are seeing a significant increase in coverage in crucial areas of the TC. For example, Figure 16a is a comparison of NOAA-QC and RONIN analyses for Beryl at 0.5 km. The 0.5 km RONIN analysis has significantly improved coverage around the eyewall of Beryl, which also allows us to see the 0.5 km wind maxima (something we are unable to see in the NOAA-QC analysis). This will likely prove crucial to forecasters as it will provide much more information on circulation and inflow structure, which also may help them predict/understand the possible impacts to society for when the TC in question makes landfall.

Flight level (3 km) to mid-level (7 km) is usually where we see the greatest coverage in TDR data (see Figures 17 & 18). Since hydrometeors in this area are closer to the radar and don't experience surface contamination, these levels often contain the most amount of MD retained by QC. Therefore, there were not significant improvements in data coverage in areas further away from the radar, as was with the boundary layer analyses. Instead, the main benefit is improved coverage of gaps within the analysis. It seems that RONIN is less aggressive at removing MD and is able to better discern the difference between MD and NMD with diminished return signals (such as at the ends of convection or smaller convective cells). The filling of these gaps by RONIN continues to allow for improved insight into a TC's activity and structure. For example, RONIN's improved coverage of Beryl's eyewall depicts a more accurate image of the TC's wind maxima at different heights (including up to the mid-levels), allowing for a better understanding of Beryl's structure and evolution (see Figures 17-18a).

BERYL
20240702H1

DEBBY
20240804H1




c)
ERNESTO
20240813H1
NOAA-QC Wind Speed 0.5 km
RONIN Wind Speed 0.5 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0
d)
HELENE
20240925H1
NOAA-QC Wind Speed 0.5 km
RONIN Wind Speed 0.5 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0

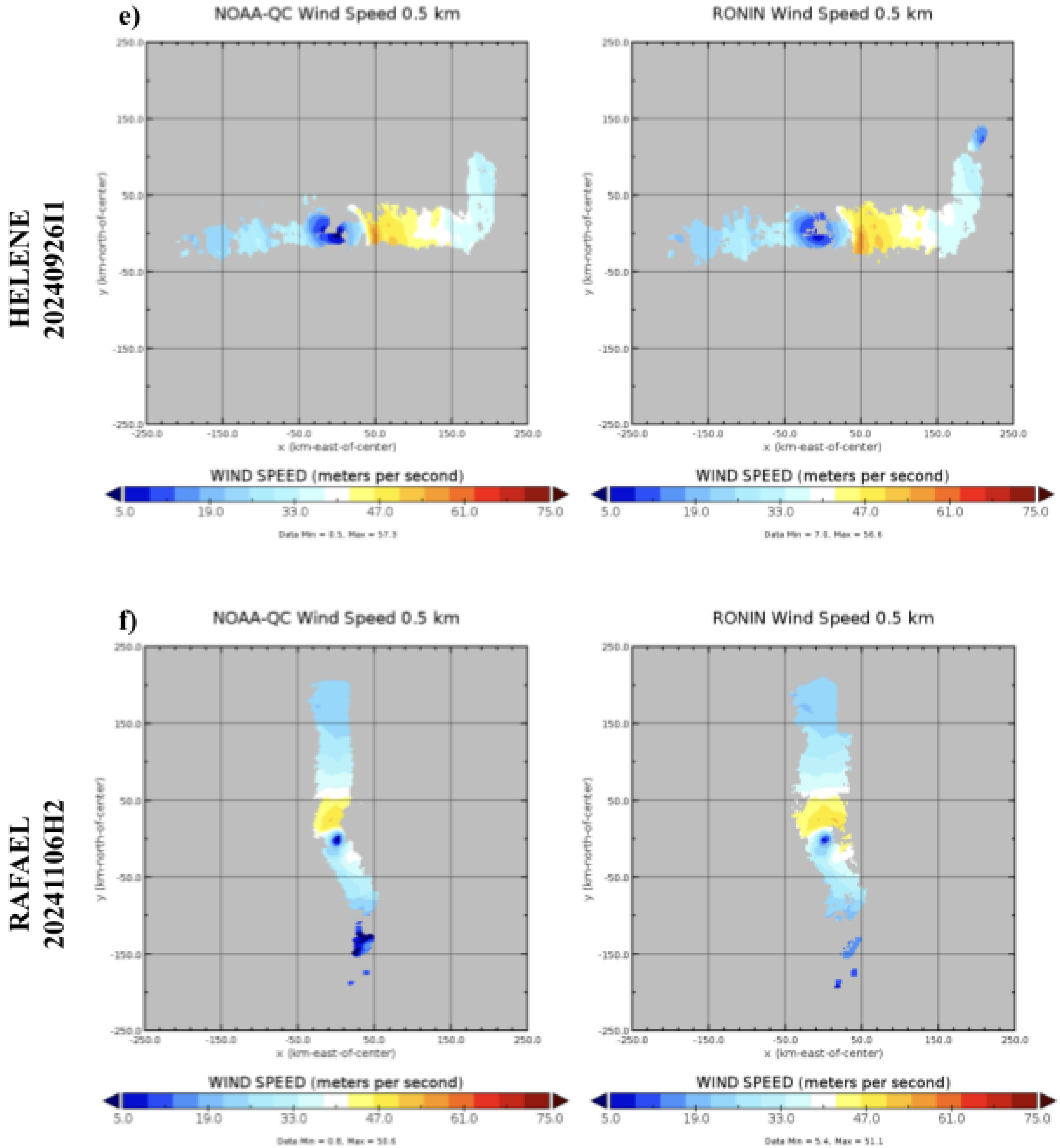
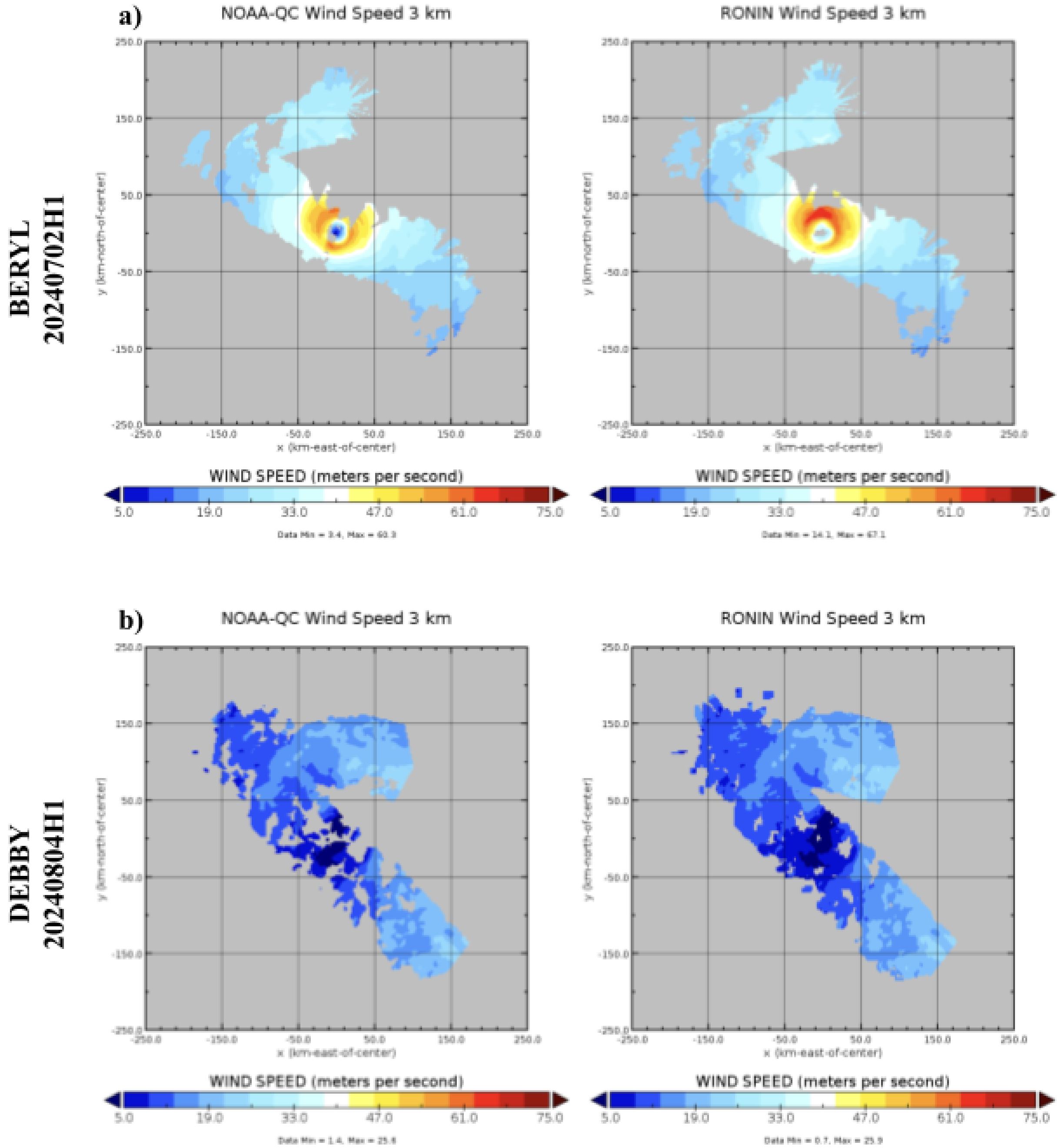
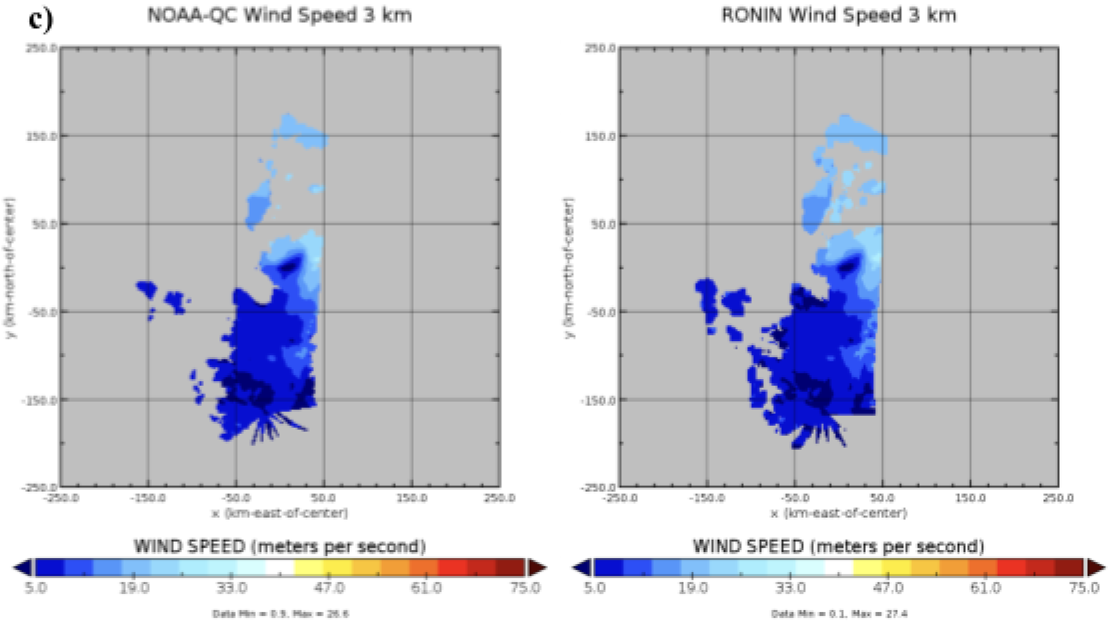


