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SCHREYER HONORS COLLEGE

DEPARTMENT OF METEOROLOGY AND ATMOSPHERIC SCIENCE

Improving Hurricane Fred (2015) Forecast with
METEOSAT-10 All Sky Infrared Radiances

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ABSTRACT

Hurricane Fred made landfall on Cape Verde August 31, 2015, as a category 1 hurricane. The hurricane originated from an African easterly wave that developed from a broad cyclonic rotation within the lower atmosphere off the coast of West Africa on August 29. The low-pressure system quickly intensified over the warm water of the Atlantic into a tropical storm and later a category 1 hurricane. Cape Verde and the eastern Atlantic Ocean are considered a data void region due to the lack of buoys and radars that are vital in providing meteorologists information on the state of the atmosphere. As a result, the track and intensification of Hurricane Fred were poorly forecasted.

The main objective of this project was to improve the forecast of Hurricane Fred using the Weather Research and Forecasting (WRF) Model together with advanced data assimilation of all-sky infrared radiances from Meteosat-10. Without assimilation of satellite all-sky infrared radiances, biases in the WRF track, minimum surface pressure, and maximum surface wind forecasts existed when compared to the best track observations from the National Hurricane Center (NHC). When comparing the observed and WRF forecasted tracks, the WRF forecasted track was shifted to the north compared to the best track observations from 1800 UTC August 30 to 1200 UTC August 31. Regarding the WRF forecasted minimum surface pressure, the WRF forecast considerably underestimated the minimum surface pressure when compared to the best track observations. Similarly, the WRF forecasted maximum surface winds significantly underestimated the observations. Lastly, the WRF forecasted brightness temperatures were also quite different from those based on the Meteosat-10 radiances.

Data assimilation (DA) served as a way for us to improve Hurricane Fred track and intensity forecasts. DA is a statistical technique that combines information from model forecasts

and observations to create a best estimate of the atmosphere. In this study, data assimilation was used to create more accurate forecasts of Hurricane Fred. To this end, the Penn State WRF Ensemble Kalman Filter (EnKF) system was used to assimilate conventional observations and all-sky infrared radiances from Meteosat-10 into the WRF model. With updated initial conditions via data assimilation, four deterministic forecasts were initialized: i) CONV 08/29 18Z, ii) CONV 08/30 00Z, iii) IR 08/29 18Z, and iv) IR 08/30 00Z. CONV represents experiments in which only conventional observations were assimilated, and IR represents experiments in which both conventional and all-sky infrared radiances were assimilated. Both the CONV and IR forecasts initiated at 1800 UTC August 29 were nearly spot on with the best track observations on August 31. When assessing the surface minimum pressure, the IR 08/30 00Z forecasts had much smaller absolute errors compared to the CONV forecasts. For the maximum wind speed forecasts, all four forecasts captured the highest maximum wind speed that occurred on August 31, with the IR forecasts having smaller absolute errors compared to the CONV forecasts. Satellite all-sky infrared radiance data assimilation improved the intensity forecast of Hurricane Fred, demonstrating potential value of this approach for hurricane forecasting in the eastern Atlantic Ocean.

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Chapter 1

Introduction and Background.

Hurricanes are one of the greatest wonders of all extreme weather phenomena. Not only do they have the power to cause substantial damage over broad coastal regions and thereby alter lives, but they can also be extremely difficult for meteorologists to anticipate and forecast. Hurricane Fred was a prime example of this as it was the first hurricane to pass through Cape Verde (a small island nation in the eastern Atlantic Ocean located 789 km to the west of Senegal) in over 120 years. Hurricane Fred originated from the African Easterly Jet as a tropical disturbance, and it developed a cyclonic structure around 0000 UTC August 29 as it moved westward toward Cape Verde (Hsieh and Cook, 2005). The low pressure associated with the disturbance deepened to the east of Cape Verde, reaching a minimum surface pressure of 1008 mb. Over the course of the day, the low-pressure system moved westward until it gradually intensified into a tropical depression by August 30. As the warm sea surface water continued providing energy to the depression, the storm eventually intensified into a category 1 hurricane by August 31. Figure 1 shows the wind fields associated with Hurricane Fred when it was located over Cape Verde on the morning of August 31. Hurricane Fred soon moved past Cape Verde as its maximum wind speeds began to drop and its clouds became more disorganized.

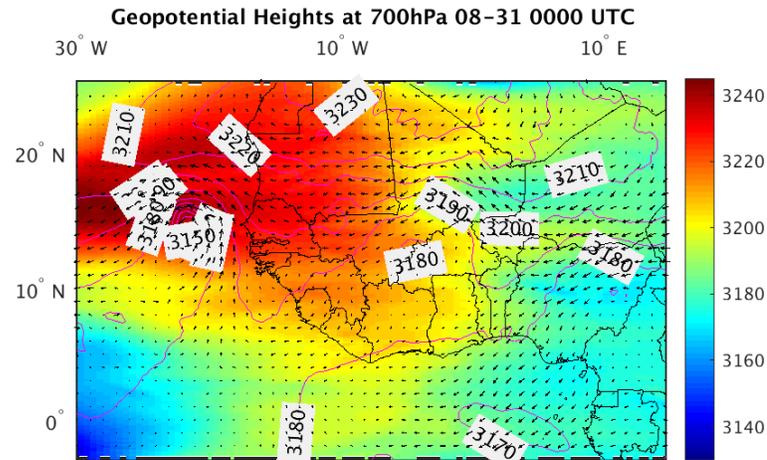


Figure 1. Geopotential Heights Associated with Hurricane Fred.

Although Hurricane Fred was short-lived, it still left behind significant damage that was estimated to cost well over 2 billion U.S. dollars. In addition, two fishermen from Cape Verde went missing and were therefore presumed dead. One major issue associated with this storm was the lack of preparation for it by the people on Cape Verde (Jenkins et al., 2018). Ultimately, the unexpected occurrence of this hurricane, along with the poor forecast for it, were to blame.

Cape Verde is considered as a data void region where there are extremely limited in-situ meteorological observations. The closest in-situ measurement site is a moor buoy that is located 296 km (about 184 miles) north of Cape Verde. The lack of in situ data makes it difficult for traditional data assimilation approaches to create accurate initial conditions for numerical model forecasts in the region. The first portion of this study focuses on analyzing errors associated with a Weather Research Forecast (WRF) model forecast initialized from conventional Global Forecast System (GFS) analysis fields. Comparing observations provided by the National Hurricane Center (NHC) with the WRF forecasts produced from the GFS initial conditions, we will investigate the forecast errors associated with Hurricane Fred for this traditional approach.

