Evaluation and guidance development of HAFS version A QPF over the Caribbean and surrounding regions

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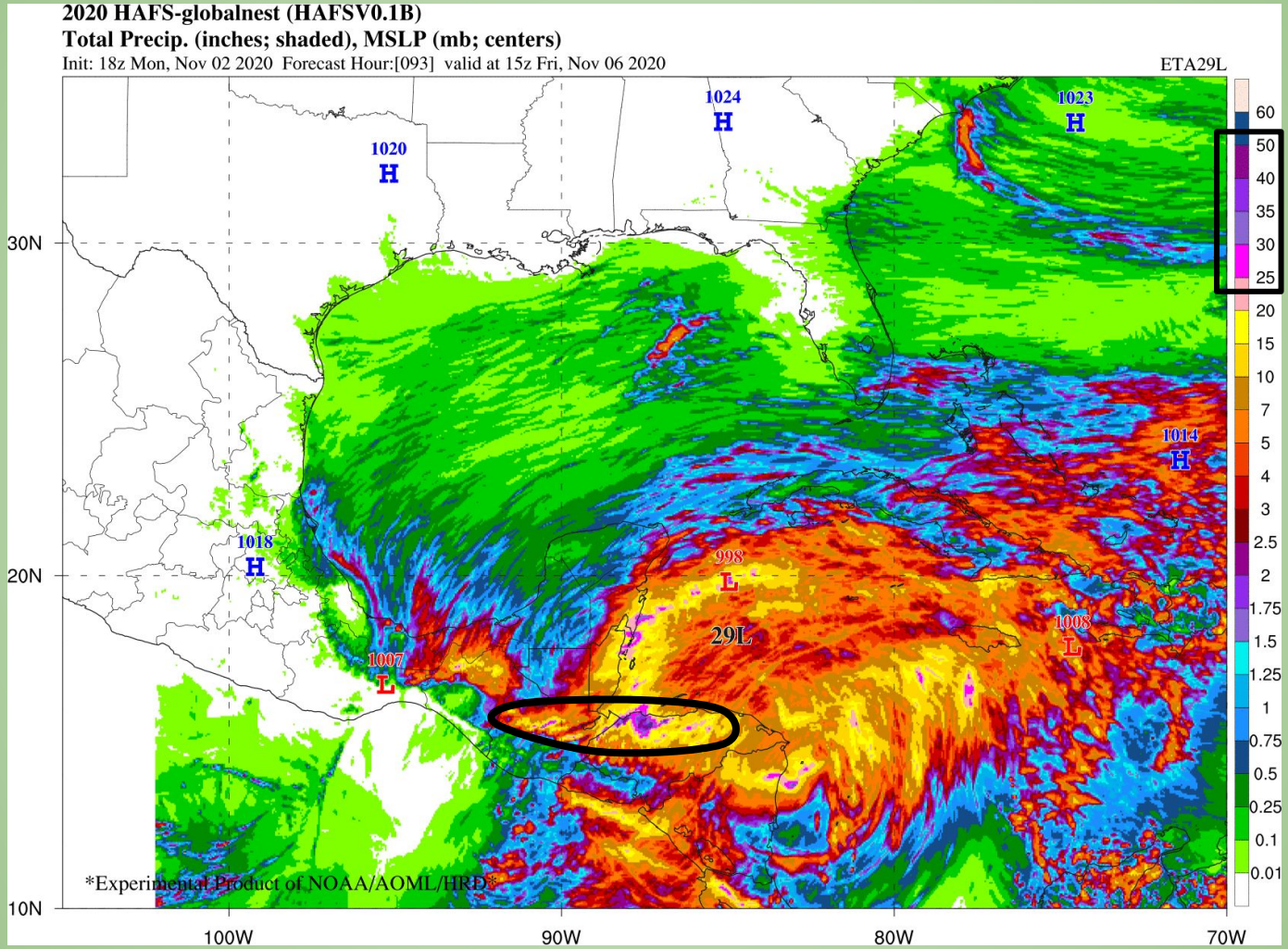
In collaboration with developers and scientists in Atlantic Oceanographic and Meteorological Laboratory (AOML)

Why focus on extreme rainfall associated with TCs?

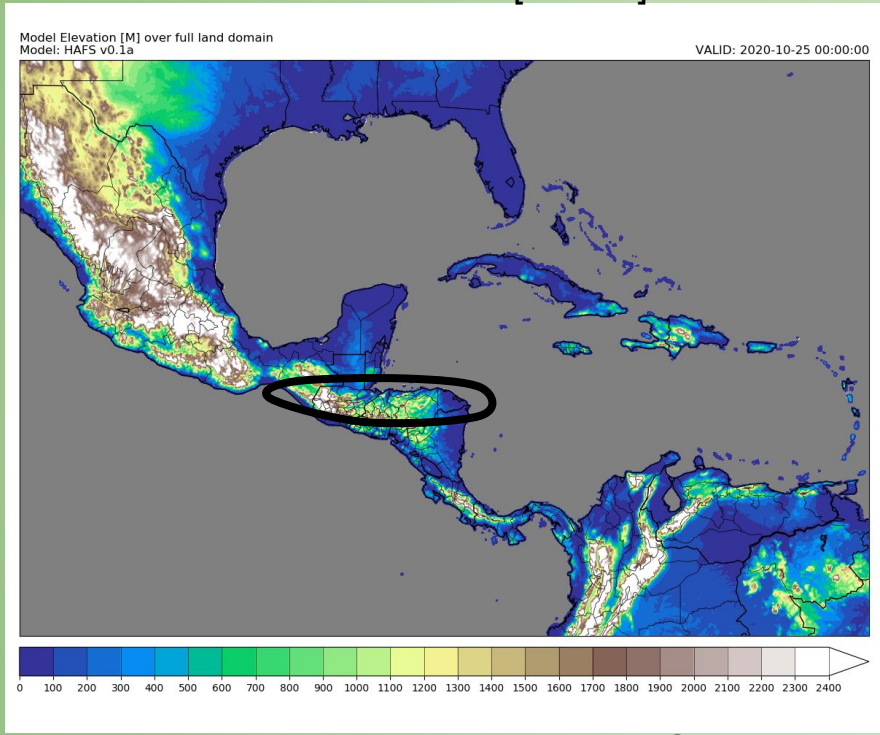
- Freshwater floods caused by rainfall from a tropical cyclone (TC) accounts for 27% of deaths (Rappaport, 2014).
- Flood deaths caused by TC rainfall occur more often than any other hazard associated with these events (Rappaport, 2014).
  - i.e. Storm surge, surf, offshore,wind, tornado
- Previous TC rainfall studies analyze the quantitative precipitation forecasts (QPF) skill as a product of TC track (Lonfat et al. 2007, Marchok et al. 2007).
- Other hurricane models (specifically HWRF) have shown to skillfully predict QPF and provide valuable information for operational forecasts of extreme precipitation (Ko et al. 2020).