Figure 16: *0.5 km analyses derived from NOAA-QC'd (left) and RONIN-QC'd (right) for all six cases: Beryl 20240702H1 (a), Debby 20240804H1 (b), Ernesto 20240813H1 (c), Helene 20240925H1 (d), Helene 20240926I1 (e), and Rafael 20241106H2 (f).*


a)
BERYL
20240702H1
NOAA-QC Wind Speed 3 km
RONIN Wind Speed 3 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0
b)
DEBBY
20240804H1
NOAA-QC Wind Speed 3 km
RONIN Wind Speed 3 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)

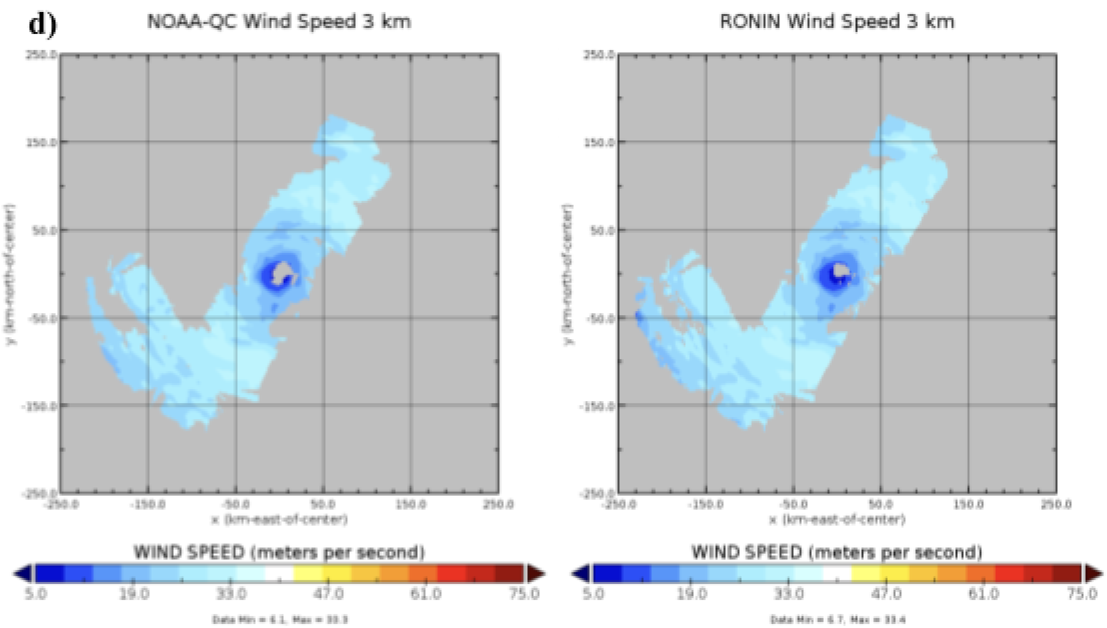
ERNESTO
20240813H1

c)