The second portion of this study focuses on assimilating satellite all-sky infrared brightness temperatures, in addition to conventional observations, in an attempt to improve the forecasts for Hurricane Fred. The purpose of this research is to better understand potential improvements in tropical cyclone prediction by using ubiquitous satellite-based radiances. Beyond improving the forecasts for tropical cyclones, it is also important that we have effective forms of communication to the public prior to a major weather event. Such effective communication must begin with good forecasts that accurately represent the overall intensity changes in time of a hurricane.

To produce an accurate forecast, it is important to have initial conditions that represent accurately the current state of the atmosphere. Data Assimilation (DA) is best described as a statistical technique that combines model forecasts with newly updated observations to generate an improved estimate of the atmospheric state. This technique leads to more accurate forecasts by improving the initial conditions from which they are generated. The atmosphere is extraordinarily complex, and even the smallest inconsistencies between the initial conditions and the true atmospheric state can cause dramatic changes in the outcome of a potential forecast. This phenomenon is also referred to as the “butterfly effect” in meteorology (Sun and Zhang, 2016). In tropical cyclone prediction, data assimilation serves as an opportunity to improve forecasts of a storm’s intensity and track by continually reducing errors in the model states used to produce the forecasts.

A study conducted at The Pennsylvania State University used an ensemble-based data assimilation system to ingest high resolution airborne doppler radar observations into a hurricane forecast model to improve the intensity and track forecasts of hurricanes (Zhang and Weng, 2015). This study focused on three hurricanes: Ike (2008), Irene (2011), and Sandy (2012). All

three of these hurricanes were among the top ten costliest hurricanes in the United States from 2008 through 2012. This study found that there has been “little to no improvement” in the NHC’s intensity forecasts over the past 20 years. Zhang and Weng (2015) hypothesized that this lack of improvement is associated with “a lack of adequate routine observations to resolve the inner-core structure, and the absence of an efficient data assimilation technique”.

Therefore, Zhang and Weng (2015) developed a prototype hurricane data assimilation and prediction system that enabled cloud-permitting ensemble analysis and forecasting with an advanced data assimilation technique known as the Ensemble Kalman Filter (EnKF). This new data assimilation and prediction system used the WRF model along with the EnKF data assimilation algorithm to better estimate the initial conditions and achieve more accurate hurricane intensity and track forecasts. Compared to NHC official forecasts, the Penn State WRF-EnKF system, as the prototype system came to be known, reduced intensity forecast errors by 15-43% for forecast lead times of 24 hr. For forecasts out to 48 hr to 96 hr, the Penn State WRF-EnKF system mean absolute forecast errors for hurricane intensity were 25-28% lower than for the NHC official forecast. Overall, Zhang and Weng (2015) concluded that the Penn State WRF-EnKF system outperformed NHC forecasts in terms of intensity due to the assimilation of high-resolution inner-core airborne radar observations. This study is relevant to my current research because it highlights how hurricane intensity prediction can be improved through using advanced data assimilation algorithms.

A similar study, also conducted at Penn State, used advanced ensemble assimilation of high-spatiotemporal all-sky infrared radiances from GOES-16 to improve the analyses and forecasts of Hurricane Harvey (Zhang et al., 2019). Harvey was a category 4 storm that occurred in 2017 and caused catastrophic damage across Texas and Louisiana. This storm was of interest

because, according to this study, none of the operational forecasts accurately predicted the rapid intensification of Harvey Hurricane. Lack of rapid intensification occurred in the official forecasts from the Hurricane WRF (HWRF), Global Forecast System (GFS), and the European Center for Medium-Range Weather Forecasts (ECMWF) operational systems. Like the previous project, this study also used Penn State WRF-EnKF-data assimilation system, but this time to assimilate all sky infrared brightness temperatures from GOES-16. Infrared brightness temperatures were of particular interest in this project because they provide information on cloud-top heights and the overall structure of a developing hurricane. This study concluded that without GOES-16 radiance assimilation, the Penn State WRF-EnKF system forecasts underestimated both the intensity and precipitation of Hurricane Harvey. Although this study investigated only a single event, it did provide insight into the potential to improve hurricane prediction by utilizing satellite infrared observations and advanced data assimilation methodologies.

Zhang et al. (2017) continued to improve upon the forecasts for Hurricane Harvey. This study focused on improving Harvey's intensity and rainfall forecasts by assimilating all-sky microwave (MW), in addition to infrared (IR) radiances, into the Penn State WRF-EnKF system. IR sensors onboard geostationary satellites give insight into the overall intensity and cloud-top heights of tropical cyclones. The major benefit of MW brightness temperatures is their information content associated with precipitating hydrometeors underneath the cloud tops. Precipitation is known to be one of the hardest atmospheric parameters to forecast. Because MW brightness temperatures contain information on precipitation, they provide a means to more accurately represent the overall rainfall structure of tropical cyclones. This study concluded that assimilating all-sky MW radiances, in addition to IR radiances, significantly improved the

rainfall forecast as well as the rapid intensification of Harvey when compared to the experiment that only assimilated IR radiances. Overall, this study is relevant because, once again, it supports the utilization of data assimilation to improve tropical cyclone prediction, which is directly related to this current project.

Chapter 2

Methods

To characterize the evolution of Hurricane Fred we used several datasets. The first one contained infrared brightness temperature observations from the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) Meteosat-10 covering the period from 0000 UTC August 29 through 0000 UTC September 1 (<https://www.eumetsat.int/website/home/index.html>). These satellite data were important in characterizing the location, intensity, and cloud structures of the hurricane. Another data set that we used in this study was the European Center for Medium-Range Weather Forecasts (ECMWF) ERA5 reanalysis from 0000 UTC August 25 through 1800 UTC August 30. This data provided information on the large-scale environment and atmospheric dynamics associated with Hurricane Fred (<https://www.ecmwf.int/en/forecasts/datasets/reanalysis-datasets/era5>). For example, the ERA5 reanalysis was central to locating Hurricane Fred's center of low pressure. A third data set that we used was the best track data from the National Hurricane Center (NHC; https://www.nhc.noaa.gov/data/tcr/AL062015_Fred.pdf)—. The best track data included the observed minimum surface pressure, maximum surface wind, and center location of Hurricane Fred over its entire lifetime.

