Recent Tropical Cyclone Data Assimilation Research at NOAA/AOML Hurricane Research Division and University of Miami/CIMAS

Altu**ğ** Aksoy

University of Miami / CIMAS NOAA / AOML / Hurricane Research Division

13 April 2023



Introduction

General Overview of Talk

What TC-DA Research Do WeDo at HRD and UM?

Part 1: Data Collection, Hosting,
 & Testing

Part 2: Testing of New Observing Platforms

3

Part 3: Testing of New DA Methodologies

5 Summary / Final Thoughts

General

TC-DA Research at HRD/UM Spans All Phases of The DA Life Cycle

General

TC-DA Research at HRD/UM Spans All Phases of The DA Life Cycle

1 Data Collection:

Direct Involvement in Operationally and Research-Tasked Flight Missions

Quality Control and Hosting of Datasets

General

TC-DA Research at HRD/UM Spans All Phases of The DA Life Cycle

1 Data Collection:

Direct Involvement in Operationally and Research-Tasked Flight Missions

Quality Control and Hosting of Datasets

New Platforms:

Testing of New Observing Platforms for Data Collection and Assimilation

Testing of New Procedures of Quality Control and Preprocessing

General

TC-DA Research at HRD/UM Spans All Phases of The DA Life Cycle

Direct Involvement in Operationally and Research-Tasked Flight Missions
Quality Control and Hosting of Datasets
Testing of New Observing Platforms for Data Collection and Assimilation
Testing of New Procedures of Quality Control and Preprocessing
Development of New Data Assimilation Techniques

General

TC-DA Research at HRD/UM Spans All Phases of The DA Life Cycle

1 Data Collection:	Direct Involvement in Operationally and Research-Tasked Flight Missions
	Quality Control and Hosting of Datasets
2 New Platforms:	Testing of New Observing Platforms for Data Collection and Assimilation
	Testing of New Procedures of Quality Control and Preprocessing
③ New Methods:	Development of New Data Assimilation Techniques
4 Operational:	Implementation of Above Research in Operational Systems

Part 1: Data Collection, Hosting, & Testing

Data Collection: The Big Picture (In The Air)

ln-situ

• Wind, press., temp., moisture

Expendables

- Dropsondes
- AXBT, AXCP, buoy

Remote Sensors

- Tail Doppler Radar (TDR)
- SFMR/HIRAD
- WSRA
- Scatterometer/profiler
- UAS/sUAS



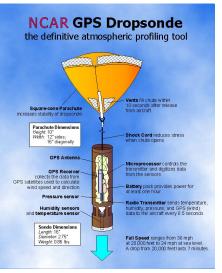




G-IV Tail Doppler Radar



Coyote sUAS



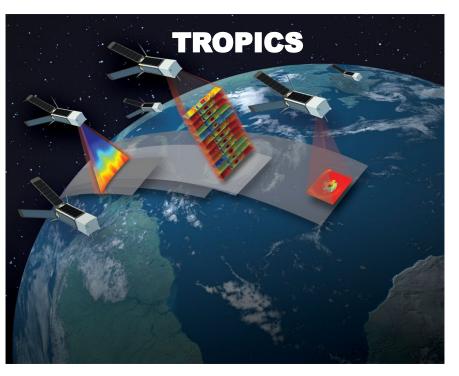
Part 1

GPS Dropsonde



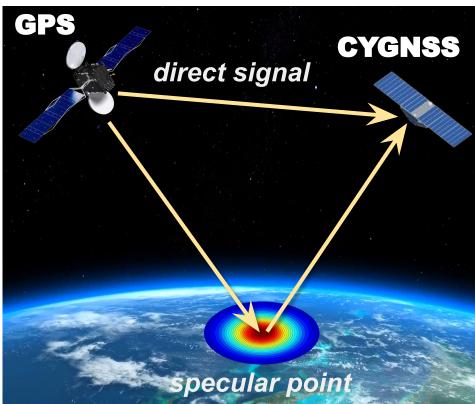
Doppler Wind Lidar

Data Collection: The Big Picture (In Space)



Time-Resolved Observations of Precipitation structure and storm Intensity with a Constellation of Smallsats (TROPICS) Thermodynamics of the Troposphere and Precipitation Structure for Storm Systems **Cyclone Global Navigation Satellite System** (CYGNSS) Surface Wind Speed Retrievals

Part 1



3

Part 1

Part 1

Hosting of "Raw" Data Is Still Based on Year/Storm/Particular Mission

https://www.aoml.noaa.gov/2022-hurricane-field-program-data/#ian

+ 20220928U3					
 20220928H1 Wednesday, September 28 					
Take Off: 0755Z Harligen		Aircraft: NOAA42		Tasking: E	MC
Landing: 1442Z Harligen		Mission ID: 2809A		Pattern:B	utterfly
Download Data:					
SFMR	Dropsond	e Radar	Flight-Level (ASCII)		Flight-Level (NetCDF)
Mission Documents & Plots:					
Lead Scientist	Dropsond	<u>e</u>	Radar		Flight Director
20220928H1 Proposed Track					
+ 20220928U4					
+ 20220929U1					
+ 20220930U1					

Part 1

- 20220928H1					
Wednesday, September 28 Take Off: 0755Z Harligen	Aircraft: NOAA4	2	Tasking: EMC		Availability Through AOML/
Landing: 1442Z Harligen	Mission ID: 280		Pattern:Butterfly		Website
Download Data:	1				
SFMR	Dropsonde Radar	Flight-Level (ASCII)	Flight-Level (NetCDF)		
		(ASCII)	(NEICDF)		
Mission Documents & Plots	Dropsonde	Radar	Flight Director	_	
20220928H1 Proposed	Track				

Ctill Decod on Very (Ctorm (Derticular Mission

Part 1

+ 20220928U3	ml.noaa.gov/2027	2-hurricane-fie	ld-program-data/#ian		
- 20220928H1 2 Wednesday, September 28 Take Off: 0755Z Harligen Landing: 1442Z Harligen	Aircraft: NOAA Mission ID: 28		Tasking: EMC Pattern:Butterfly	1	Availability Through AOML/HRD Website
Download Data:		Flight-Level	' Flight-Level		
SFMR Mission Documents & Plots:	Dropsonde Radar	(ASCII)	(NetCDF)		
Lead Scientist	Dropsonde	Radar	Flight Director	2	Availability Is Mission-Based
20220928H1 Proposed Tr	ack				
20220928U4					
20220930U1					