HELENE
20240925H1

d)



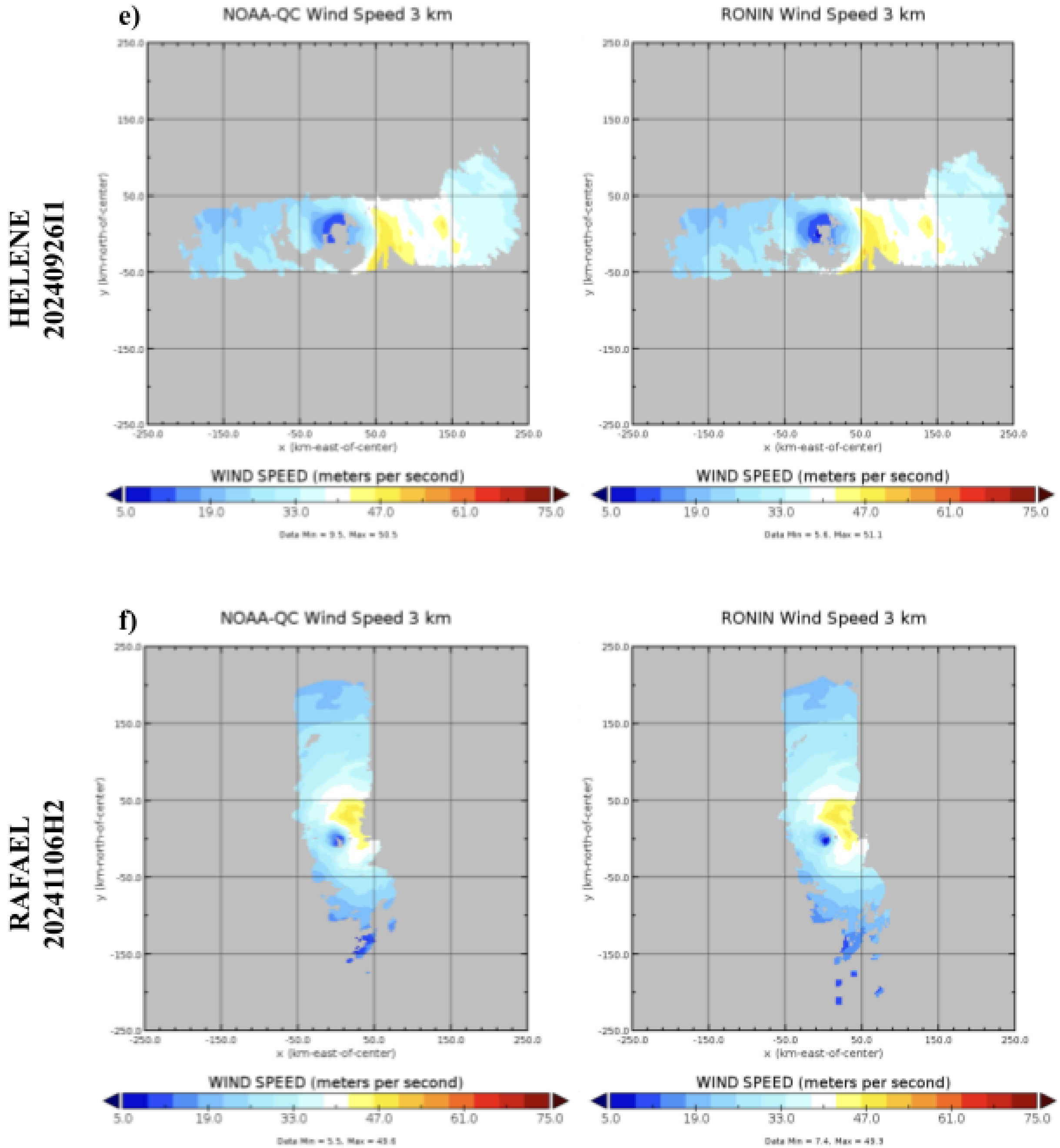
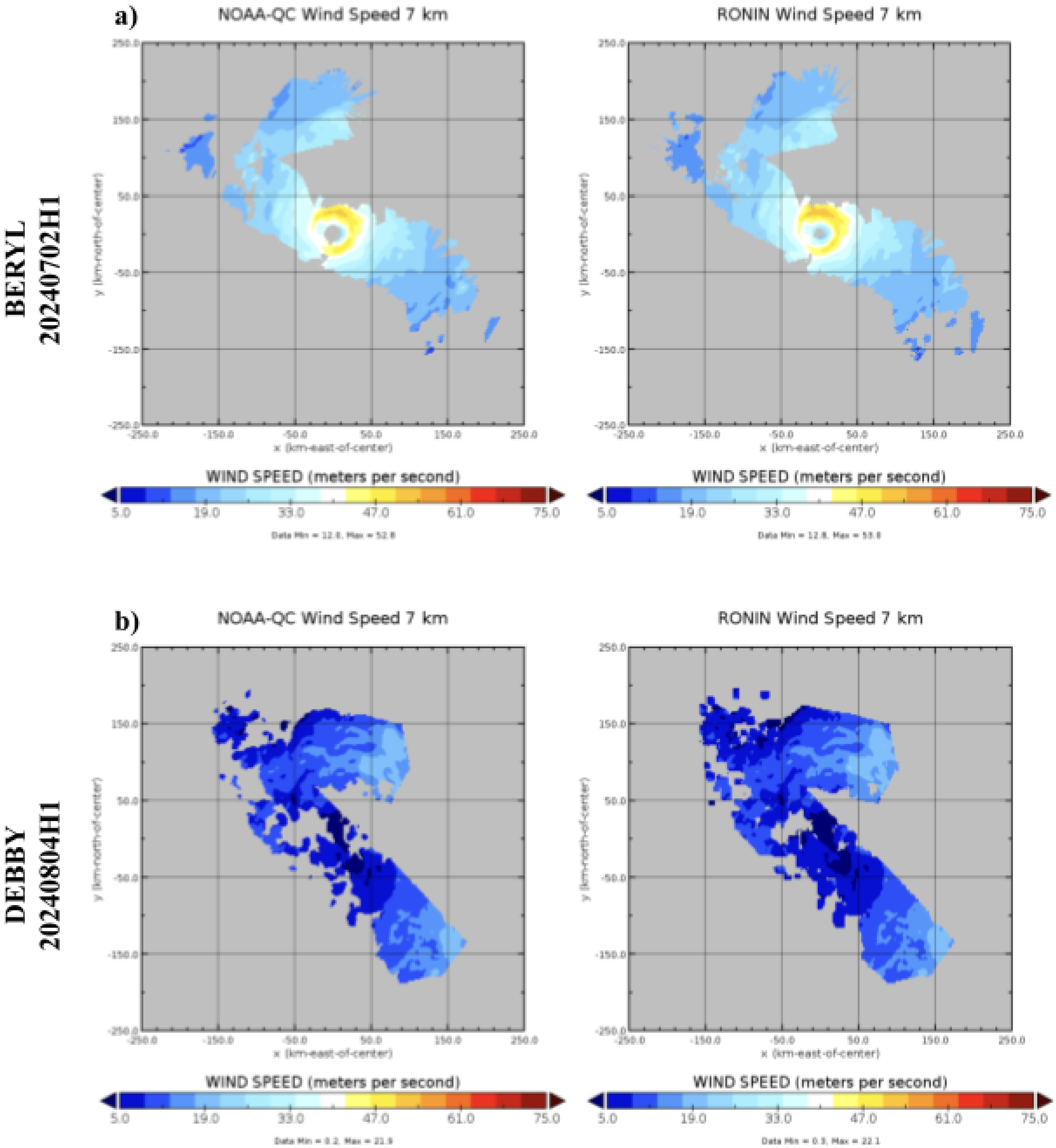
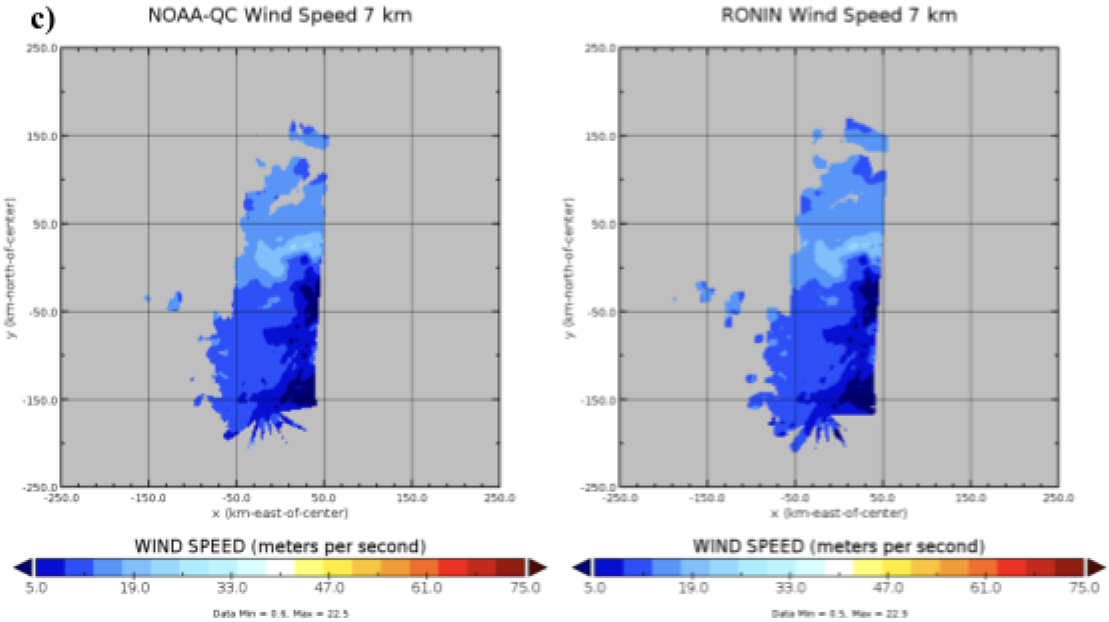