For this study we used version 4.2 of the Advanced Research WRF model, called the WRF-ARW model. The WRF-ARW model is an Eulerian nonhydrostatic mesoscale model that is fully compressible (Skamarock et al., 2008). We configured the model with two fixed domains. The outer domain (d01) had 230 (in longitude) by 180 (in latitude) by 51 (in height) grids with 15-km spacing, whereas the inner domain (d02) had 501 by 501 by 51 grids with 3-km grid spacing. These two fixed domains were designed to cover the complete track of Hurricane

Fred within the study area. Both domains used 51 vertical levels with the model top set to 50 mb. As for our choice of parameterizations, our configuration used the aerosol-aware Thompson microphysics scheme, the Rapid Radiative Transfer Model (RRTM) for General Circulation Models (GCMs) longwave and shortwave radiation schemes (Iacono et al., 2008), The Yonsei University planetary boundary scheme (Hong et al., 2008), and the Grell 3D-ensemble cumulus scheme for only the 15-km outer domain).

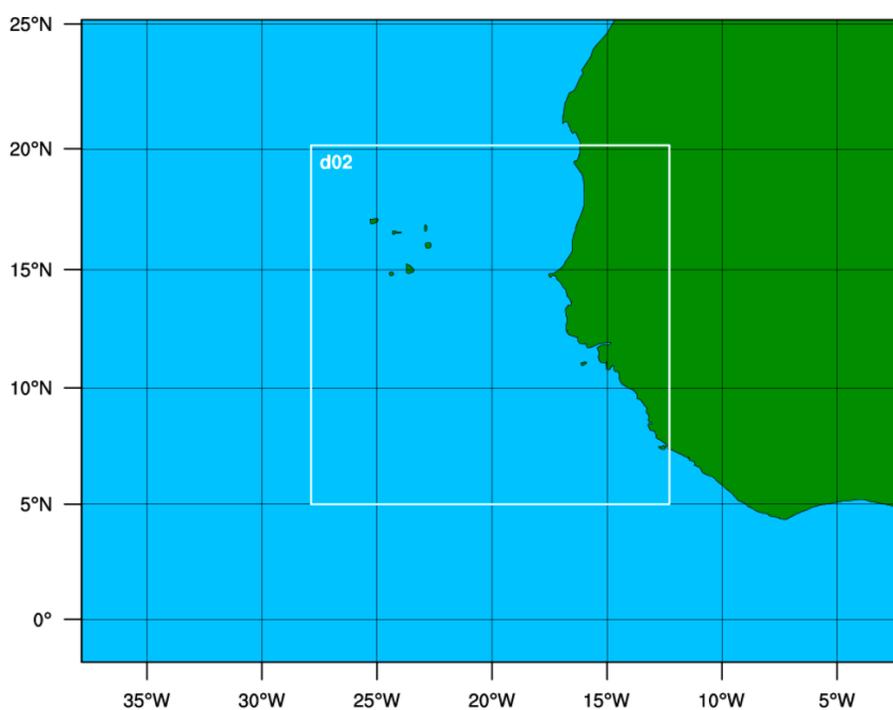


Figure 2. Coverage of the two domains within the model.

The Community Radiative Transfer Model (CRTM; Hong et al., 2008) created by the Joint Center for Satellite Data Assimilation (JCSDA) was used as the forward radiance operator for the data assimilation. Similar to previous studies, we used the Penn State WRF-EnKF) data assimilation and forecast system. We assimilated hourly radiances from channel 5 (with a central wavelength of 6.25 μm) of the SEVERI sensor onboard the Meteosat-10 satellite. Channel 5 is sensitive to tropospheric water vapor, and it is comparable to channels from sensors onboard the GOES-16 and Himawari-8 satellites that have been used in previous studies. To handle strong nonlinearities in the radiances associated with clear and cloudy regions, and thereby lead to more accurate and successful all-sky radiance assimilation, we incorporated Adaptive Observation Error Inflation (AOEI; Zhang and Minamide, 2017) and Adaptive Background Error Inflation (ABEI; Zhang and Minamide, 2019). We also used the same successive covariance localization scheme that was used by Zhang and Minamide (2017, 2019). In this scheme, the raw satellite observations were first thinned into two individual groups. The first group had a horizontal grid spacing of 12km and a horizontal radius of influence of 30km. The second group had a horizontal grid spacing of 18 km and a horizontal radius of influence of 200km. When we assimilated the second group of thinned observations, all models' variables were updated except for the hydrometeor variables. All variables, including the hydrometeor variables, were updated when we assimilated the first group of thinned observations.

We used the Global Forecast System (GFS) to generate the initial and boundary conditions for the Hurricane Fred numerical simulations. We initialized a 60-member ensemble at 0000 UTC 29 August 29 and ran it out for 6 h to 0600 UTC August 29. Hourly data assimilation began at 0600 UTC August 29, extending out to 0000 UTC August 30. In the first experiment, labeled CONV hereafter, we assimilated only conventional data, including surface

and upper-air observations. In the second experiment, labeled IR hereafter, we assimilated SEVERI channel 5 brightness temperatures (BTs) in addition to the conventional observations. We initialized two deterministic forecasts from the EnKF analyses, one starting at 1800 UTC August 29 and the other at 0000 UTC 30 August, for both experiments and ran them out to 0000 UTC 1 September. Finally, we performed a control experiment without any data assimilation, labeled NoDA hereafter, which we used to understand the impacts of any data assimilation on the track and intensity forecasts.

Chapter 3

Results & Conclusion

The first portion of our results highlights our findings based on our WRF forecast analysis without data assimilation. The second portion highlights how the Hurricane Fred forecast was improved by using data assimilation. Our conclusion gives insight into our major findings when comparing the two forecasts with and without data assimilation.

3.1 Results of WRF Forecast without Data Assimilation

We first present a comparison of WRF simulation results without data assimilation, i.e., the NoDA experiment, with the NHC best track data. One important metric for assessing forecast performance is ascertaining the accuracy of the forecasted track. As Fig. 3 illustrates, the NoDA track forecast had significant errors in it, especially in the environs of Cape Verde.