Part 1

https://www.ac	oml.noaa.gov/202	2-hurricane-field	-program-data/#ian]	
 2022092803 20220928H1 2 Wednesday, September 28 Take Off: 0755Z Harligen Landing: 1442Z Harligen Download Data: 	Aircraft: NOAA Mission ID: 28		Tasking: EMC Pattern:Butterfly	1	Availability Through AOML/HRD Website
SFMR	Dropsonde Radar	Flight-Level (ASCII)	Flight-Level (NetCDF)		
Mission Documents & Plots: Lead Scientist	Dropsonde	Radar	Flight Director	2	Availability Is Mission-Based
20220928H1 Proposed Tr + 20220928U4 + 20220929U1				3	Availability Is Instrument-Based
+ 20220930U1					

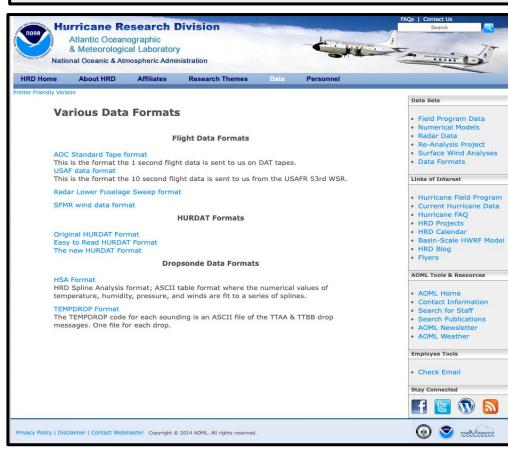
Part 1

Part 1

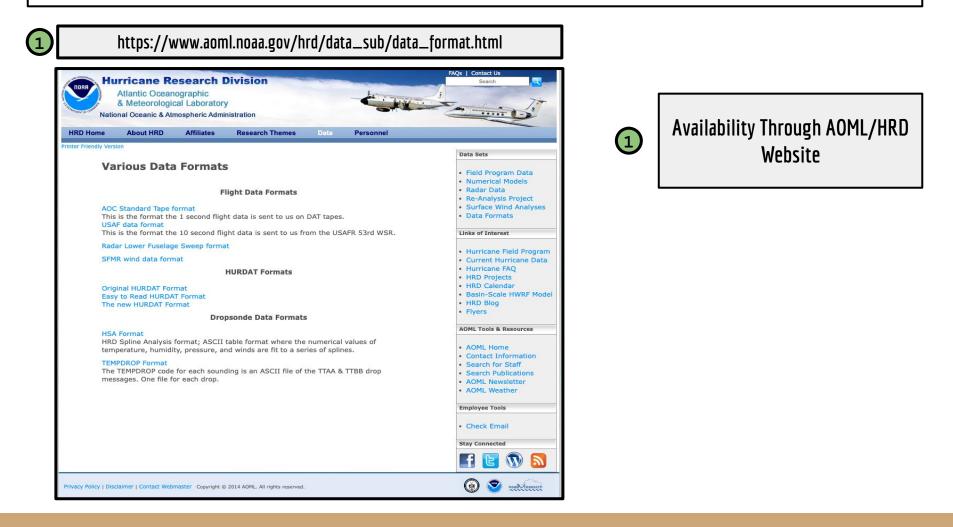
Documentation Is Based On Platforms and Info On Ob Errors Is Scarce

https://www.aoml.noaa.gov/hrd/data_sub/data_format.html

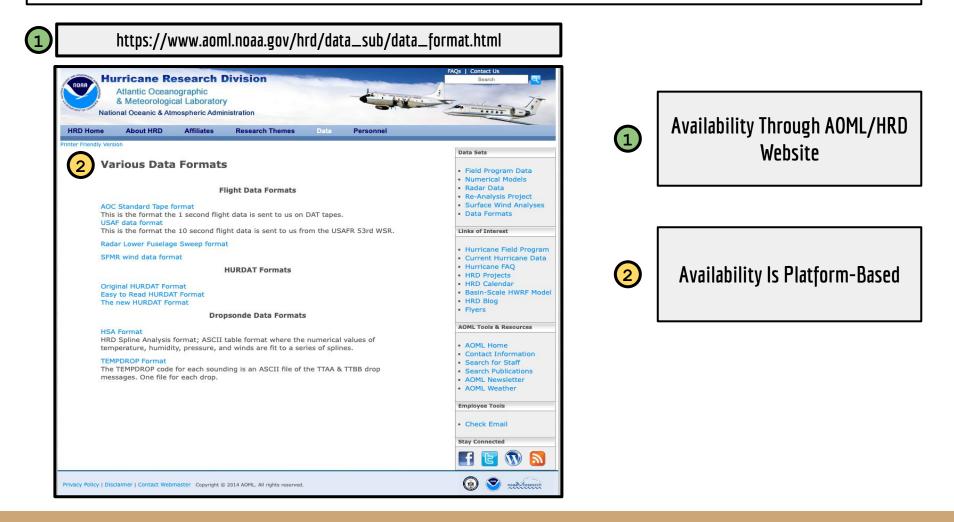
4



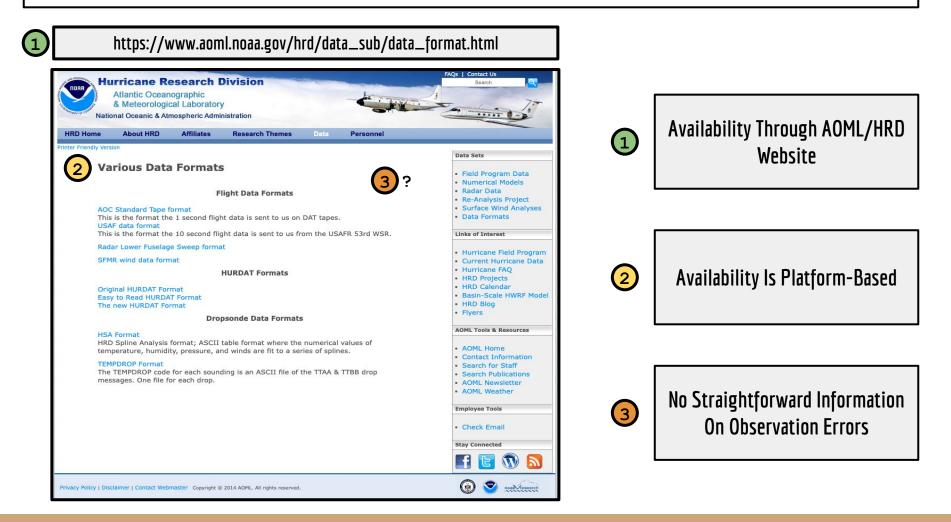
Part 1



Part 1



Part 1



HRDOBS: A Comprehensive TC Dataset For DA

Part 1

A Comprehensive Dataset For Data Assimilation And Science Applications (K. Sellwood and A. Aksoy)