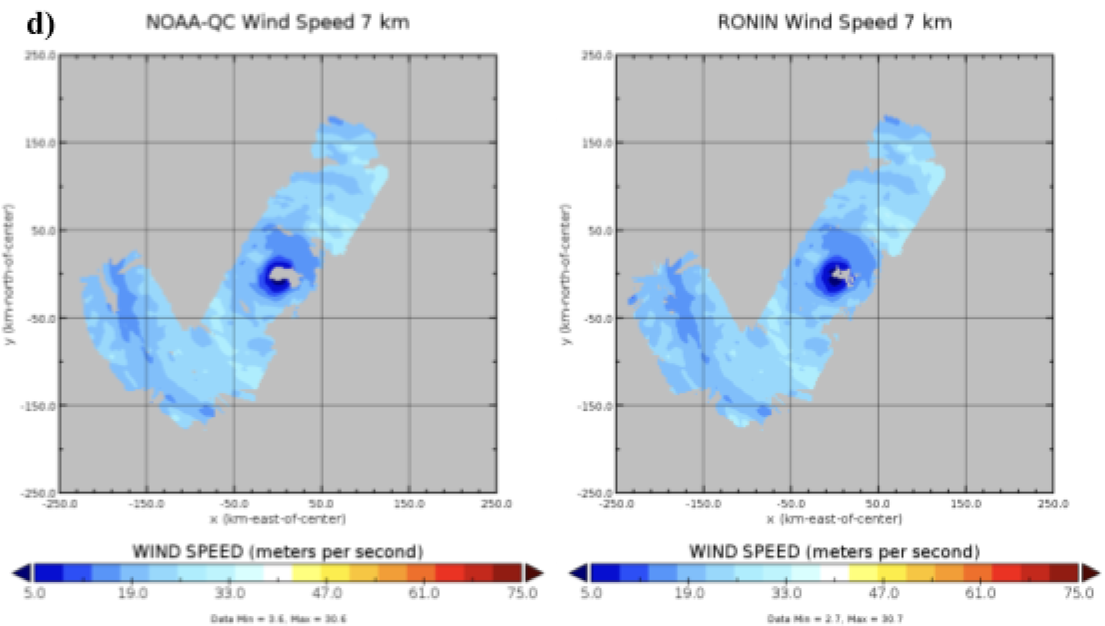
Figure 17: *3 km analyses derived from NOAA-QC'd (left) and RONIN-QC'd (right) for all six cases: Beryl 20240702H1 (a), Debby 20240804H1 (b), Ernesto 20240813H1 (c), Helene 20240925H1 (d), Helene 20240926I1 (e), and Rafael 20241106H2 (f).*


BERYL
20240702H1
a)
NOAA-QC Wind Speed 7 km
RONIN Wind Speed 7 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0
DEBBY
20240804H1
b)
NOAA-QC Wind Speed 7 km
RONIN Wind Speed 7 km
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0