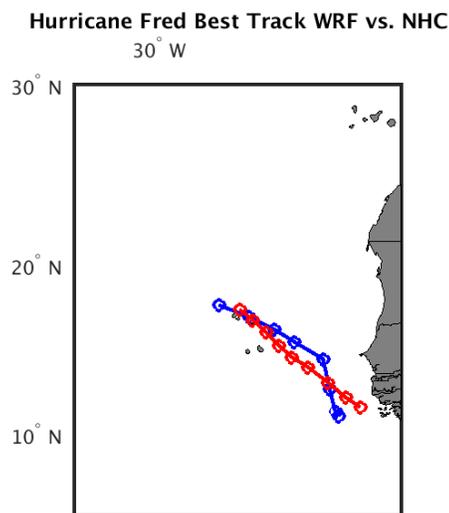


Figure 3. The observed best track from NHC (in red) versus the forecasted track from WRF (in blue) starting at 0000 UTC 30 August. The open circles represent the location of the hurricane at six-hour intervals.

At 0000 UTC 30 August, the NoDA track was south of the NHC best track. Over the next 18 h, the NoDA track went northward, crossing over the NHC best track around 1200 UTC 30 August. The NoDA track stayed to the north of the best track over the next 24 h to about 1800 UTC 31 August. This is the most important time period because, as previously mentioned, Hurricane Fred passed over Cape Verde on the 31 August and accurately forecasting Hurricane Fred's location at this time was vital to providing the public reliable information. As 1 September approached, the NoDA forecast track began to overlap with the NHC best track, but then the NoDA track was too far to the west of the NHC best track. In the NoDA forecast, Hurricane Fred moved faster and farther towards the west compared with the observed best track.

The NoDA forecast also had large discrepancies in minimum sea-level pressure relative to the NHC best track (Fig. 4). The lowest value of minimum sea-level pressure in the NoDA forecast was 996 mb, compared to 986 mb for the NHC best track. This large discrepancy in minimum sea-level pressure is an important result because this 10-mb difference is significant in terms of hurricane intensity and the potential damage that the hurricane could produce. Not only was the intensity of the NoDA forecast off, the timing of the onset of the relevant (to Cape Verde) rapid intensification was off too. The NHC best track contained a steep drop in the pressure starting at 1200 UTC 30 August. This drop lasted for 24 h. However, the NoDA forecast had a much less substantial drop which didn't start until 0000 UTC 31 August.

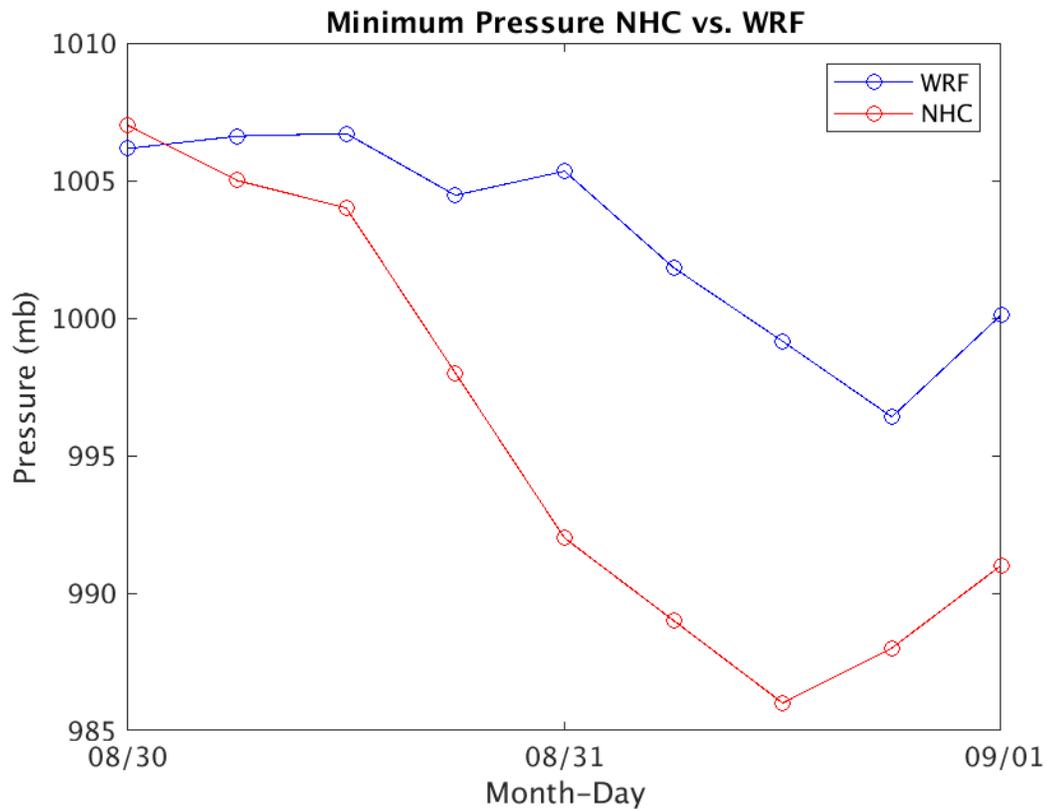


Figure 4. The difference in minimum surface pressure reported by WRF and NHC.

There were also significant discrepancies in the NoDA forecasted maximum winds relative to the maximum winds for the NHC best track (Fig. 5). Inspecting the maximum winds every six hours from 0000 UTC 30 August to 0000 UTC 1 September, the maximum value in the NHC best track was 75 knots and it occurred at 1200 UTC 31 August. For the NoDA forecast, the maximum wind was 47.3 knots and it occurred at 0600 UTC 31 August 31, six hours prior to the time of the observed peak wind speed. The NoDA forecasted maximum wind speed was not only 28 knots weaker than the observed maximum wind speed, but it would also be too low to declare Hurricane Fred as a category 1 hurricane.