- Uses A common observation-processing environment to apply quality control, estimate errors, and convert to standard observation types and scientific units
- Collects observations for all tropical cyclones for which a TC-Vitals file exists
- Centered on 6-h synoptic times (e.g., 00Z, 06Z,12Z,18Z) within +/- 3 h of syn. time
- Contains observations within 20 geographical degrees of the TC-Vitals center
- HDF-5 file format with all platforms/data contained in a single file
- Contains metadata: Storm position & motion, available platforms & instruments
- Supplemental info file with observation counts for each platform
- Currently available for years 2014-2020 with the full dataset to go back to year 2010
- Will be hosted with a DOI following general data hosting standards

HRDOBS: A Comprehensive TC Dataset For DA

A Comprehensive Dataset For Data Assimilation And Science Applications (K. Sellwood and A. Aksoy)

Part 1

INSTRUMENT	AVAILABLE OBSERVATIONS
DROPSONDE	U V wind, Temperature, Specific Humidity every 5 mb
FLIGHT-LEVEL	U V wind, Temperature, Specific Humidity, Pressure
SFMR	Surface Wind Speed, Rain Rate, RR dependent wind error
TDR	Radial Wind Speed Superobs
SUAS	U V wind, Temperature, Specific Humidity, Pressure
DWL	U V wind profiles
BEST TRACK	Center lat/lon, Vmax, Pmin, RMW
HIGH RESOLUTION TRACK	Center lat/lon
VORTEX MESSAGE	Center lat/lon, Observed Vmax (spd and dir) and Pmin

HRDOBS: A Comprehensive TC Dataset For DA

Part 1

A Comprehensive Dataset For Data Assimilation And Science Applications (K. Sellwood and A. Aksoy)

Sample Supplemental Info File That Contains Number of Observations From Each Observing Platform

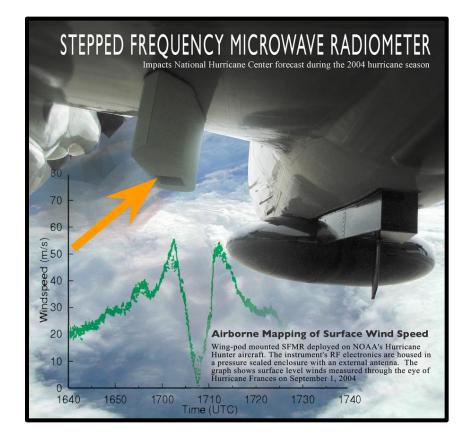
	CENTER LON: -8 TIME VALID: 18	39.0	
PLATFORM	#OBS	#OBS	
	RAW DATA		
NOAA 42 Dropsonde	5310	 4995	
NOAA 43 Dropsonde	0	0	
NOAA 49 Dropsonde	0	0	
USAF Dropsonde	0	0	
GHAWK Dropsonde	0	0	
NOAA 42 Flight-Level	1408	1408	
NOAA 42 SFMR	1408	1408	
NOAA 43 Flight-Level	0	0	
NOAA 43 SFMR	0	0	
USAF Flight-Level	1008	994	
NOAA 49 Flight-Level	0	0	
NOAA 49 SFMR	0	0	
USAF SFMR	1008	994	
NOAA 42 TDR	45252	45252	
NOAA 43 TDR	0	0	
NOAA 49 TDR	0	0	
Coyote	0	0	
DWL	0	0	
Vortex Message	0	0	
Best Track	35	35	
Hi-Res Track	2215	2215	
TOTAL	57644	57301	

SFMR High-Wind/Rain Errors: Further Analysis

H. Hollbach (FSU, NGI, AOML/HRD)

Stepped Frequency Microwave Radiometer (SFMR)

- Installed underneath the NOAA P-3 and Air Force Reserves' C-130 Hurricane Hunter aircraft
- Downward-looking infrared radiometer passively reads the microwave radiation coming from the ocean surface
- Estimates of the ocean surface brightness temperature are made at six frequencies between 4.6 and 7.2 GHz
- Regression relationships are then used to make estimates of the surface wind speed and rain rate

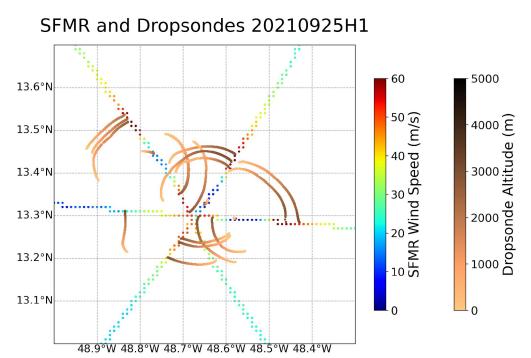


SFMR High-Wind/Rain Errors: Further Analysis

H. Hollbach (FSU, NGI, AOML/HRD)

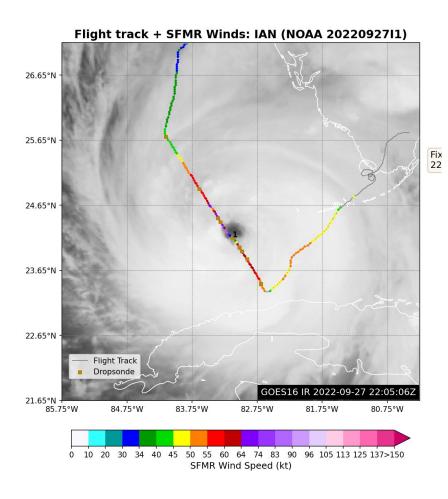
Stepped Frequency Microwave Radiometer (SFMR): Problems Identified