ERNESTO
20240813H1



HELENE
20240925H1



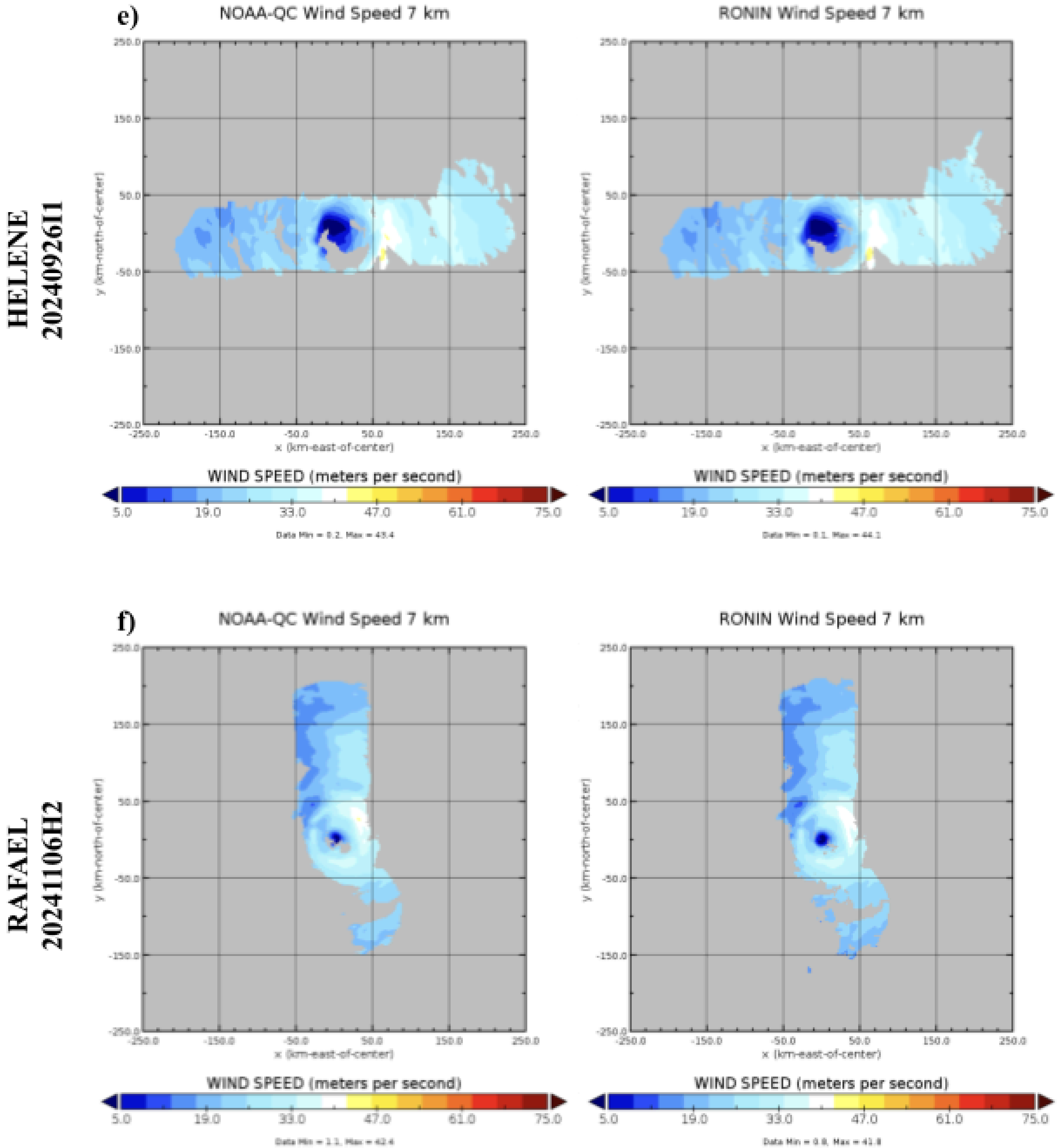
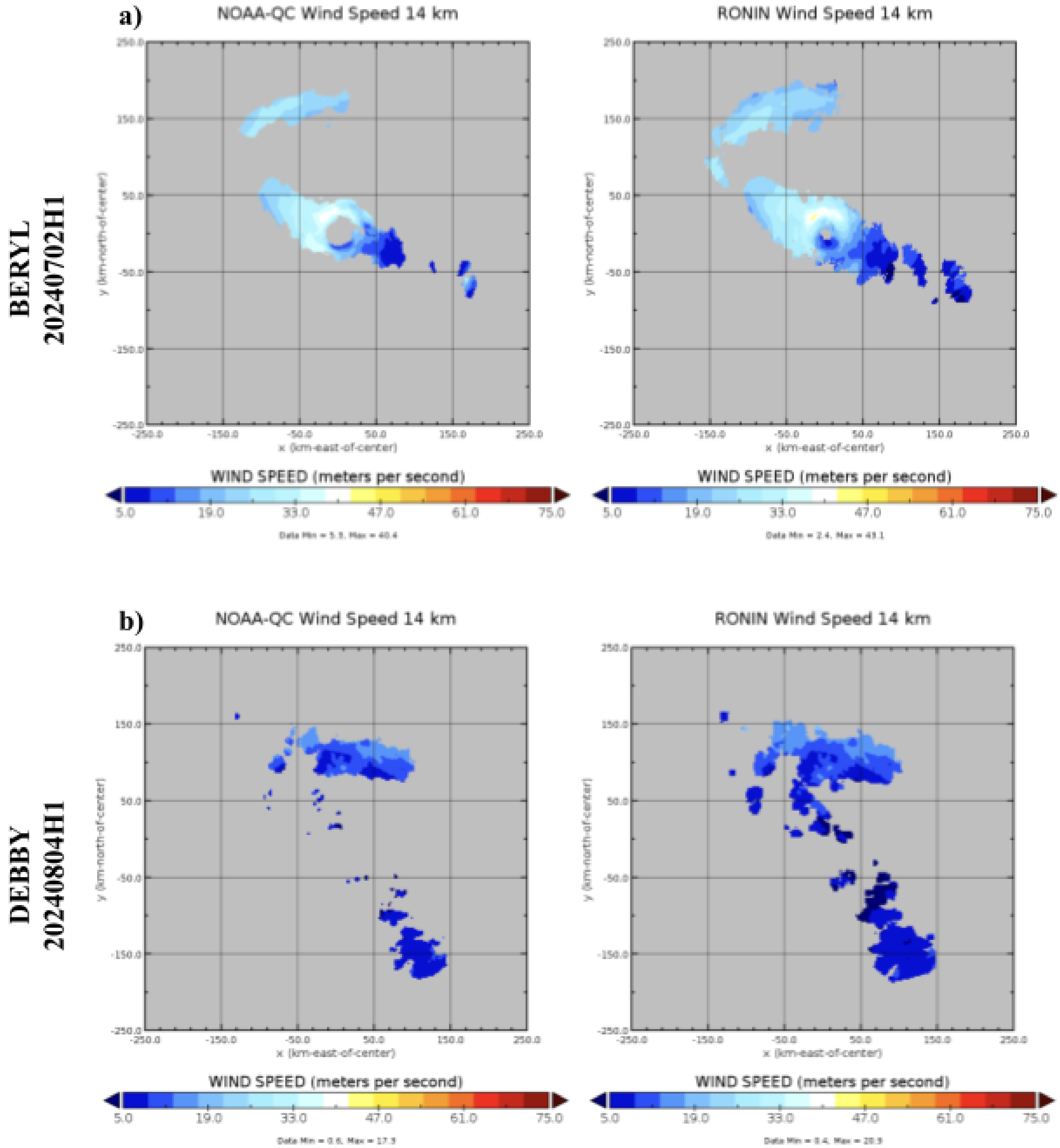
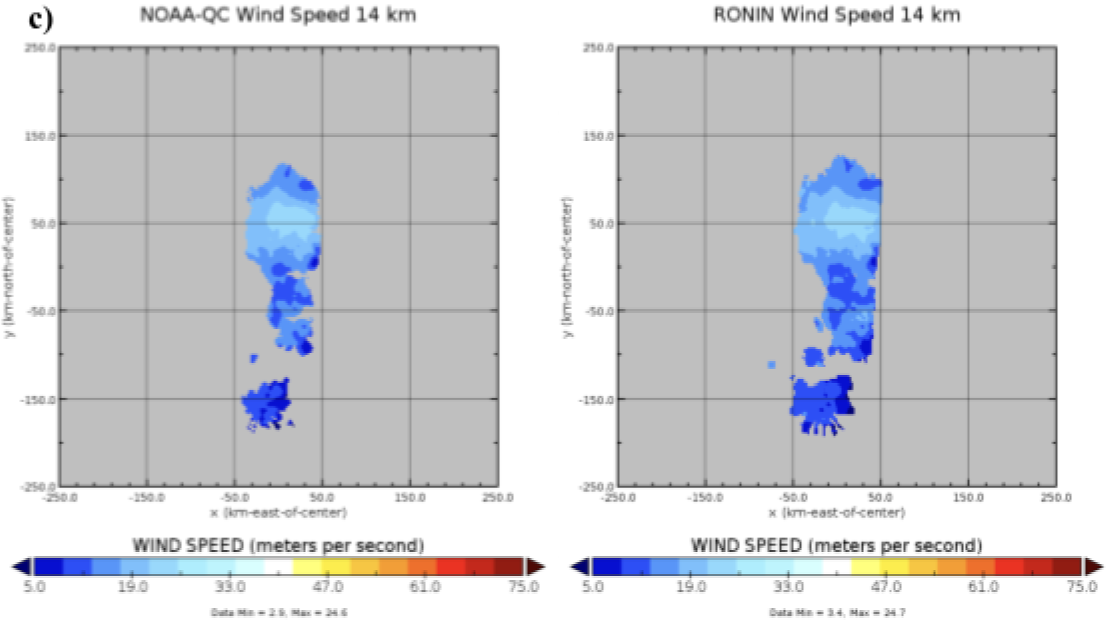