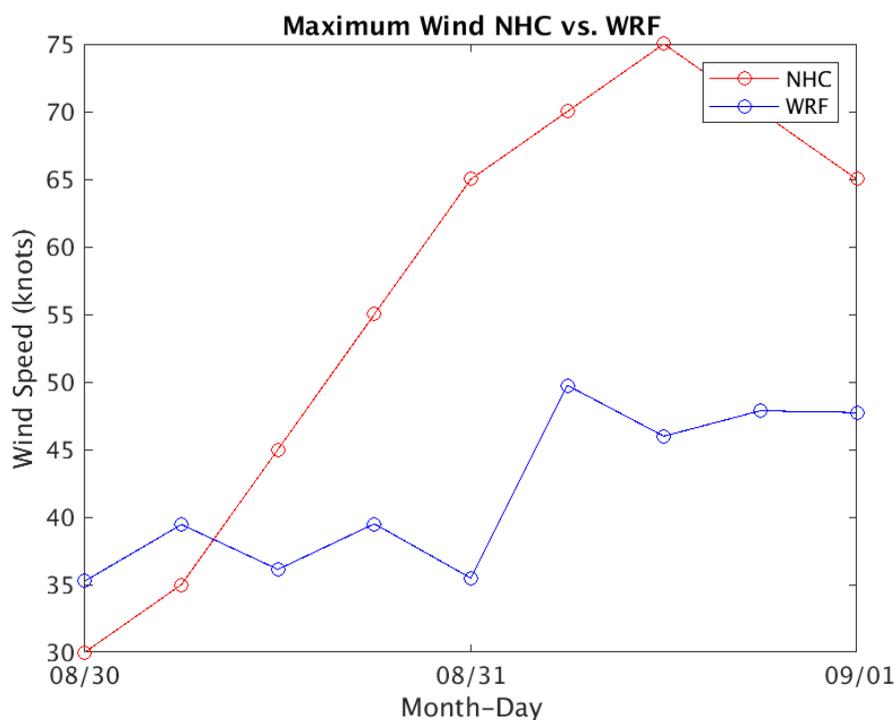
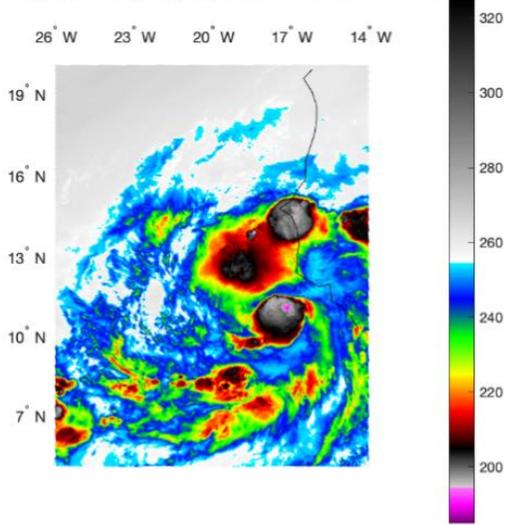


Figure 5. Maximum wind values for the NHC best track (in red) and the NoDA forecast (in blue).

Finally, we found significant differences in infrared brightness temperatures in the environs of Hurricane Fred between the NoDA forecast and the observations. Note that cloudy-sky infrared brightness temperatures decrease as the cloud tops with which they are associated increase in altitude. At 2100 UTC 29 August, the observed infrared brightness temperatures (Fig. 6a) show a more organized storm than the NoDA forecast brightness temperatures at the same time (Fig. 6b). In particular, a large-scale circulation pattern is evident in the observations that is completely missing in the NoDA-based brightness temperatures.

Observed Brightness Temp : Associated With Hurricane Fred 08292100



a.

1

b.

2015082900 CH-6: 201508292100

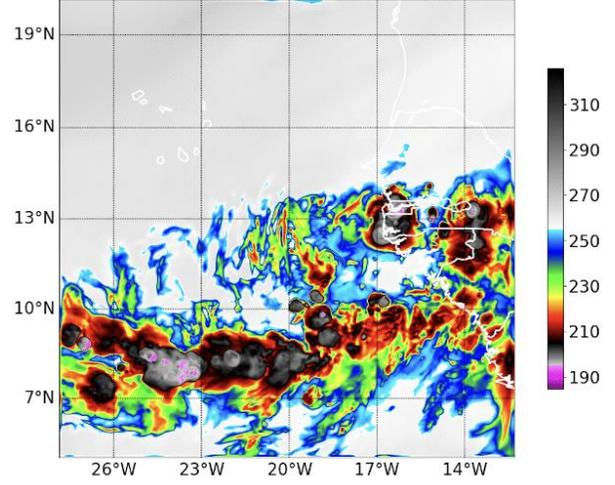


Figure 6. (a) Observed brightness temperature at 2100 UTC 29 August from SEVERI onboard Meteosat-10, and (b) NoDA forecast model brightness temperature for the same time as the observations.

3.2 Improving Hurricane Fred Forecasts with Data Assimilation

When we incorporated conventional and infrared brightness temperatures into the Penn State WRF-EnKF data assimilation system, noticeable improvements occurred in the Hurricane Fred track, intensity, and brightness temperature analyses. Although all four forecasted tracks were noticeably southward of the observed best track at the beginning of the forecasts (Fig. 7), both the CONV and IR tracks for the forecasts initiated at 1800 UTC 29 August 29 converged toward the NHC best track from 0000 UTC to 1800 UTC 31 August (see the last four open circles in Fig. 7 for these two forecasts). That is, both of these forecasts showed convergence to the best track as Hurricane Fred moved through the Cape Verde region on 31 August, the most important day when Hurricane Fred was at its peak intensity and in the environs of Cape Verde.