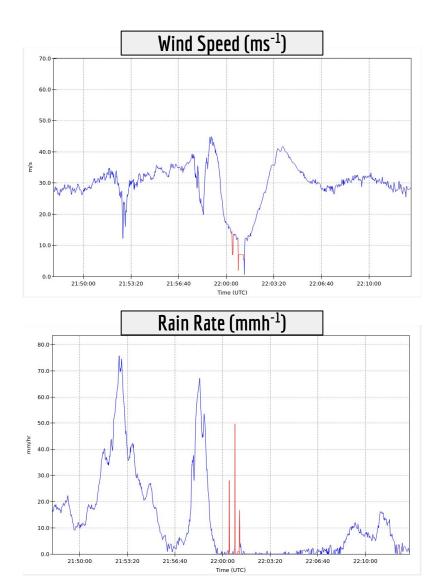
- Colocations with dropsondes in high winds are challenging
- Primary option for independent rain rate source is TDR, which does not have a calibrated reflectivity archive
 - Previous TDR Z-R relationship may not be reliable
- Coincident IWRAP data show misalignment of near-surface wind speed peak compared to SFMR in high winds and high rain



⁸ SFMR High-Wind/Rain Errors: Example in Hurricane Ian

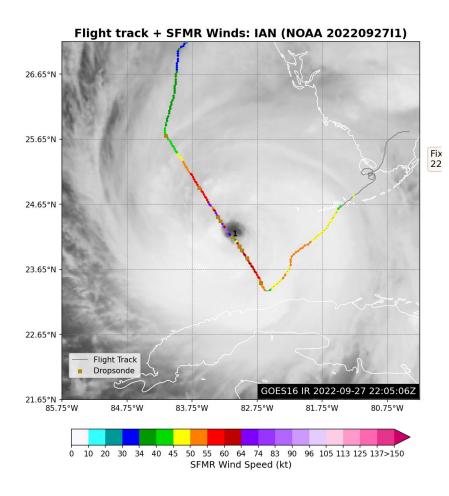
H. Hollbach (FSU, NGI, AOML/HRD)

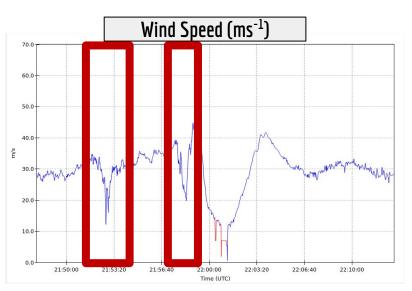


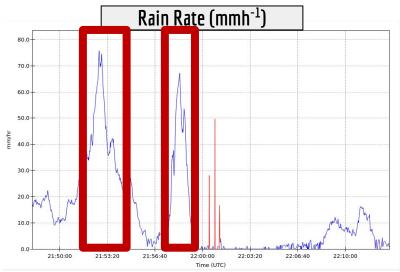


⁹ SFMR High-Wind/Rain Errors: Example in Hurricane Ian

H. Hollbach (FSU, NGI, AOML/HRD)

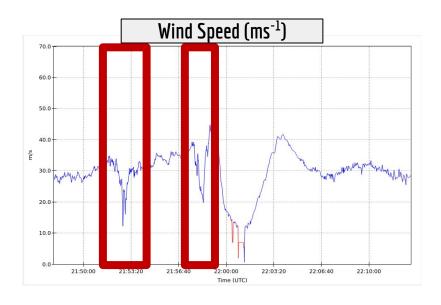






SFMR High-Wind/Rain Errors: Implications

H. Hollbach (FSU, NGI, AOML/HRD)



• SFMR radiative transfer equations may not be accounting for rain correctly when larger drops are present

Part 1

- Uncertainty in magnitude and location of peak wind speed
- Additional uncertainty for intensity estimation
- Potential mismatches between NHC Best Track intensity and DA analyses that incorporate more than just SFMR data

Part 2: Testing Of New Observing Platforms

Example: Assimilation of sUAS Observations

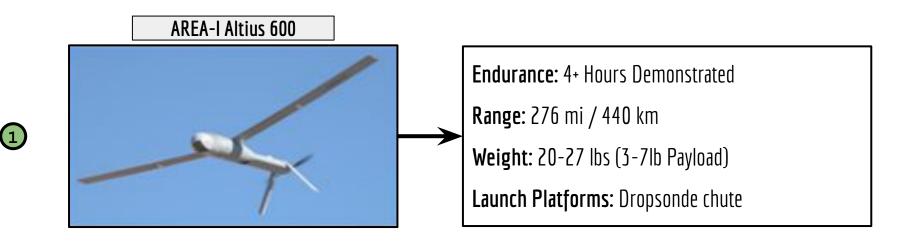
Part 2

AOML/HRD and UM/CIMAS Are Involved In The Testing of Several sUAS Platforms

Example: Assimilation of sUAS Observations

Part 2

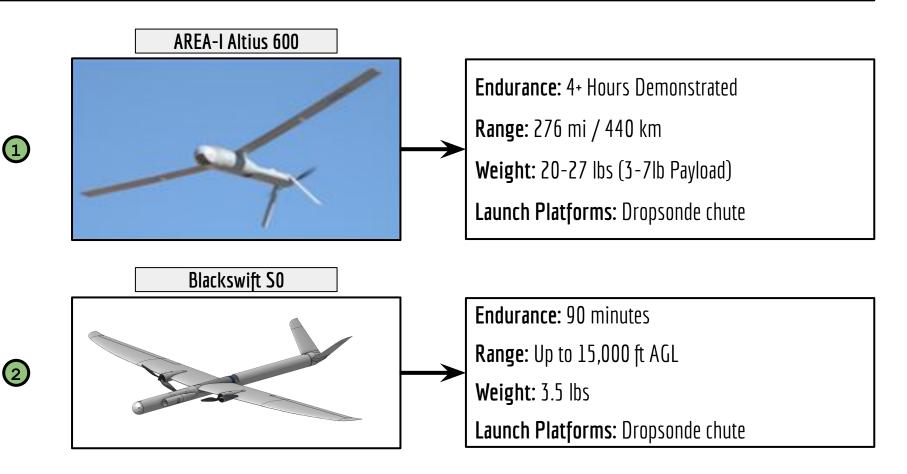
AOML/HRD and UM/CIMAS Are Involved In The Testing of Several sUAS Platforms