Goals of this project

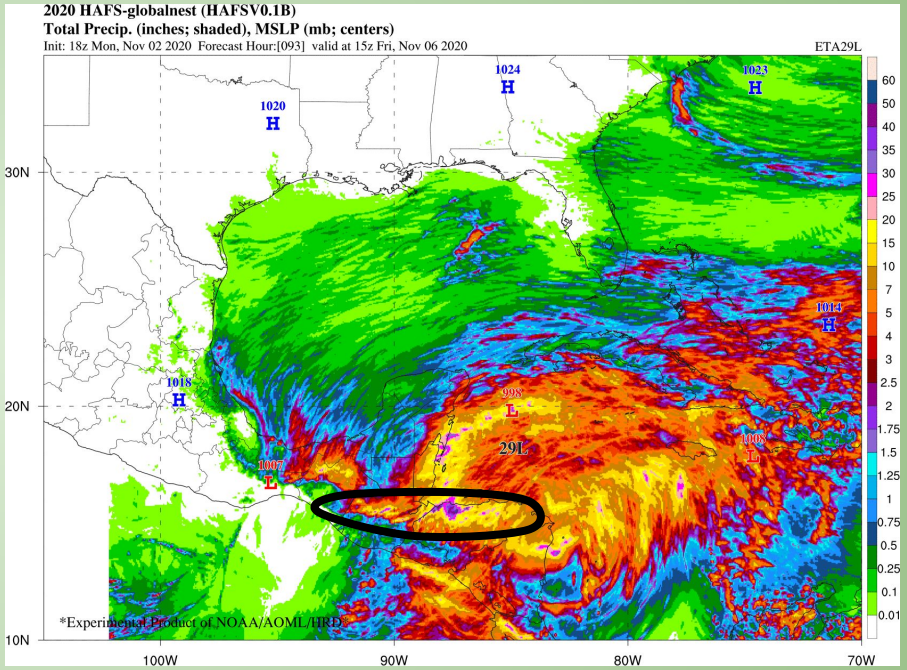
1. Analyze 2020 hurricane season for extreme percentiles of precipitation over tropical regions of the Caribbean and Latin America, especially regions of high terrain.
2. Post-process high-percentile precipitation for 2021 hurricane season over the Caribbean and Latin America while considering high terrain rainfall characteristics.


2020 HAFS-globalnest (HAFSV0.1B)
Total Precip. (inches; shaded), MSLP (mb; centers)
Init: 18z Mon, Nov 02 2020 Forecast Hour:[093] valid at 15z Fri, Nov 06 2020
ETA29L
1024
H
1023
H
1020
H
1014
H
1018
H
998
L
29L
1008
L
1007
L
Experimental Product of NOAA/AOML/HRD
30N
20N
10N
100W
90W
80W
70W
60
50
40
35
30
25
20
15
10
7
5
4
3
2.5
2
1.75
1.5
1.25
1
0.75
0.5
0.25
0.1
0.01

Model Elevation [meters]



HAFS v0.1A 93-hr Accum. QPF [inches]



High terrain in Guatemala and Honduras coincident with high total accumulated rainfall during Eta.

Data and Methodology

- Evaluating HAFS v0.1A quantitative precipitation forecasts (QPF)
  - Goal is to use the version closest to operational implementation
  - QPF data available for July 2020 - November 2020
  - 00z and 12z runs used for verification
  - 3-hr HAFS accumulated forecasts summed to create 24-hr rainfall totals for comparison to gauges
- Using a variety of observational datasets
  - Collecting a network of gauges over the Caribbean and surrounding regions
  - Using Stage IV QPE over CONUS for a QPF verification based on the TC best-track dataset
- GFS 0.25 degree QPF is used to compare HAFS v0.1A QPF
  - GFS is used by Weather Prediction Center (WPC) in many rainfall forecasting applications
  - Archived at the WPC for retrospective evaluation
- Majority of verification is completed using Model Evaluation Tools (MET) products developed by Developmental Testbed Center.

Gauge network established for this project

Collection of networks from four entities:

1. Caribbean Institute for Meteorology and Hydrology (CIMH)
2. National Meteorological Institute in Costa Rica (IMN)
3. Climate Prediction Center (CPC)
4. Community Collaborative Rain, Hail, and Snow network (CoCoRaHS)

Gauge network established for this project

- Station data begins July 1, 2020 and ends November 30, 2020
- Total Number of stations: 2004
  - This number fluctuates daily due to some stations not reporting consistently.
- Reporting at 12 UTC
- Elevation data used for stations was obtained using ArcGIS 1km elevation dataset
  - Done to limit the inconsistencies within the station metadata.
- Partition observations into two elevation groups
  - Analyze rainfall characteristics by elevation

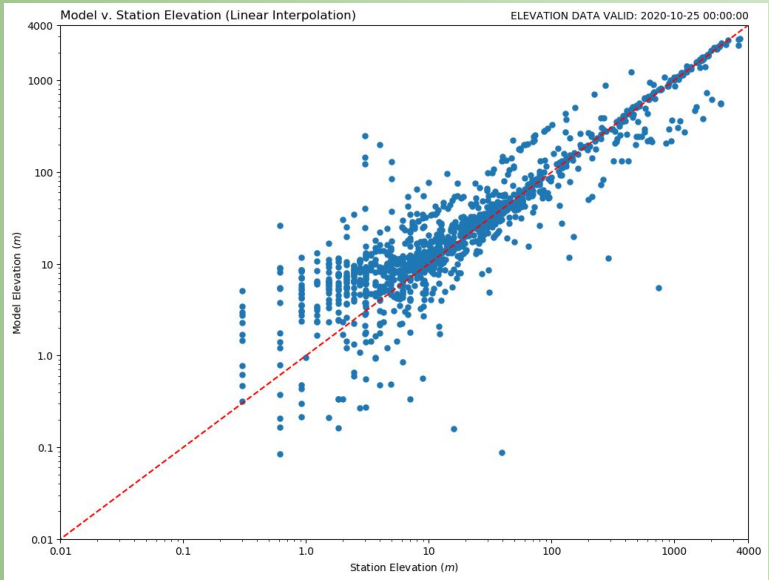
2020-07-01 Reporting Rain Gauges

Why partition the data by elevation?

- Want to investigate if there is a difference in forecasted rainfall between stations near sea level and stations in higher terrain (likely further from coast).
- Orographic features are known to influence precipitation, but is this observed within model forecast?
- If a pattern is observed within forecast, can we work to adjust for this in bias-correction?

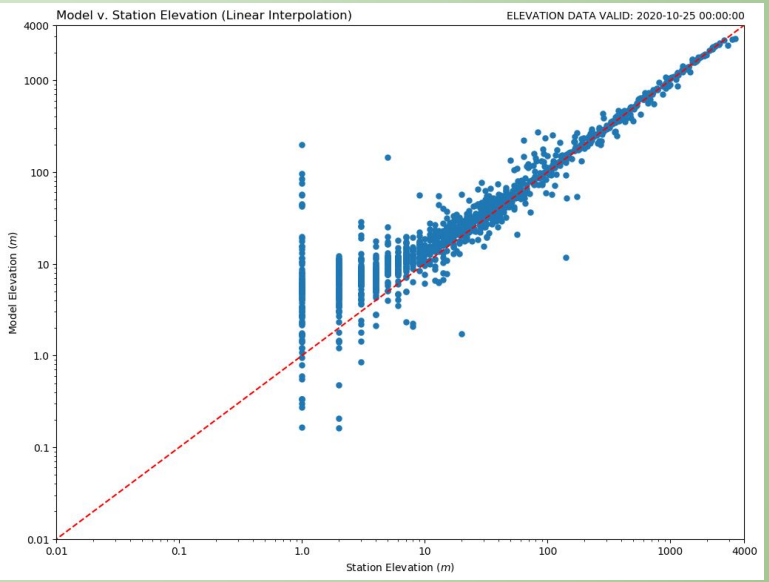
Can we trust elevation data from gauge datasets? Short answer: no…

Model v. RAW station elevation



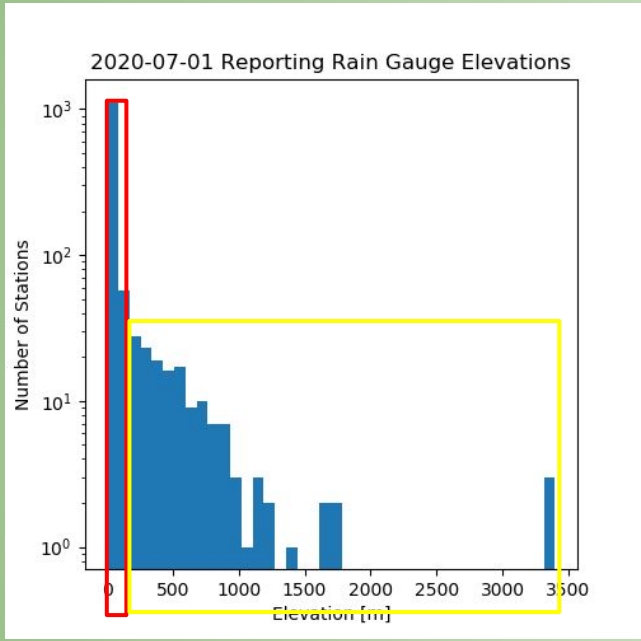
Station data elevation units were ambiguous and difficult to correct.