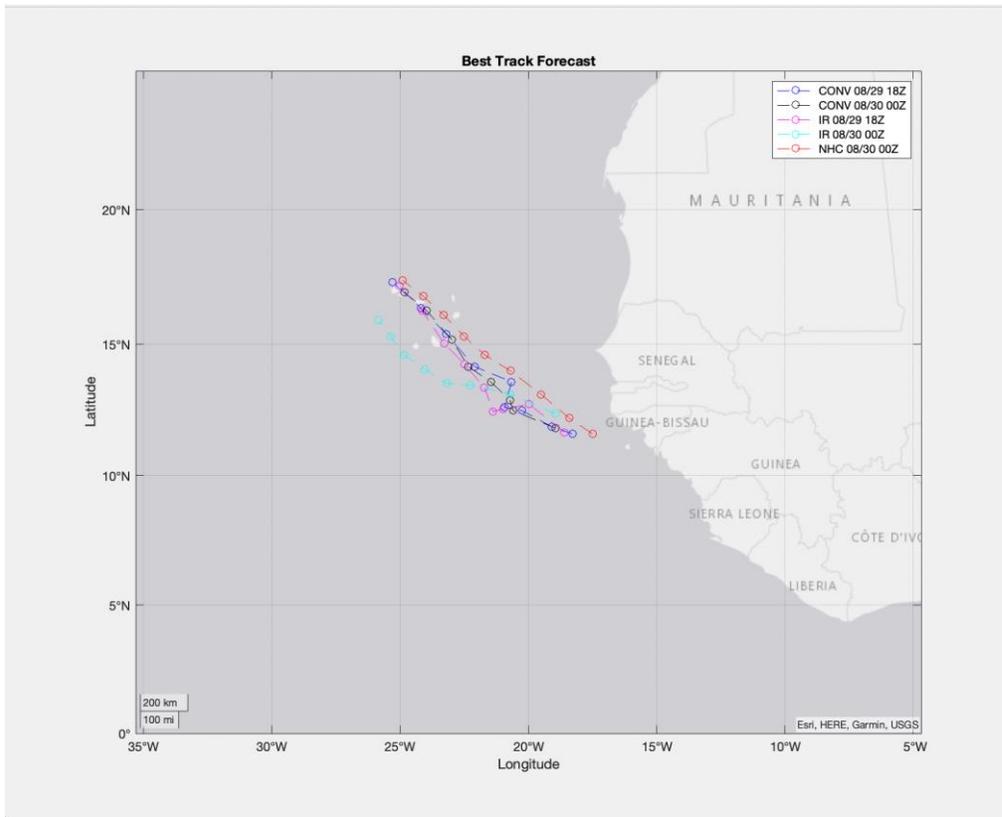
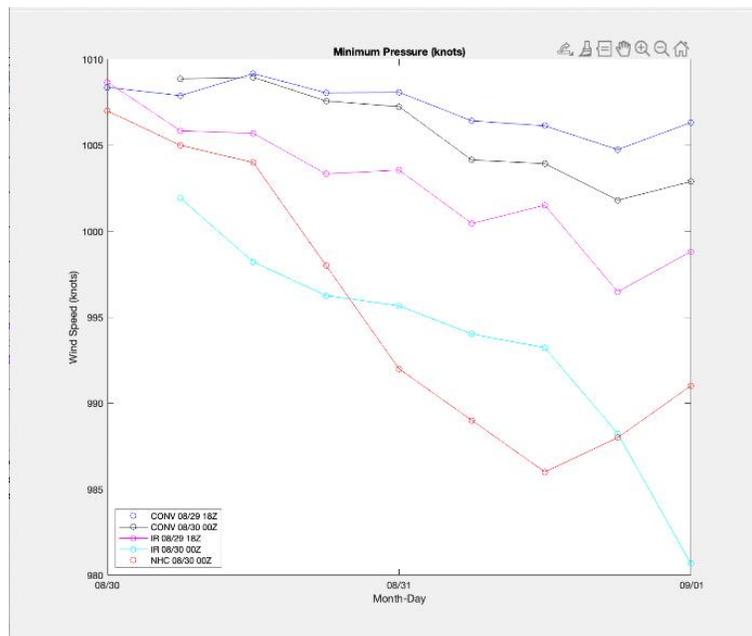


Figure 7. Hurricane Fred tracks for the CONV and IR experiment deterministic forecasts started at 1800 UTC 29 August (CONV in blue and IR in magenta) and 0000 UTC 30 August (CONV in black and IR in cyan). The NHC observed best track is in red, and the open circles occur in six-hour interval.

The CONV and IR data assimilation experiments also had improved intensity forecasts. Both the CONV and IR forecasts captured the drop in minimum sea-level pressure that occurred throughout 30 August and into 31 August (Fig. 8). Additionally, the minimum sea-level pressure for the IR forecast initiated at 0000 UTC 30 August exhibited the lowest errors relative to what was observed (Fig. 8), though this forecast had the largest track errors (Fig. 7). Over the course of the 2-day forecast, the IR forecast initiated at 0000 UTC 30 August remained generally within 10 mb of the observed minimum sea-level pressure and best captured the timing of the rapid intensification of Hurricane Fred.

a.



b.

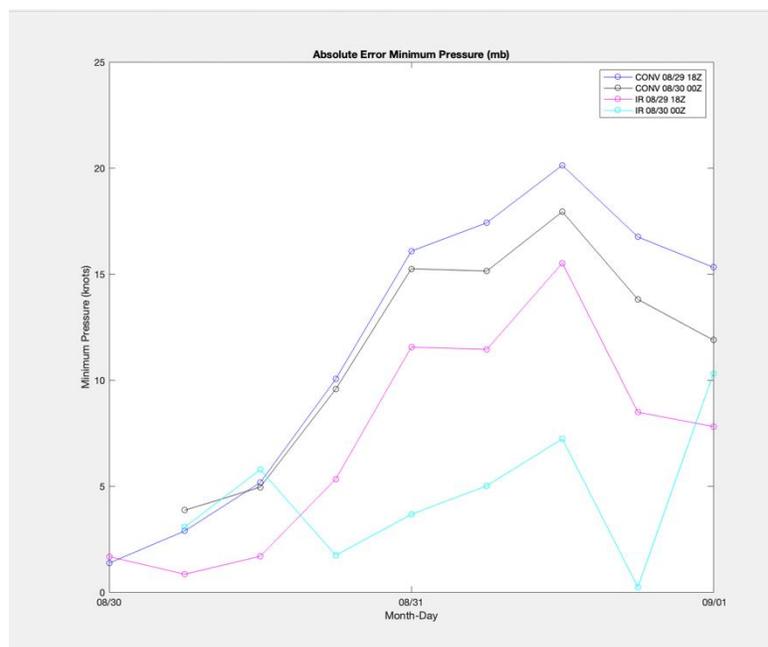


Figure 8. (a) Hurricane Fred minimum sea-level pressure for the CONV and IR experiment deterministic forecasts started at 1800 UTC 29 August (CONV in blue and IR magenta) and 0000 UTC 30 August (CONV in black and IR in cyan). The NHC observed track in red, and the open circles occur at six-hour intervals (b) Same as for (a), except for the absolute errors in the forecasted sea-level pressure relative to those observed.