Figure 18: *7 km analyses derived from NOAA-QC'd (left) and RONIN-QC'd (right) for all six cases: Beryl 20240702H1 (a), Debby 20240804H1 (b), Ernesto 20240813H1 (c), Helene 20240925H1 (d), Helene 20240926I1 (e), and Rafael 20241106H2 (f).*


a)
NOAA-QC Wind Speed 14 km
RONIN Wind Speed 14 km
BERYL
20240702H1
b)
NOAA-QC Wind Speed 14 km
RONIN Wind Speed 14 km
DEBBY
20240804H1
y (km-north-of-center)
x (km-east-of-center)
WIND SPEED (meters per second)
5.0
19.0
33.0
47.0
61.0
75.0

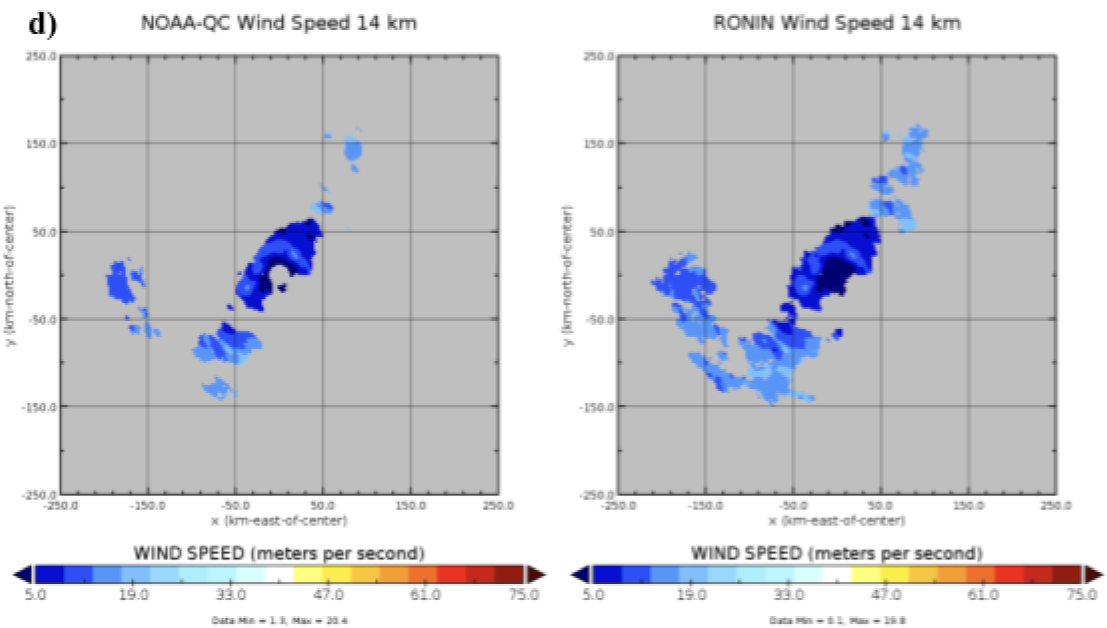
c)

ERNESTO 20240813H1



d)

HELENE 20240925H1



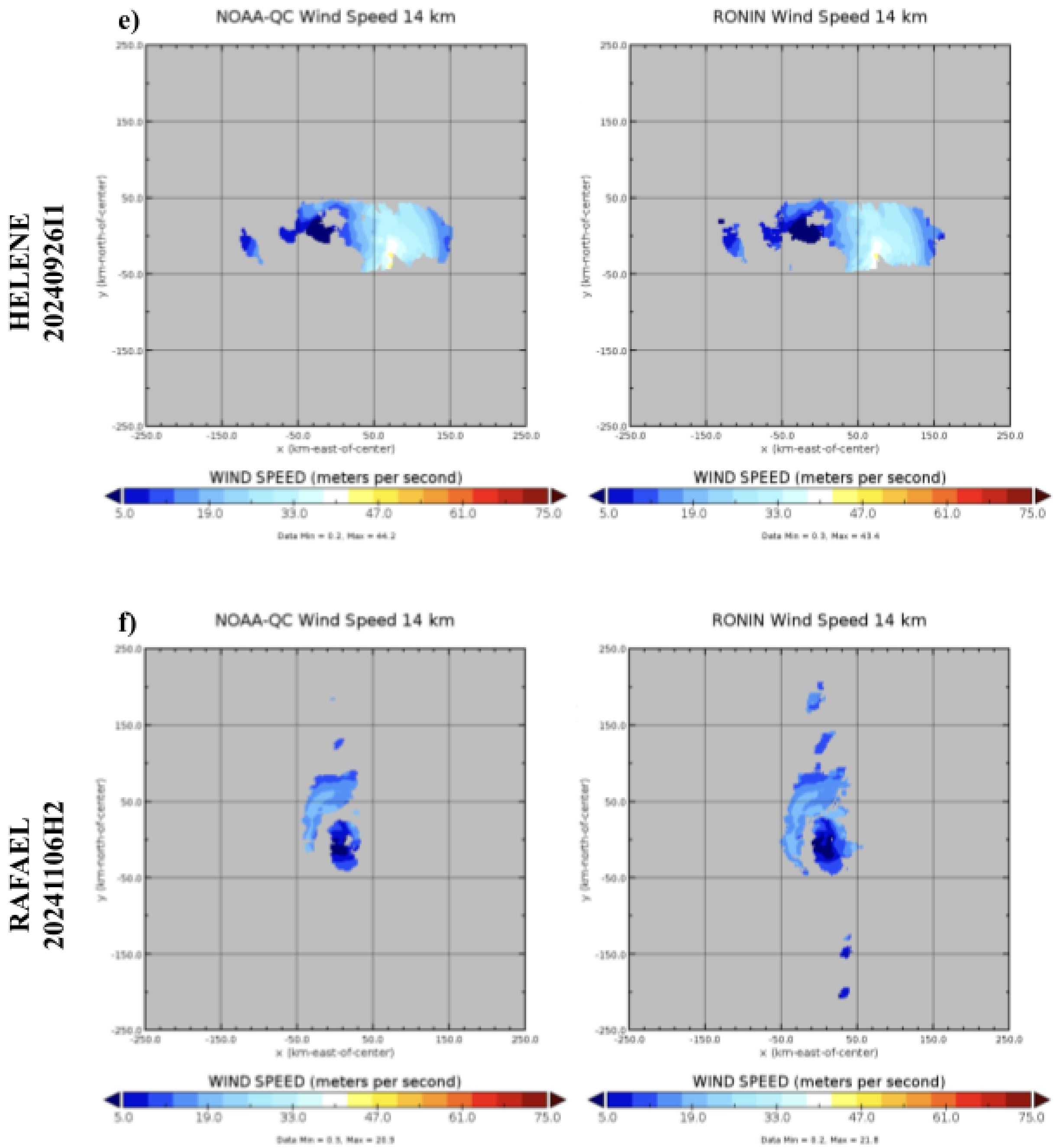


Figure 19: *14 km analyses derived from NOAA-QC'd (left) and RONIN-QC'd (right) for all six cases: Beryl 20240702H1 (a), Debby 20240804H1 (b), Ernesto 20240813H1 (c), Helene 20240925H1 (d), Helene 20240926I1 (e), and Rafael 20241106H2 (f).*