Model v. ArcGIS generated station elevation

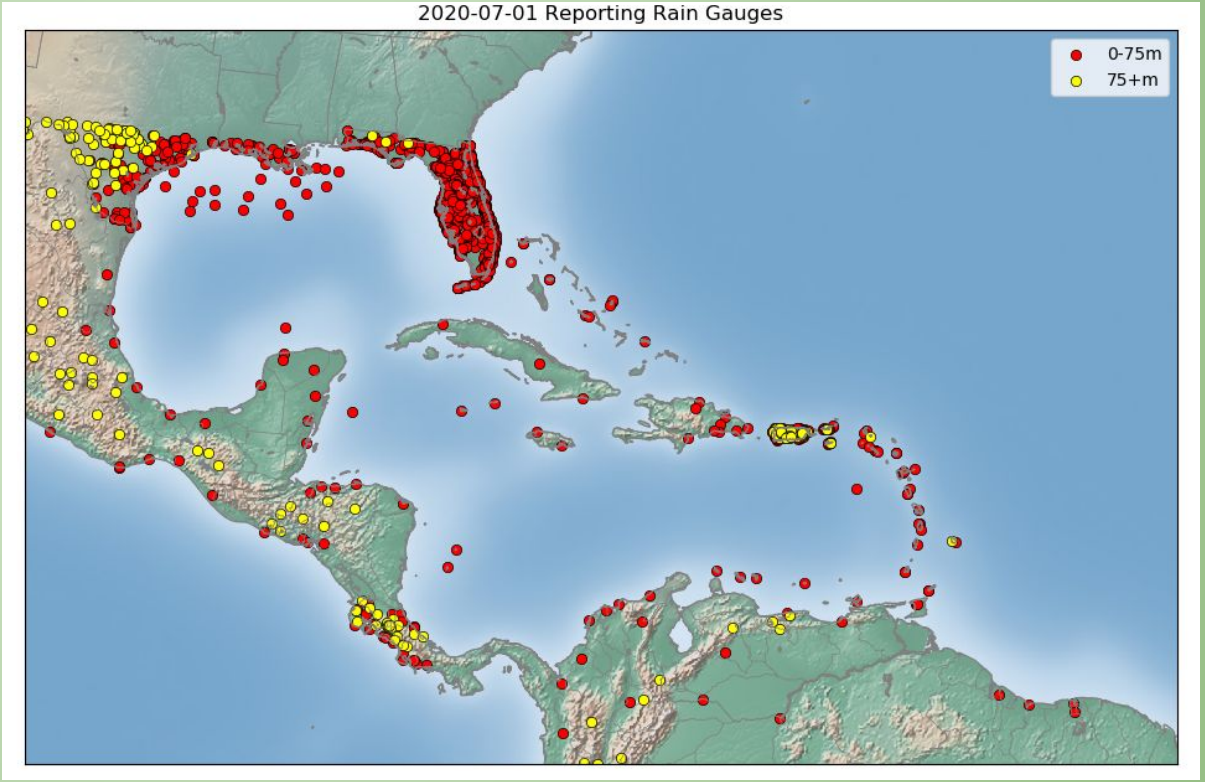


Lat/Lon precision likely adding noise at near sea level stations.

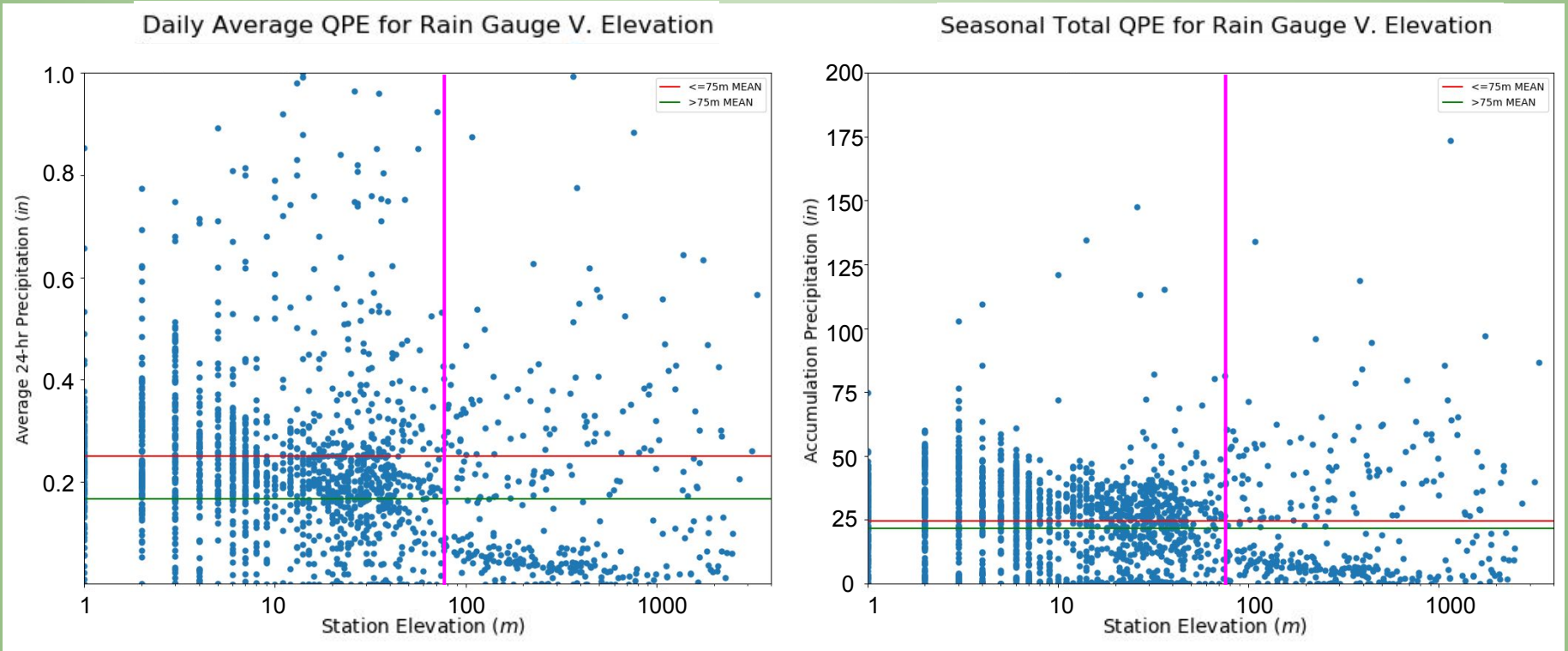
What elevation should we use to separate dataset?



75 meters ASL appears to provide geographically diverse elevation dataset.