Analyzing forecasted and observed surface maximum wind speeds, the IR forecast initialized at 0000 UTC 30 August once again produced the smallest errors overall (Figs. 9a,b). In terms of absolute errors relative to the observed maximum wind speeds (Fig. 9b) absolute error, this forecast remained within 25 knots of what was observed, representing a significant improvement over the NoDA results. The IR forecast from 1800 UTC 29 August performed better than both of the CONV forecasts in terms of minimum sea-level pressure (Fig. 8) and surface maximum wind speed (Figs. 9a,b). That said, while all four forecasts underestimated the maximum wind speed, all of them performed reasonably well in capturing the steep increase in the surface maximum wind speed throughout 30 August and into 31 August. Considering both

track and intensity forecasts, the IR forecast initiated from 1800 UTC 29 August was perhaps the best one overall.

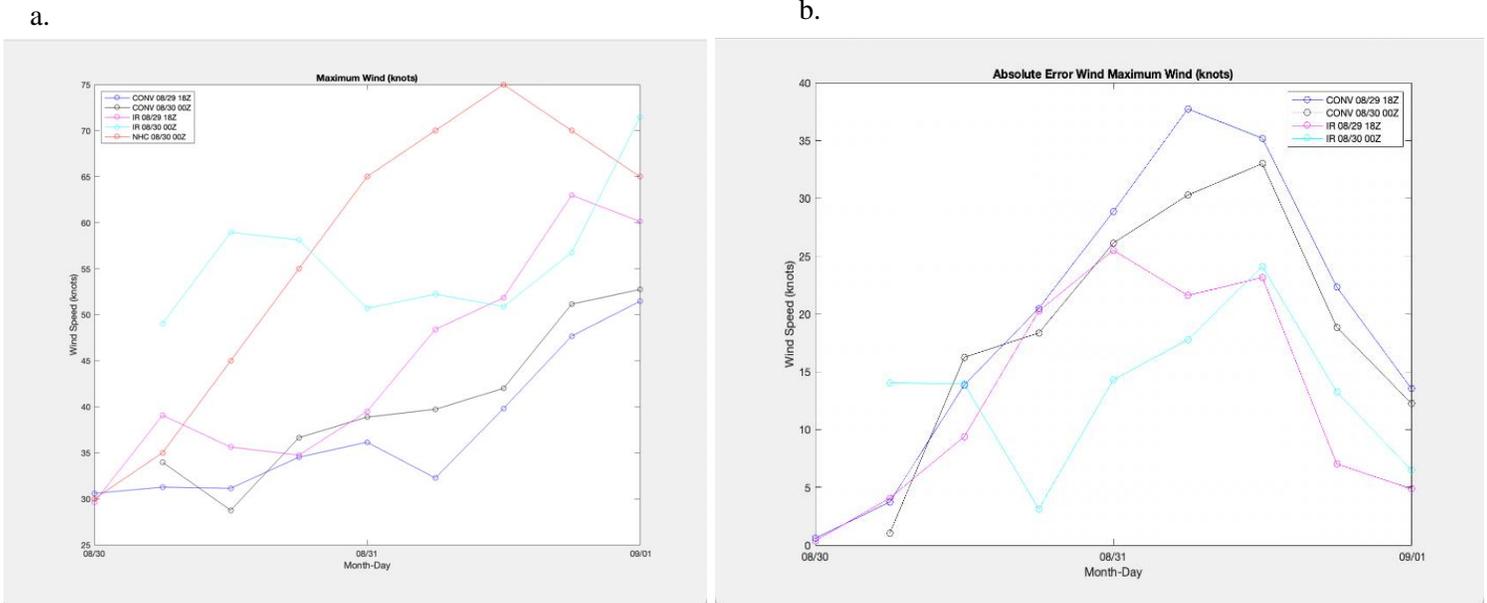


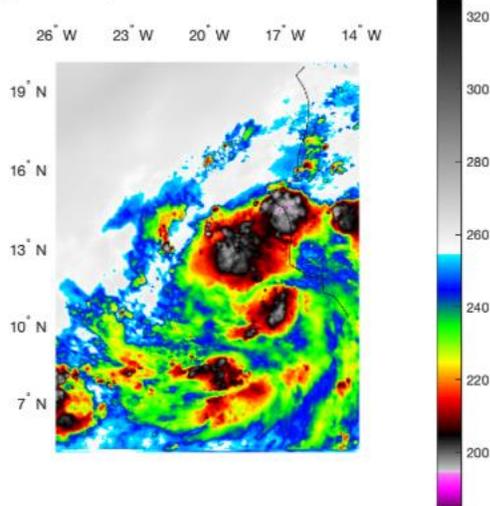
Figure 9. (a) Hurricane Fred surface maximum wind speed for the CONV and IR experiment deterministic forecasts started at 1800 UTC 29 August (CONV in blue and IR in magenta) and 0000 UTC 30 August (CONV in black and IR in cyan). The NHC surface maximum wind speeds along the best track are red, and the open circles occur at six-hour intervals. (b) Same as for (a), except for the absolute errors in the forecasted surface maximum wind speeds relative to those observed.

Our most striking results occurred when we compared the brightness temperatures from the CONV and IR analyses with the observations. Both the CONV and IR brightness temperatures analyses (Figs. 10a,b) better captured the high cloud tops and the overall structure of Hurricane Fred than those from the NoDA forecast (Fig. 6b). For example, the infrared brightness temperatures from both the CONV and IR analyses captured the eastward-moving deep convection in the rain bands between 17-23°W longitude and 6-10°N latitude (compare Figs. 10a, b to Fig. 10c). Moreover, the storm structures in the IR analysis (Fig. 10b) have much greater fidelity to the observations (Fig. 10c) than the ones for the CONV analysis (Fig. 10a).

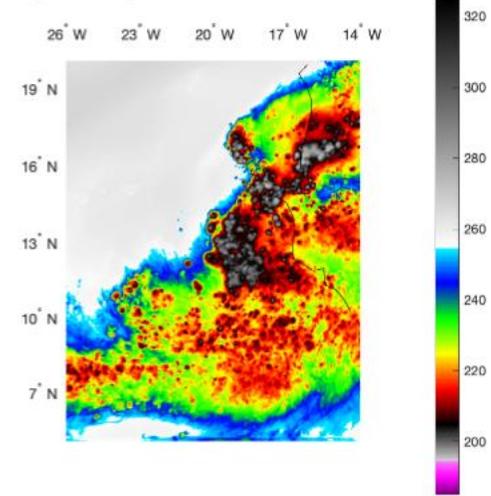
This finding demonstrates that brightness temperature assimilation provides meaningful information to the forecasts on the timing and severity of a developing hurricane.

a.