Understanding of a TC's outflow layer is crucial to TC research, as it provides a key to improving our overall knowledge of structure and flow (Rappin et al. 2011). Neighbour et al. (2024) concluded that NOAA-QC has the highest percentage of data removal in the outflow layer. This is likely because outflow convection is often cirrus in nature, which produces smaller returns on a radar (as a reminder, NOAA-QC's mask filters out gates that don't meet or exceed a certain reflectivity value). Outflow data on a WP-3D TDR is usually scarce, so any loss in MD has more of an impact than it would at other levels. RONIN, on the other hand, is able to recognize that smaller return values in the outflow don't always correlate with NMD (see Figure 19). This leads to significantly improved coverage in the outflow analyses, including areas that NOAA-QC originally removed completely.

Another important improvement with RONIN is the location of retained NMD in the analyses. Although it was shown previously that RONIN is slightly less accurate in removing NMD, it seems that less NMD is infiltrating the RONIN analyses compared to those from NOAA-QC'd data. One example of this is the 1 km Rafael analysis (see Figure 20). As a reminder, due to the aircraft flying over land, Rafael had some NMD present in the

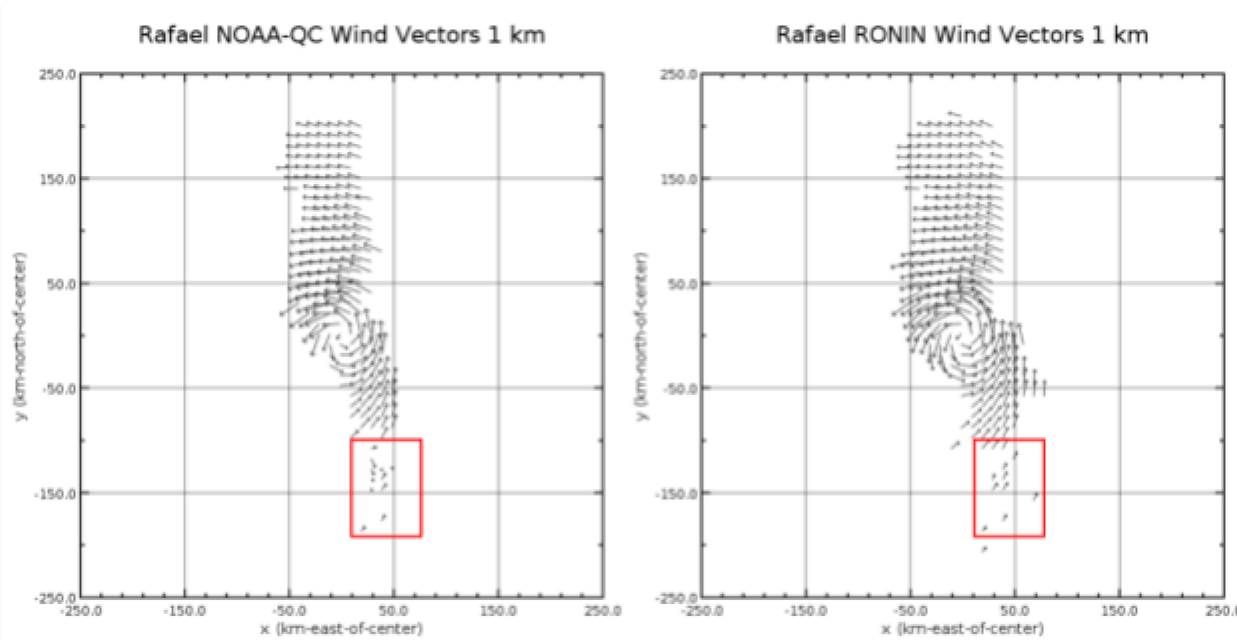


Figure 20: *14 km analysis wind vectors derived from NOAA-QC'd (left) and RONIN-QC'd (right) for Rafael 20241106H2. The red box on the left shows NMD retained by NOAA-QC. The red box on the right depicts the same area in the RONIN analysis, but RONIN was able to recognize and remove the NMD in question.*

NOAA-QC'd, real-time analysis. The NMD in velocity is present in the 1 km wind vectors (highlighted in the box), likely due to the influence of La Isla de Juventud. On the other hand, the RONIN analysis doesn't have visible NMD infiltration. For these cases, the NMD being retained by RONIN is in less crucial locations in the RONIN-QC'd analyses.

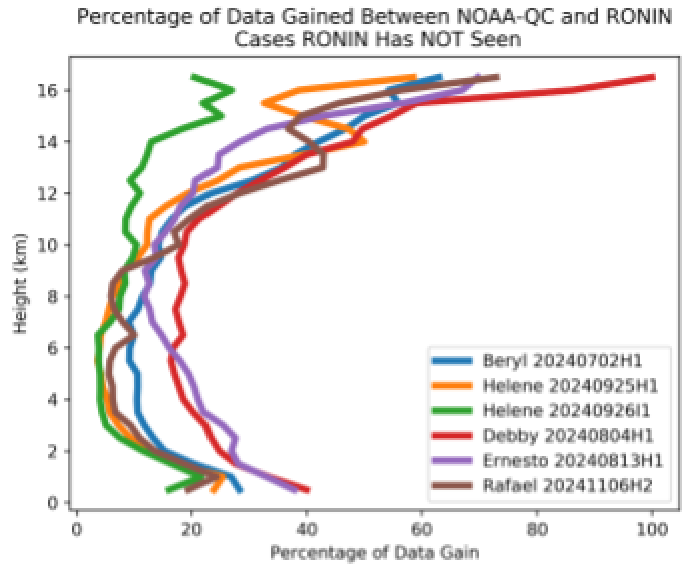


Figure 21: *Percentage of data gained with height in 3D analyses when using RONIN over NOAA-QC.*

Finally, we graphed the change in data coverage between the two QC methods' analyses with height to show the impact that the increased coverage has at different height levels (see Figure 21). It is apparent that all six cases see an increase in data coverage at all height levels when RONIN is used to QC the TDR data. The two cases that saw the largest increase in coverage were the Tropical Storms: Debby and Ernesto. This is likely because NOAA-QC's mask does not perform as well with less-organized TCs with lower reflectivity returns. This is a crucial result because the development stages of TCs are the most difficult to predict, particularly due to their chaotic, ill-defined structure (Nguyen & Kieu 2024). Dramatically improved MD coverage at all levels within earlier stage TCs will likely improve the derived structure and circulation cores. Having more accurate information on structure for early development TCs would provide more useful data for assimilation into forecasting models and to forecasters.