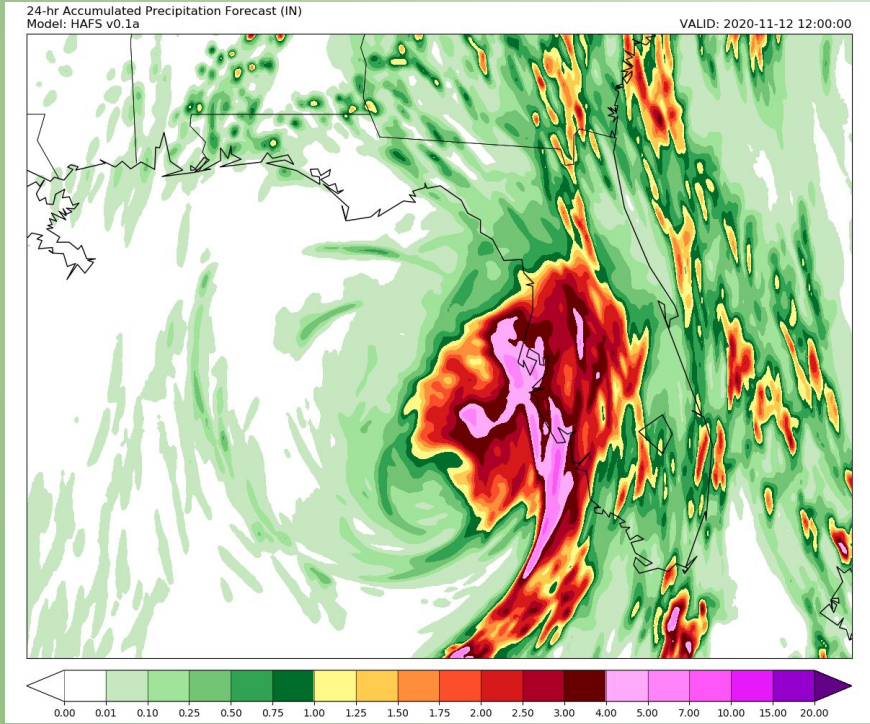


Does 75m make sense for observed rainfall characteristics?