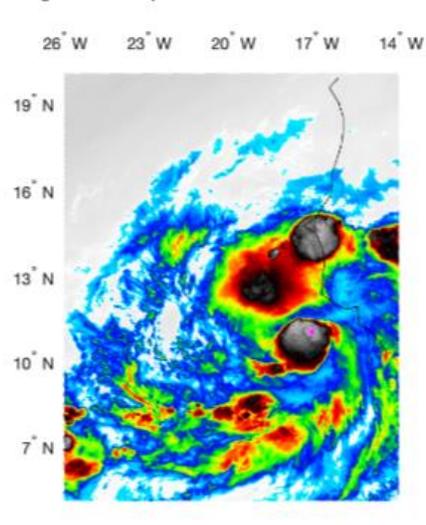
IR Brightness Temp : Associated With Hurricane Fred 08292100



CONV Brightness Temp : Associated With Hurricane Fred 08292100



Observed Brightness Temp : Associated With Hurricane



c.

Figure 10. Brightness temperature at 2100 UTC 29 August for (a) the CONV and (b) IR analyses initiated at 1800 UTC 29 August. (c) Satellite-observed brightness temperature at 2100 UTC 29 August.

3.3 Conclusions

When comparing the NoDA forecast to observations from the NHC best track, we found significant discrepancies between them. The NoDA forecast track did not follow the observed

track. The lowest observed minimum sea-level pressure was more than 10 mb lower than in the NoDA forecast. The observed highest surface maximum wind speed was 27 knots higher than in the NoDA forecast. Lastly, brightness temperatures from the NoDA forecast were less organized with warmer brightness temperatures suggesting weaker convection. All together, these results demonstrate that the NoDA forecast underestimated intensification of Hurricane Fred. Recall that Cape Verde is a data void region, and without data assimilation the initial and boundary conditions for the NoDA forecast have errors in them that significantly impacted the forecast.

Assimilating both conventional and satellite-based observations significantly improved the forecasts of Hurricane Fred in every aspect. In terms of the track, both the CONV and IR forecasts performed better than the NoDA forecast in capturing the trajectory of Fred. In terms of the intensity forecasts, the minimum sea-level pressure for the IR forecast initialized at 0000 UTC 30 August was within 7 mb when compared with the NHC best track minimum sea-level pressure. For the surface maximum wind speed, every forecast showed an improvement relative to the NoDA forecast in capturing the surface maximum wind speeds from 30 August and into 31 August. The IR forecast initialized at 0000 UTC on 30 August even remained within 25 knots of the observed surface maximum wind speed. Our most important finding was the significant improvement in the brightness temperatures. Both the CONV and IR analyses captured the structure and intensification of Hurricane Fred as it moved towards Cape Verde. Ultimately, data assimilation with satellite observations led to improved forecasts of Hurricane Fred by more accurately representing its overall track and intensity.

Chapter 4

Discussion

In this project, we were able to bridge the gap between observations and simulations of Hurricane Fred (2015) as we improved its forecasts. We improved forecasts for Hurricane Fred by assimilating satellite observations, thereby improving the initial conditions for the forecasts and creating more accurate forecasts of this hurricane. With Cape Verde being a data void region, assimilation of satellite observations is one of the few methods available to us to improve the accuracy of forecasts in this region. Going forward, reproducing these results for additional hurricanes is an important next step. Although we obtained promising results for Hurricane Fred, the complexity and nonlinearity of our atmosphere makes forecasting accurately a challenge. Repeating this study for more hurricanes will help avoid storm-specific results and allow us to confidently conclude how well all-sky radiance data assimilation performs.

This project has implications for emergency management. Accurate forecasts are important, especially for vulnerable communities that experience extreme weather events like hurricanes. Improved forecasts will help in creating better preparation protocols that reduce will reduce risks associated with hurricanes, especially for underdeveloped countries like Cape Verde. Meteorologists play a vital role in learning about our atmosphere and finding ways to educate communities all around the world on severe weather and climate. Improving weather forecasting and communication are important parts of the future of atmospheric science as we will come to know it.

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ACADEMIC VITAE

Alisha Wellington

EDUCATION

Penn State University, State College, PA - *Meteorology and Atmospheric Science*

AUG 2018 - PRESENT

EXPERIENCE

Penn State University, Virtual - *Climate Science Researcher*

MAY 2020 - PRESENT

- Actively conduct research to better understand forecast discrepancies related to the study of 2015 Hurricane Fred.
- Use computer programming languages to visually represent observations and data reported from this hurricane.

APEX Clean Energy Intern - *Resource Assessment Intern*

JUNE 2021 - AUG 2021

- Gained entry level experience in the renewable energy industry.
- Conducted market research to find new weather forecasting services to best suit the company.

Planalytics Inc, Berwyn, PA - *Intern*

MAY 2019 - AUG 2019

- Gained experience in the private sector meteorology field through effectively communicating in weather discussions with meteorologists, administrators, and clients.

EXTRACURRICULAR ACTIVITIES

Caribbean Student Association, State College, PA - *Treasurer*

AUG 2019 - MAY 2021

- Attend weekly meetings with the executive board to discuss and plan upcoming events.
- Work on contract agreements and ensure the organization is in good financial standing.

Minorities in Earth and Mineral Sciences, State College, PA - *President*

MAY 2021 - PRESENT

- Attend monthly meetings with members to create connections among students from underrepresented backgrounds in STEM.
- Attend community events to bring new members to the organization.

VOLUNTEER

Meals on Wheels, State College, PA - *Delivery Driver*

NOV 2020 - PRESENT

- Deliver groceries and pre-made meals to the elderly community in State College and surrounding areas.
- Communicate with the elderly clients to discuss food drop-offs and scheduling.

Millennium Scholar Peer Mentor State College, PA - *Mentor*

AUG 2020 - PRESENT

- Meet with younger scholars to discuss academics and social life at Penn State.

- Assist younger scholars with academic questions and decisions throughout their college journey.

NCSE EnvironMentors, State College, PA - *Undergraduate Mentor*

JAN 2020 - MAY 2021

- Mentor a high school student from the state college area and assist them with a STEM-related research project.
- Provide emotional and academic support for high school students when needed.

AWARDS

NOAA NCAS-M Fellow

Penn State Millennium Scholar

Schreyer's Honors Scholar