CHAPTER 8

DISCUSSION

While the use of airborne radar in TCs is relatively new, it has provided the world of tropical meteorology with invaluable knowledge and improved understanding of TC structure, flow, and evolution. Therefore, any increase in MD coverage without further NMD infiltration would prove to be a significant improvement to TC researchers and forecasters. For example, forecasters at NHC rely on TDR data for both forecasting and nowcasting. Having access to improved TDR-derived analyses and data would help them make more accurate classifications, better understand how a TC is evolving or how it may impact society, and improve both short-term and long-term predictions of TCs. TDR data has also shown to be a crucial tool in TC research. We expect that improved coverage of MD within TDR data and analyses, especially within the TCBL and outflow, will allow researchers to further our knowledge of TC structure and processes. Especially with TDR radar being easily accessible to the public through TC-RADAR (Fischer et al. 2022), reprocessing the data within TC-RADAR with RONIN will allow for all TC researchers across the globe to use the improved TDR data.

There are, however, some limitations of applications of this study. For example, there are some processes that RONIN may not improve coverage of. This includes ERCs. We included the 20240926I1 Helene case because at this time, NHC reported that Helene was completing an ERC. Shortly thereafter, the TC rapidly intensified to a Category 4 Hurricane (Hagen et al. 2025). Unfortunately, RONIN did not provide any improved coverage into the ERC process for the 095214-111021 UTC leg from this case (see Figure 16e). Considering that we have only analyzed one case for ERC coverage with RONIN, we are unable to make a conclusion until we have assessed both additional legs/flights from the Helene case in addition to other cases also undergoing ERC. We are hopeful that the improved MD coverage in the TCBL and outflow will provide necessary information on TC structure and flow to hurricane forecasting models that they can use to increase output accuracy. However, due to model limitations, TDR data is parsed down significantly before being assimilated into hurricane forecasting models, and there is always a possibility the model could reject the new data altogether.

We also expect that the improved MD coverage from RONIN will likely not significantly impact TDR-derived structural diagnostics, such as radially averaged flow. As structural diagnostics often involve taking the average of data along individual ranges, it only takes into account data that is already accessible. The only locations we are expecting to see any change, be it significant or not, would be in the TCBL and outflow. In the TCBL, the improved coverage of crucial areas of the TC, such as the wind maxima in the 20240702H1 Beryl case, may demonstrate itself through slightly more accurate results near the TCBL (however, we are still expecting to see the gap present when comparing studies like Fischer et al. 2022 and Zhang et al. 2023). The improved MD coverage in the outflow will at most slightly improve outflow coverage in structural diagnostics by providing data that originally wasn't present with those created by NOAA-QC'd TDR data.

The main limitation with this work has been the timeline. This research has been completed though UGA's DoubleDawgs Program, which is a five year bachelor/master's degree pathway. I was the first to attempt the DoubleDawgs in Atmospheric Sciences. Not only was my master's experience truncated, so was the timeline for this research. The basis for this study lay in my previous research as an undergraduate at AOML with Paul Reasor and John Gamache. The majority of the work completed for this thesis was done within six months. There were other avenues I wished I could have explored more, such as ERC coverage and structural diagnostics, but I was unable due to the time constraint. Another timeline constraint was with the manually edited data. As mentioned previously, manually editing TDR data is a long and tedious process. Due to my timeline, the manually edited data was provided to me. In an ideal situation, I would have had the time to manually edit some of my own data for inclusion in this study.

CHAPTER 9

CONCLUSIONS AND FUTURE WORK

The main goal of this study was to compare how applying different QC methods to TDR data affects our ability to derive TC structure. The two QC methods we compared were NOAA-QC, a rules-based method written in Fortran and has been operational on the WP-3Ds for nearly 20 years; and RONIN, a novel machine learning method written in Julia and trained on manually edited TDR data. This study aimed to answer two main questions: how does RONIN's performance compare to that of NOAA-QC, and how does using RONIN to QC TDR data affect TDR-derived analyses when compared to analyses from data QC'd by NOAA-QC?

Neighbour et al. (2024) discovered that NOAA-QC has an NMD removal rate above 99.5%, but it is aggressive, as it also removes around 30% MD. In order to compare these statistics with RONIN among a diverse array of cases, we utilized the methods from Neighbour et al. (2024) on Hurricane Earl (2022), Tropical Storm Fiona (2022), Hurricane Lee (2023), and Tropical Storm Beryl (2024). Over all four cases combined, RONIN has an NMD removal rate slightly less than that of NOAA-QC at 99.05%, yet a significantly lower MD removal rate at 9.11%. For these same cases, NOAA-QC performed as expected to Neighbour et al. (2024) with regards to the high MD removal rate, but the NMD detection was lower than usual. We rejected this to be a crucial finding due to the inclusion of Tropical Storm Beryl in these four cases, which NOAA-QC performed particularly poorly due to the environmental conditions. Upon comparing the results from all cases overall and the individual Tropical Storm Beryl case, we found that unlike NOAA-QC (which is one size fits all), RONIN is able to pivot for similar performance between various cases in differing environments. When we perused through the individual sweeps of NOAA-QC'd and RONIN-QC'd TDR data, we discovered that the main improvements in data coverage are within the TCBL, outflow, and areas further away from the radar.

In collaboration with NHC, we then selected six different cases from 2024, all cases that RONIN has never seen with varying intensities and data reprocessing needs, to create RONIN-QC'd TDR-derived 3-dimensional wind analyses using NOAA-Synthesis. We found that when using RONIN to create these TDR-derived analyses, data coverage increases immensely. Specifically, RONIN expands the range of analyses further away from the flight track, covers holes in the analyses, and provides improved coverage on crucial areas of the TC (such as the eyewall). While the majority of improvements were within the TCBL and outflow, we demonstrate that all heights within all six cases see improvements in data coverage when using RONIN. In cases such as Hurricane Rafael (2024) where there was NMD retained in the analyses created by NOAA-QC'd data (due to TDR interactions with land), RONIN was able to recognize and remove the NMD while still retaining more MD in the same area. We expect the reasoning for this is due to RONIN's framework using spatial awareness in MD identification as well as RONIN being trained on manually edited data.

Overall, we have concluded that RONIN is the better QC method for WP-3D TDR data in comparison to NOAA-QC. In terms of future work, there are two grants in the proposal stage looking to move forward. One is under Michael Fischer at the University of Miami, which will investigate how using RONIN to QC WP-3D TDR data will impact data assimilation into and output of hurricane forecasting models. The other grant is under Michael Bell at Colorado State University and seeks to recreate the entire TDR data QC to analysis process using solely machine learning. Personally, I plan to continue working with TDR data in my PhD at the University of Miami. In the short term, I would like to continue this project by analyzing how different QC methods affect structural diagnostics (such as azimuthally-averaged winds). If I get the results I am expecting (which is not a significant improvement with RONIN), I also plan to investigate NOAA-Synthesis to see how we can optimize the process for the most accurate results. In addition, I will continue to work with NHC in the further analysis and presentation of RONIN as the new QC method for TDR. This includes expanding my analyses for Research Question #2 to all cases within 2024 and possibly within other seasons.

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