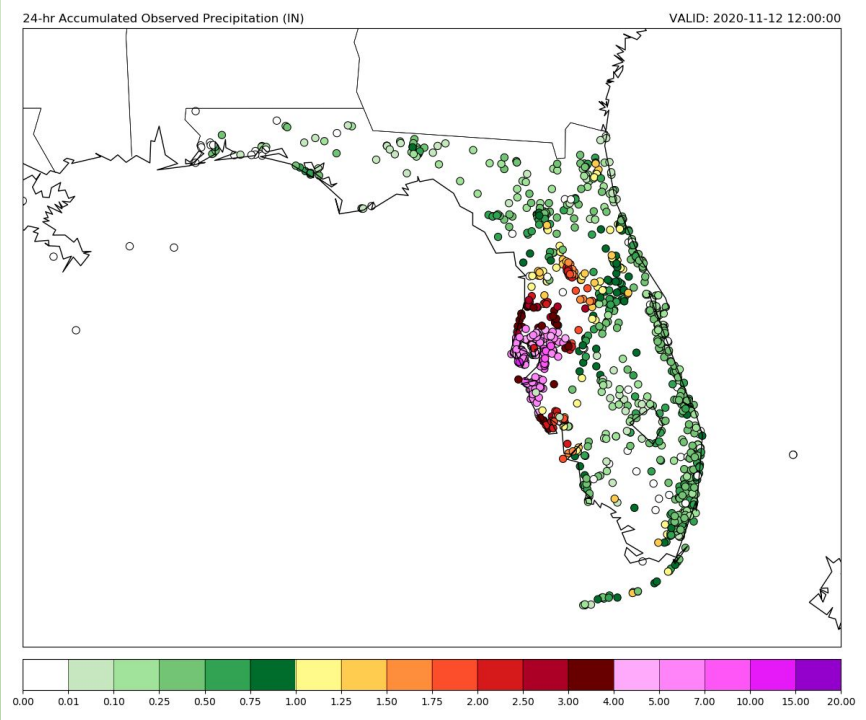


TC QPF case over Florida

HAFS v0.1A 24-hour Accum. QPF

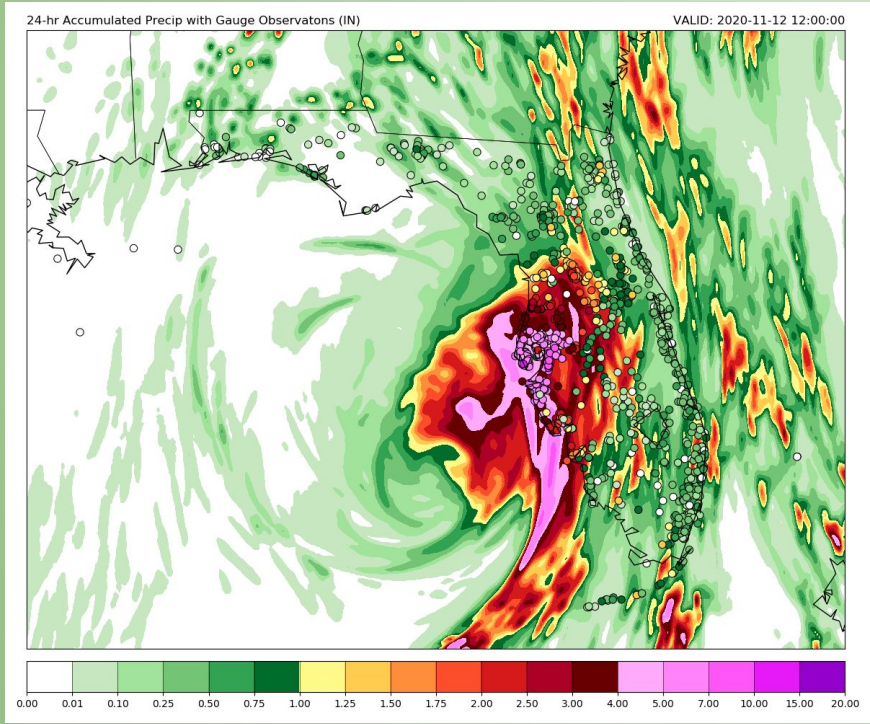


Rain Gauge Obs. 24-hour Accum. QPE

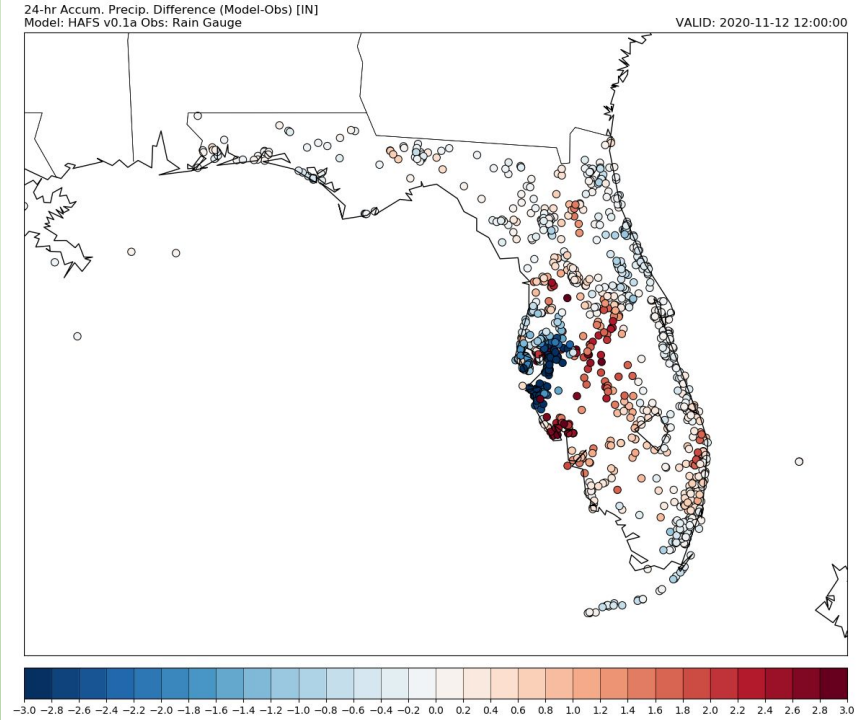


TC QPF case over Florida

HAFS vs. Obs. overlay

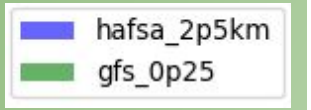


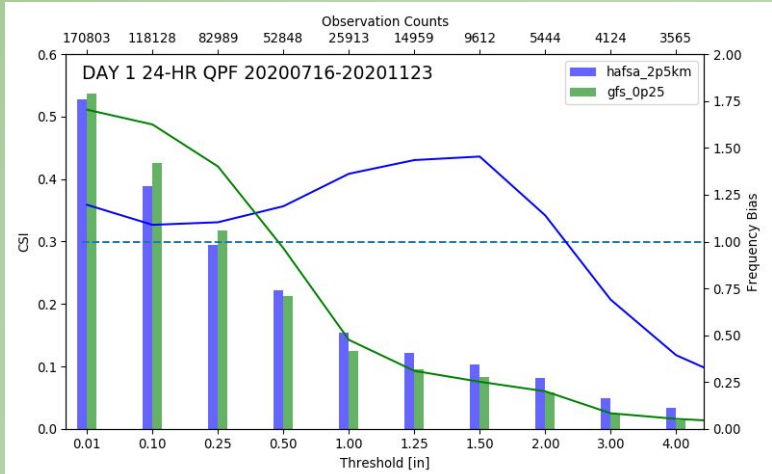
Model - Obs Difference

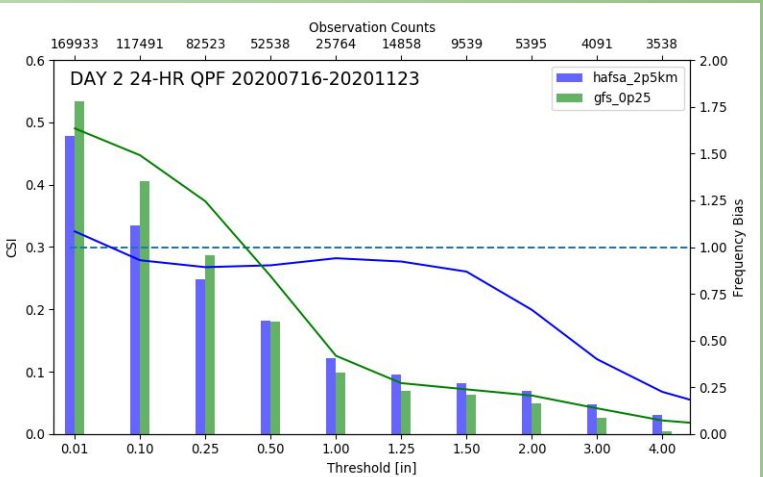


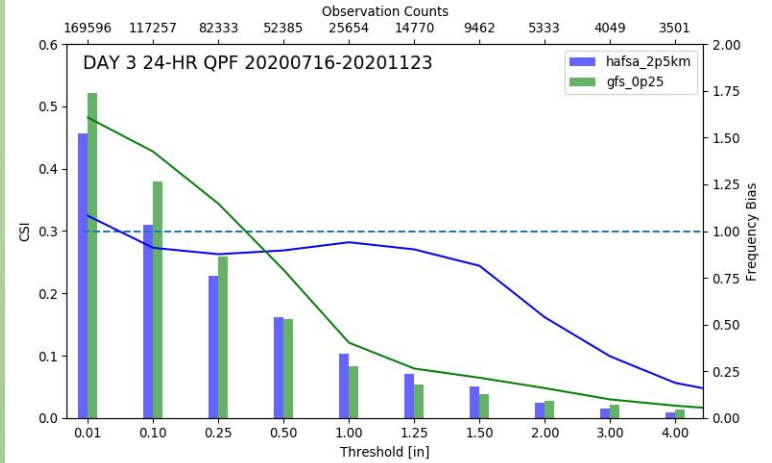
Bulk Statistics for 2020 hurricane season

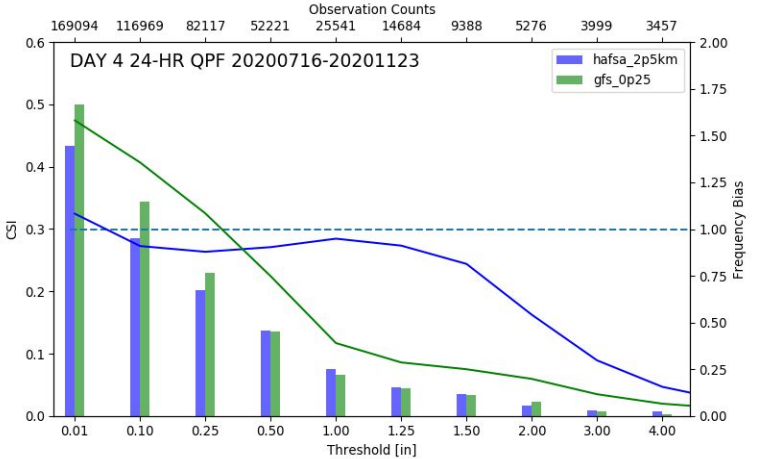
- HAFS 00z and 12z combined to analyze respective 24-hr accumulated forecasts valid at 12z daily
  - Example 00z - F036 and 12z - F024 are evaluated for Day 1
- GFS 0.25 is used as a comparison
- Days 1 - 4 are evaluated
  - Longest lead time is F108 for 00z initialized run (Day 4).
- Verified using rain gauge network
- Critical Success Index
  - (hits) ÷ (hits + false alarms + misses)