Example: Assimilation of sUAS Observations

Part 2

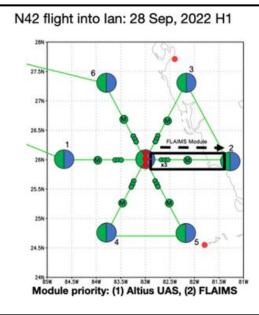
AOML/HRD and UM/CIMAS Are Involved In The Testing of Several sUAS Platforms

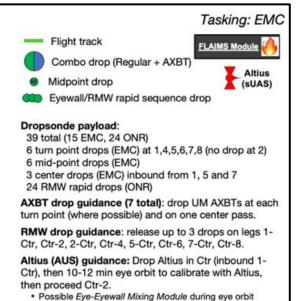


Altius sUAS DA: Case & Data

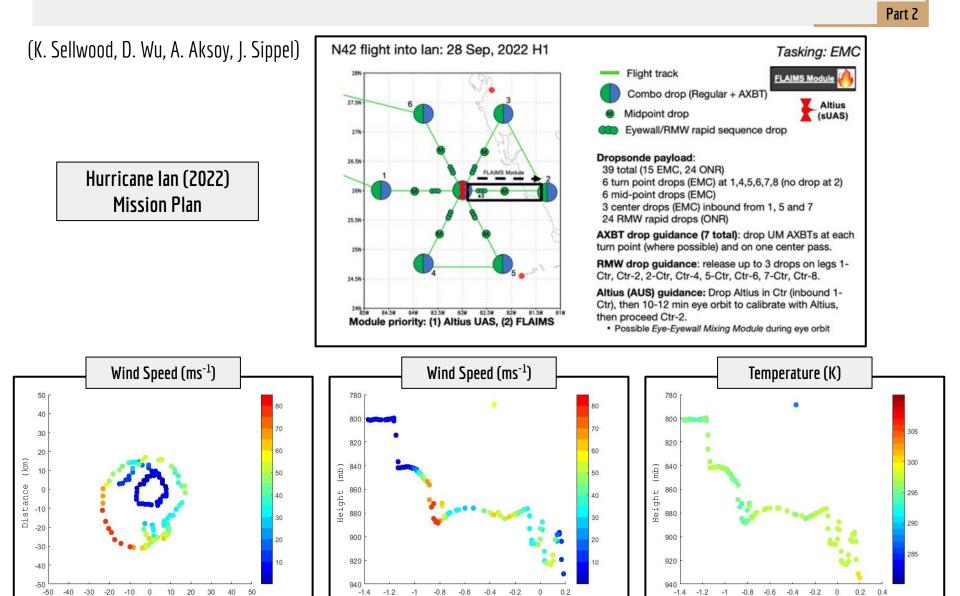
(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)







Altius sUAS DA: Case & Data



Time Offset (h)

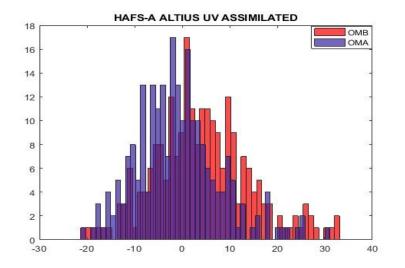
Time Offset (h)

Distance (km)

Altius sUAS DA: OMA/OMB Stats (UV)

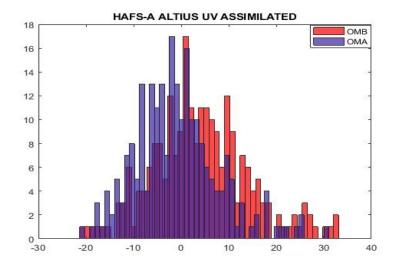
Part 2

(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

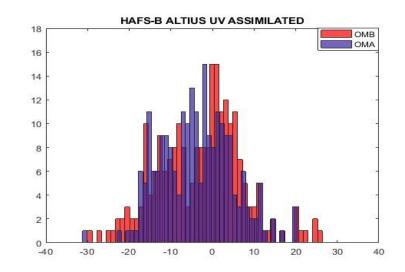


HAFS-A ALTIUS UV	ACCEPTED OMB	OMA	REJECTED OMB) OMA
#OBS	234	234	4	4
RMS ERROR	10.96	8.85	72.36	71.21
ABS ERROR	8.42	6.82	62.79	61.92
BIAS	4.16	-0.94	44.76	43.01

(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

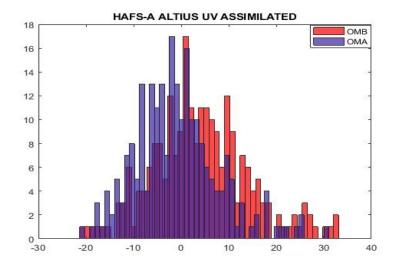


HAFS-A ALTIUS UV	ACCEPTED OMB OMA		REJECTED OMB OM	
#OBS	234	234	4	4
RMS ERROR	10.96	8.85	72.36	71.21
ABS ERROR	8.42	6.82	62.79	61.92
BIAS	4.16	-0.94	44.76	43.01

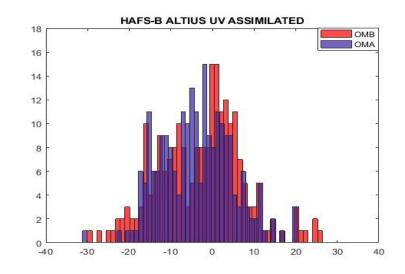


Part 2

HAFS-B ALTIUS UV	ACCEPTED OMB OMA		REJECTED OMB	OMA
#OBS	228	228	4	4
RMS ERROR	10.53	9.43	68.19	68.85
ABS ERROR	8.19	7.60	58.84	59.65
BIAS	-2.67	-3.79	39.54	39.96



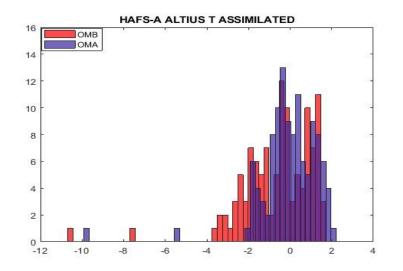
HAFS-A ALTIUS UV	ACCEPTED OMB OMA		REJECTED OMB OMA	
#OBS	234	234	4	4
RMS ERROR	10.96	8.85	72.36	71.21
ABS ERROR	8.42	6.82	62.79	61.92
BIAS	4.16	-0.94	44.76	43.01