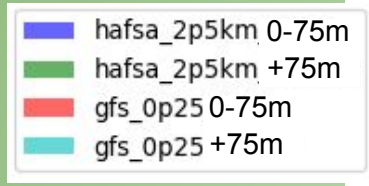

hafsa_2p5km
gfs_0p25

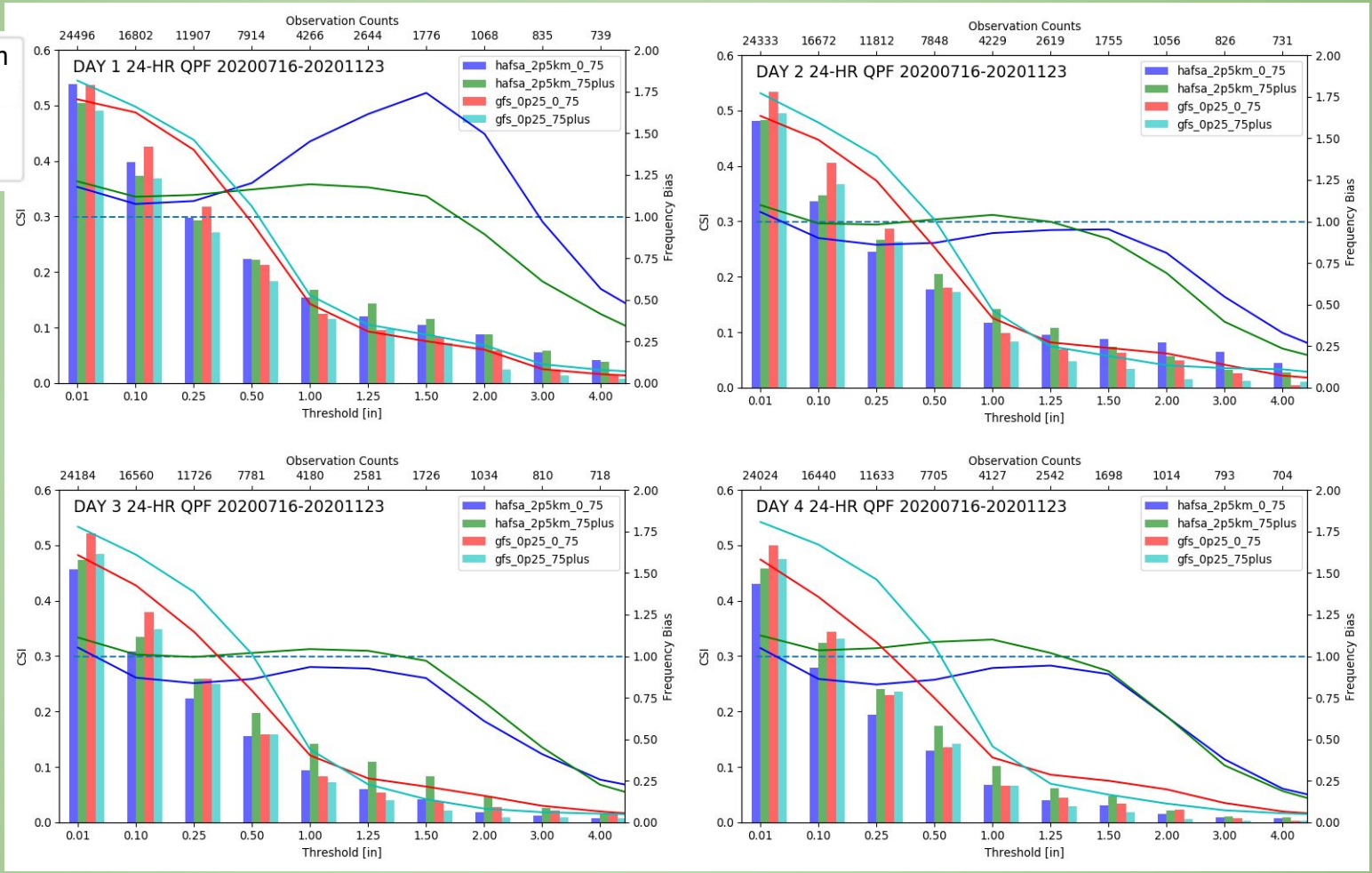

Observation Counts
170803 118128 82989 52848 25913 14959 9612 5444 4124 3565
DAY 1 24-HR QPF 20200716-20201123
hafsa_2p5km
gfs_0p25
CSI
Frequency Bias
Threshold [in]
0.01 0.10 0.25 0.50 1.00 1.25 1.50 2.00 3.00 4.00


Observation Counts
169933 117491 82523 52538 25764 14858 9539 5395 4091 3538
DAY 2 24-HR QPF 20200716-20201123
hafsa_2p5km
gfs_0p25
CSI
Frequency Bias
Threshold [in]
0.01 0.10 0.25 0.50 1.00 1.25 1.50 2.00 3.00 4.00


Observation Counts
169596 117257 82333 52385 25654 14770 9462 5333 4049 3501
DAY 3 24-HR QPF 20200716-20201123
hafsa_2p5km
gfs_0p25
CSI
Frequency Bias
Threshold [in]
0.01 0.10 0.25 0.50 1.00 1.25 1.50 2.00 3.00 4.00


Observation Counts
169094 116969 82117 52221 25541 14684 9388 5276 3999 3457
DAY 4 24-HR QPF 20200716-20201123
hafsa_2p5km
gfs_0p25
CSI
Frequency Bias
Threshold [in]
0.01 0.10 0.25 0.50 1.00 1.25 1.50 2.00 3.00 4.00

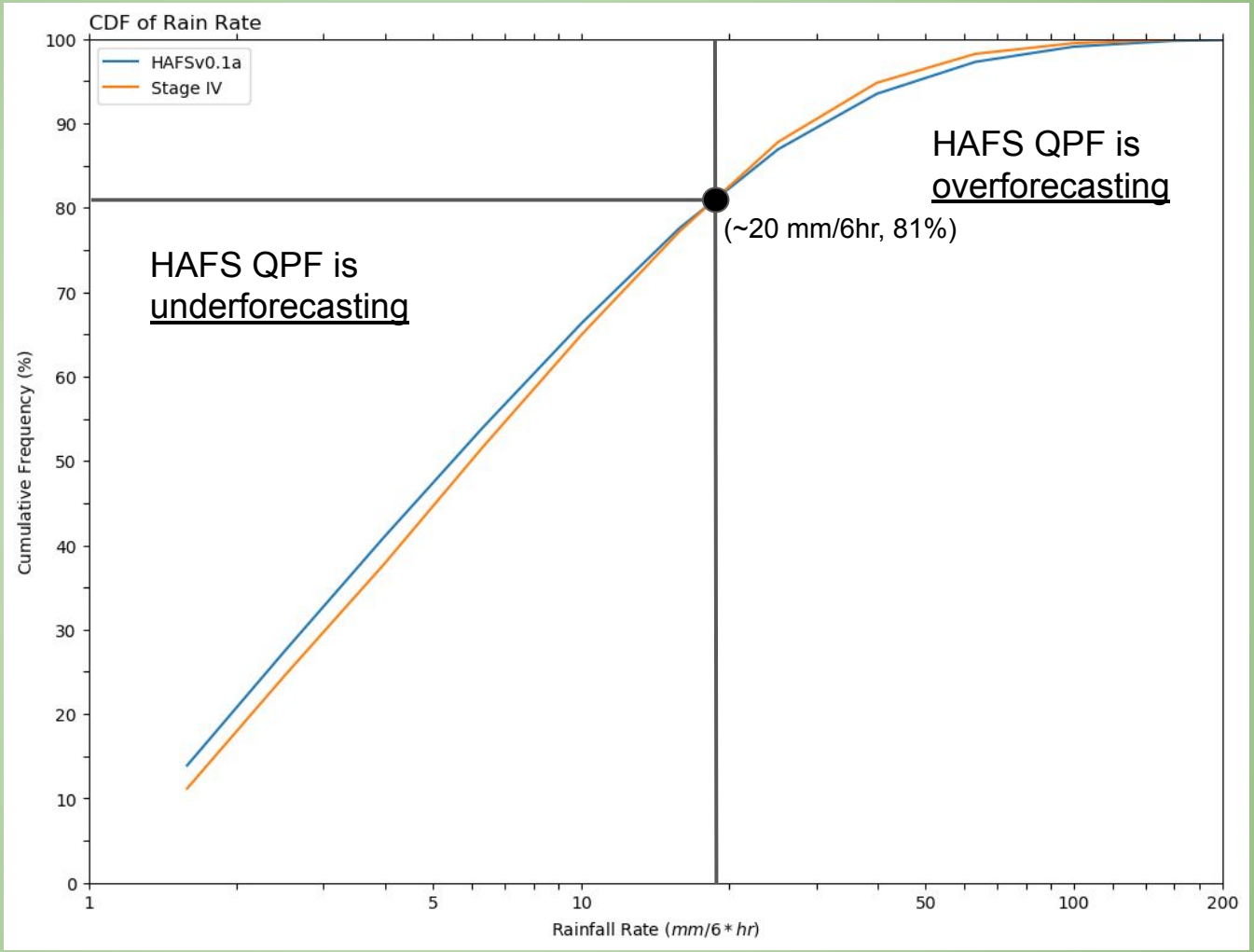

hafsa_2p5km 0-75m
hafsa_2p5km +75m
gfs_0p25 0-75m
gfs_0p25 +75m


DAY 1 24-HR QPF 20200716-20201123
Observation Counts
24496 16802 11907 7914 4266 2644 1776 1068 835 739
DAY 2 24-HR QPF 20200716-20201123
Observation Counts
24333 16672 11812 7848 4229 2619 1755 1056 826 731
DAY 3 24-HR QPF 20200716-20201123
Observation Counts
24184 16560 11726 7781 4180 2581 1726 1034 810 718
DAY 4 24-HR QPF 20200716-20201123
Observation Counts
24024 16440 11633 7705 4127 2542 1698 1014 793 704
hafsa_2p5km_0_75
hafsa_2p5km_75plus
gfs_0p25_0_75
gfs_0p25_75plus
CSI
Frequency Bias
Threshold [in]
0.01 0.10 0.25 0.50 1.00 1.25 1.50 2.00 3.00 4.00

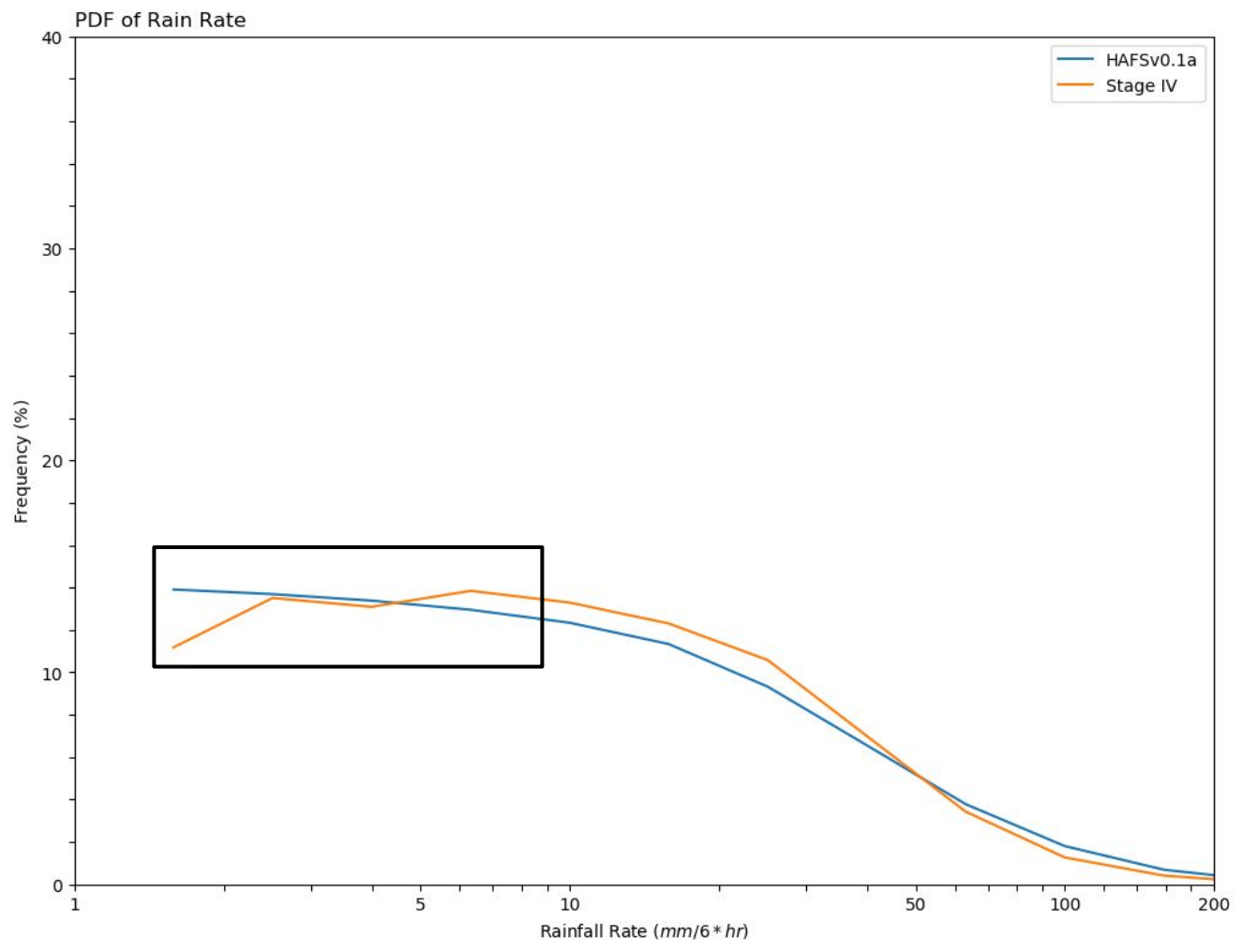
Cumulative Distribution Function (CDF) Analysis of HAFS QPF

- Frequency of rain rate threshold exceedance within 600 km radius of TC best-track
  - Similar method to Marchok et al. 2007 and Ko et al. 2020
  - Since rainfall is typically log-normally distributed, rain rates are converted to decibel rain rate
- HAFS v0.1A 00z 3-hr accumulated QPF is used to retrieve 6-hr rain rates
- Stage IV 6-hr QPE is used as the observed rain rate over CONUS
- Rain rates kept in mm/6hr to conserve known rate
  - Avoid assuming hourly rain rate

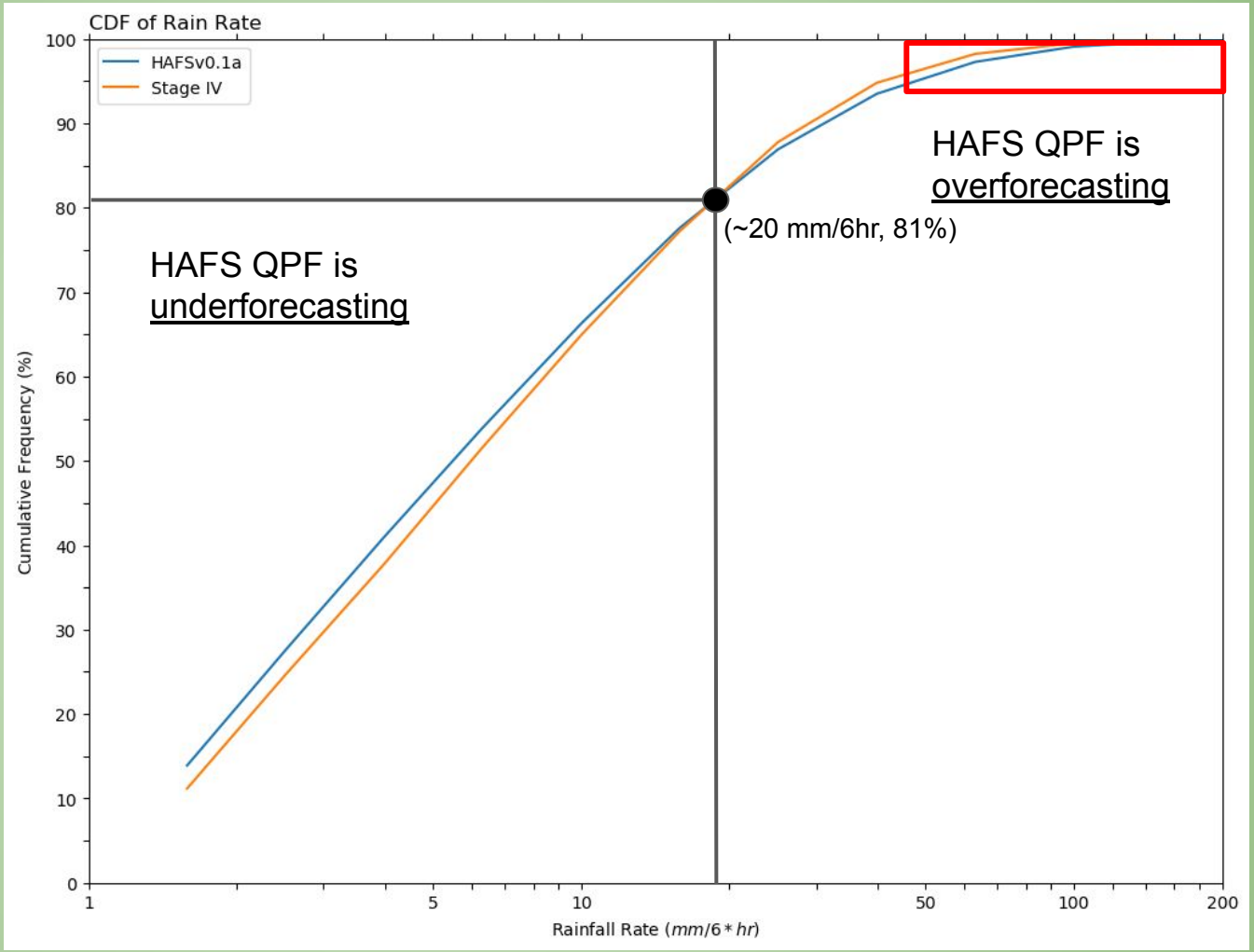
CDF of 2020 hurricane season rain rates for all TC tracks over CONUS