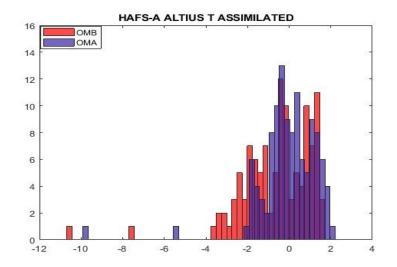
HAFS-B ALTIUS UV	ACCEPTED OMB OMA		REJECTED OMB OMA	
#OBS	228	228	4	4
RMS ERROR	10.53	9.43	68.19	68.85
ABS ERROR	8.19	7.60	58.84	59.65
BIAS	-2.67	-3.79	39.54	39.96

Altius sUAS DA: OMA/OMB Stats (T)

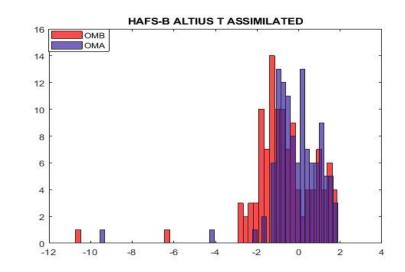
Part 2



HAFS-A	ACCEPTED		REJECTED	
ALTIUS T	OMB	OMA	OMB	OMA
#OBS	116	116	0	0
RMS ERROR	1.88	1.45	n/a	n/a
ABS ERROR	1.33	0.95	n/a	n/a
BIAS	-0.63	-0.04	n/a	n/a

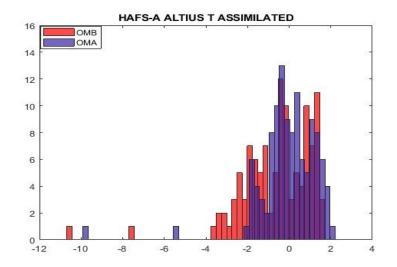


HAFS-A ALTIUS T	ACCEPTED OMB OMA		REJECTED OMB OMA	
#OBS	116	116	0	0
RMS ERROR	1.88	1.45	n/a	n/a
ABS ERROR	1.33	0.95	n/a	n/a
BIAS	-0.63	-0.04	n/a	n/a

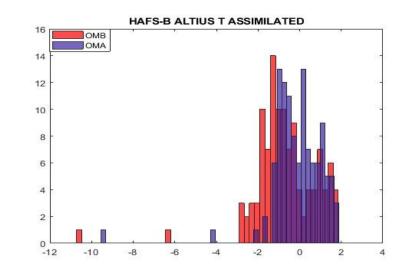


HAFS-B ALTIUS T	ACCEPTED OMB OMA		REJECTED OMB	OMA
#OBS	115	115	0	0
RMS ERROR	1.74	1.32	n/a	n/a
ABS ERROR	1.23	0.88	n/a	n/a
BIAS	-0.71	-0.11	n/a	n/a

(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)



HAFS-A ALTIUS T	ACCEPTED OMB OMA		REJECTED OMB	OMA
#OBS	116	116	0	0
RMS ERROR	1.88	1.45	n/a	n/a
ABS ERROR	1.33	0.95	n/a	n/a
BIAS	-0.63	-0.04	n/a	n/a



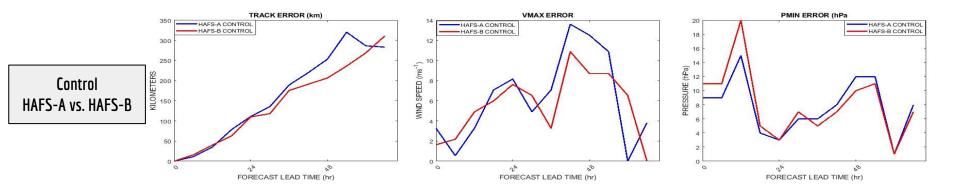
HAFS-B ALTIUS T	ACCEPTED OMB OMA		REJECTED OMB OMA	
#OBS	115	115	0	0
RMS ERROR	1.74	1.32	n/a	n/a
ABS ERROR	1.23	0.88	n/a	n/a
BIAS	-0.71	-0.11	n/a	n/a

(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

MEAN ERROR	TRACK	VMAX	PMIN
HAFS-A CONTROL	160.39	6.26	7.75
HAFS-A ALTIUS	158.94	6.71	7.67
HAFS-B CONTROL	144.73	5.58	8.17
HAFS-B ALTIUS	151.40	5.94	8.5

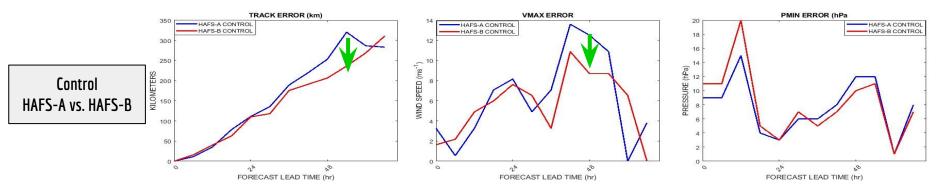
(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

MEAN ERROR	TRACK	VMAX	PMIN
HAFS-A CONTROL	160.39	6.26	7.75
HAFS-A ALTIUS	158.94	6.71	7.67
HAFS-B CONTROL	144.73	5.58	8.17
HAFS-B ALTIUS	151.40	5.94	8.5



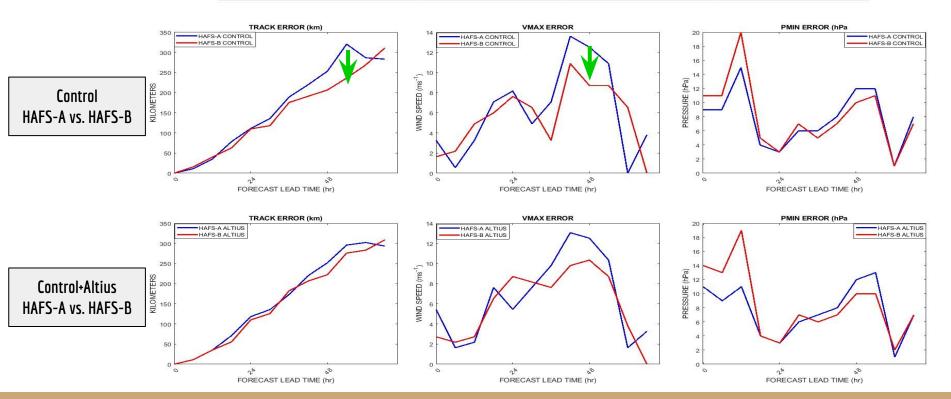
(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

MEAN ERROR	TRACK	VMAX	PMIN
HAFS-A CONTROL	160.39	6.26	7.75
HAFS-A ALTIUS	158.94	6.71	7.67
HAFS-B CONTROL	144.73	5.58	8.17
HAFS-B ALTIUS	151.40	5.94	8.5

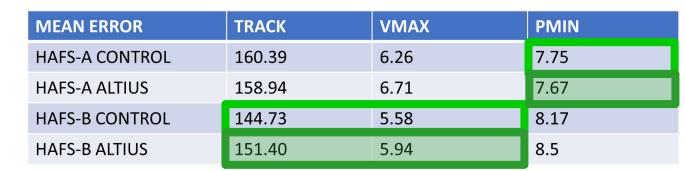


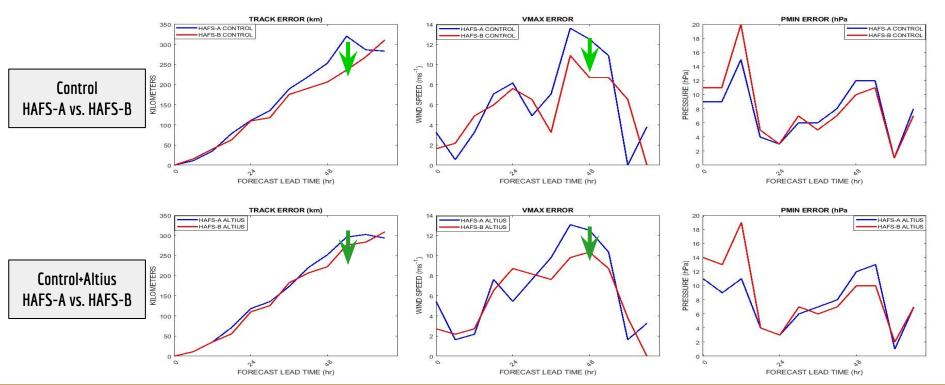
(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)

MEAN ERROR	TRACK	VMAX	PMIN
HAFS-A CONTROL	160.39	6.26	7.75
HAFS-A ALTIUS	158.94	6.71	7.67
HAFS-B CONTROL	144.73	5.58	8.17
HAFS-B ALTIUS	151.40	5.94	8.5

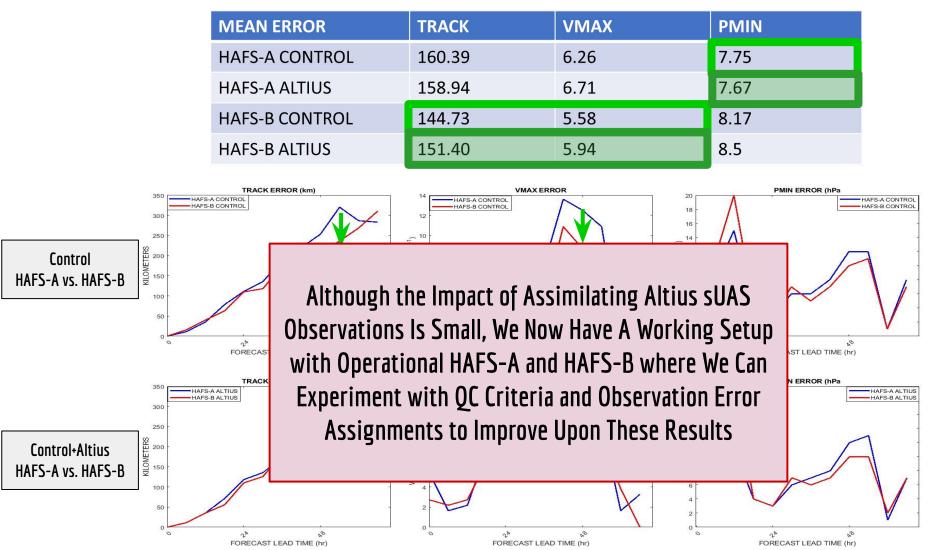


(K. Sellwood, D. Wu, A. Aksoy, J. Sippel)





Part 2



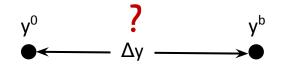
Part 3: Testing Of New DA Methodologies

Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Part 3

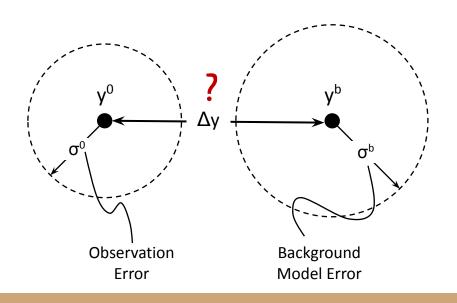
During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?



Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Would Knowing The Estimated Errors $\sigma^{\rm b}$ and $\sigma^{\rm o}$ Help?

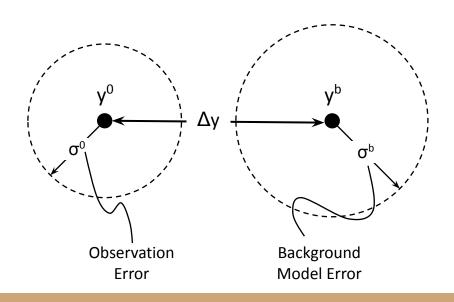


Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Would Knowing The Estimated Errors $\sigma^{
m b}$ and $\sigma^{
m o}$ Help?

Shouldn't We Compare To The Typical Distribution Of The Normalized Error $\Delta y' = OMB / [\sigma^{b2} + y^{02}]^{1/2}$?