Probability Density Function of 2020 hurricane season rain rates for all TC tracks over CONUS

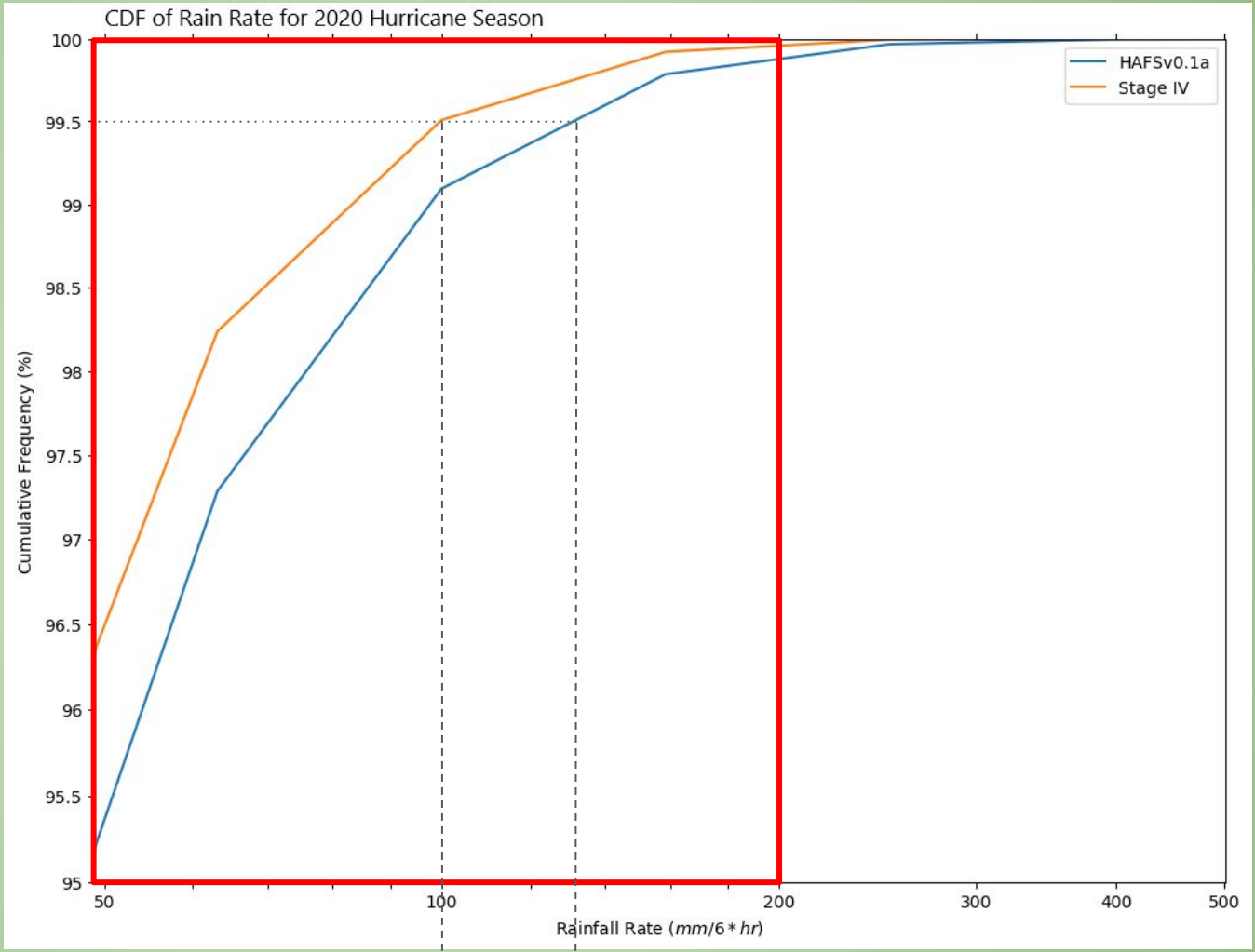


CDF of 2020 hurricane season rain rates for all TC tracks over CONUS



CDF of 2020 hurricane season rain rates for all TC tracks over CONUS

Looking at cumulative frequencies greater than 95%.



Conclusions: Bulk Statistics

- GFS outperforms HAFS QPF in rainfall thresholds UP TO 0.25 inches.
- HAFS improves skill over GFS at higher thresholds at relatively shorter lead times (Days 1 & 2).
  - Days 3 & 4 do not show large enough difference to conclude a similar result.
- HAFS frequency bias is much closer to 1 in all situations compared to GFS.
  - Small degradation in f-bias at higher thresholds (greater than 2.00 inches).
- When evaluating skill by elevation, higher terrain forecasts perform better for HAFS compared to near sea-level forecasts for days 3 & 4.
  - Days 1 & 2 show difference by threshold, but are not consistent between the forecasts

Conclusions: CDF Statistics

- Overall, HAFS produces rain rates very closely to Stage IV.
- For lower rain rates (less than 20 mm/6hr), HAFS underforecasts compared to Stage IV.
- For higher rain rates (greater than 20 mm/6hr), HAFS overforecasts rain rates.
- HAFS initially produces higher frequency of lowest rain rates providing prolonged underforecast.
- High percentile events (greater than 95% cumulative frequency) have potential for large differences in forecasted and observed rain rates.

Constructing bias-corrected QPF guidance

- GOAL: Use observed QPE and model QPF along with other atmospheric parameters to reduce bias and increase skill of forecast QPF
- Testing sample:
  - “Fitting” dataset will be 2020 hurricane season using HAFS v0.1A
  - “Evaluation” dataset will be 2021 hurricane season using HAFS v0.2A
- Starting “simple”
  - Use linear regression to calibrate the model
  - Although most commonly used for probabilistic forecasting, this method can be applied to deterministic forecasts.
- Progress to machine learning algorithm
  - Allow for a more thorough fitting of the model by removing linear dependence and decrease developer bias.

Constructing linear regression calibrated QPF guidance

- Separate deterministic forecast into rainfall thresholds
  - Example: 0.01”, 0.25”, 0.5”, 1.0”, 2.0”, 3.0”, 4.0”, 5.0”, 8.0”, 10.0”
- Run regression model on threshold categories
  - Result from model is probability of exceedance for each threshold
- Informing the bias-correction model using atmospheric parameters
- Inclusion of the influence of upslope flow on precipitation
  - The product of U and V wind components with the first derivatives of elevation in the x and y direction
- Assemble CDF of rainfall frequencies from regression model and use percentile threshold to determine deterministic QPF value.

Future Work

- Produce bias-corrected products while considering the influence of elevation on QPF.
  - Build method using HAFS 0.1A, evaluate using HAFS 0.2A
  - Using both linear regression and machine learning techniques (likely neural networks).
- Verify the skill of calibrated method using metrics already established for HAFS v0.1A evaluation.
- Expand verification to gridded analysis over the region to supplement rain gauge verification.
  - Two possible datasets to use for this are CMORPH (CPC) and IMERG (NASA).
  - Caveats: Satellite derived QPE carry their own bias to account for in verification analysis.
- END GOAL: Produce a vetted bias-correction method to recommend for implementation into future versions of HAFS that provides informed QPF forecasts for high terrain.

Questions?

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