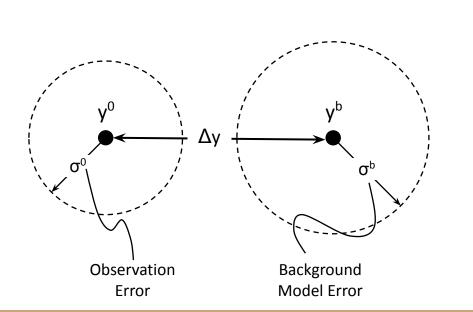


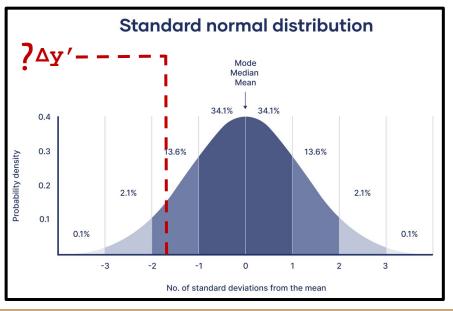
Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Would Knowing The Estimated Errors $\sigma^{
m b}$ and $\sigma^{
m o}$ Help?

Shouldn't We Compare To The Typical Distribution Of The Normalized Error $\Delta y' = OMB / [\sigma^{b^2} + y^{o^2}]^{1/2}?$





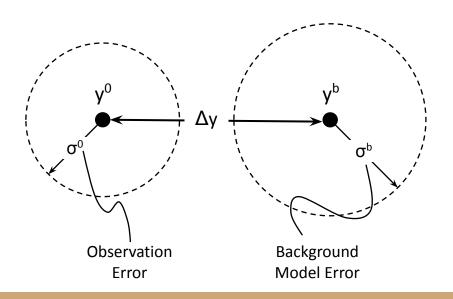
Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Would Knowing The Estimated Errors $\sigma^{
m b}$ and $\sigma^{
m o}$ Help?

Shouldn't We Compare To The Typical Distribution Of The Normalized Error $\Delta y' = OMB / [\sigma^{b2} + y^{o2}]^{1/2}$?

But What If The Distribution Of $\Delta y'$ Isn't Gaussian?



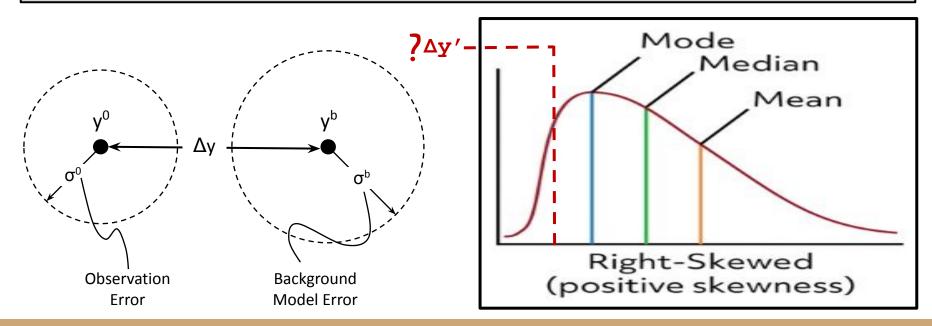
Part 3

During The DA Process, We Are Typically Presented An Observation's Difference From The Model Background: The Decision We Need to Make Is: Is $OMB = \Delta y = y^{b} - y^{o}$ Too Big?

Would Knowing The Estimated Errors $\sigma^{
m b}$ and $\sigma^{
m o}$ Help?

Shouldn't We Compare To The Typical Distribution Of The Normalized Error $\Delta y' = OMB / [\sigma^{b^2} + y^{o^2}]^{1/2}$?

But What If The Distribution Of $\Delta y'$ Isn't Gaussian?



We Already Established That Best Is To Consider The Normalized OMB For QC: $\Delta \mathbf{y'} = \mathbf{OMB} / [\sigma^{b^2} + \mathbf{y}^{o^2}]^{1/2}?$

We Already Established That Best Is To Consider The Normalized OMB For QC: $\Delta \mathbf{y'} = \mathbf{OMB} / [\sigma^{b^2} + \mathbf{y}^{o^2}]^{1/2}?$

The Reason We Call The Method "Online" Is Because We Can Use The Updated $\Delta y'$ Within The DA Cycle

We Already Established That Best Is To Consider The Normalized OMB For QC: $\Delta y' = OMB / [\sigma^{b^2} + y^{o^2}]^{1/2}?$

The Reason We Call The Method "Online" Is Because We Can Use The Updated $\Delta y'$ Within The DA Cycle

But The Outlier Method Needs To Be Robust To Account For Non-Gaussian Background Distributions

We Already Established That Best Is To Consider The Normalized OMB For QC: $\Delta \mathbf{y'} = \mathbf{OMB} / [\sigma^{b^2} + \mathbf{y}^{o^2}]^{1/2}?$

The Reason We Call The Method "Online" Is Because We Can Use The Updated $\Delta y'$ Within The DA Cycle

But The Outlier Method Needs To Be Robust To Account For Non-Gaussian Background Distributions

Nonparametric Methods Do Not Rely On A Certain Assumption For The Underlying Distribution And Typically Use *Percentiles Of Distributions*

> Method Used: "Interquartile Range"

We Already Established That Best Is To Consider The Normalized OMB For QC: $\Delta y' = OMB / [\sigma^{b^2} + y^{o^2}]^{1/2}?$

The Reason We Call The Method "Online" Is Because We Can Use The Updated $\Delta y'$ Within The DA Cycle

But The Outlier Method Needs To Be Robust To Account For Non-Gaussian Background Distributions

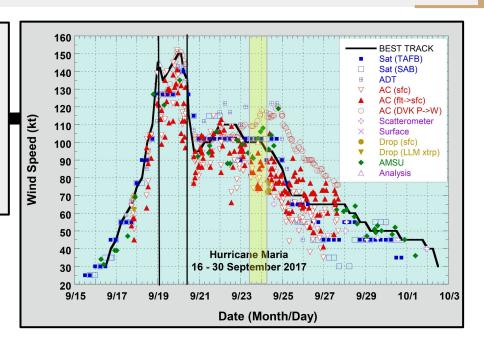
Nonparametric Methods Do Not Rely On A Certain Assumption For The Underlying Distribution And Typically Use *Percentiles Of Distributions*

> Method Used: "Interquartile Range"

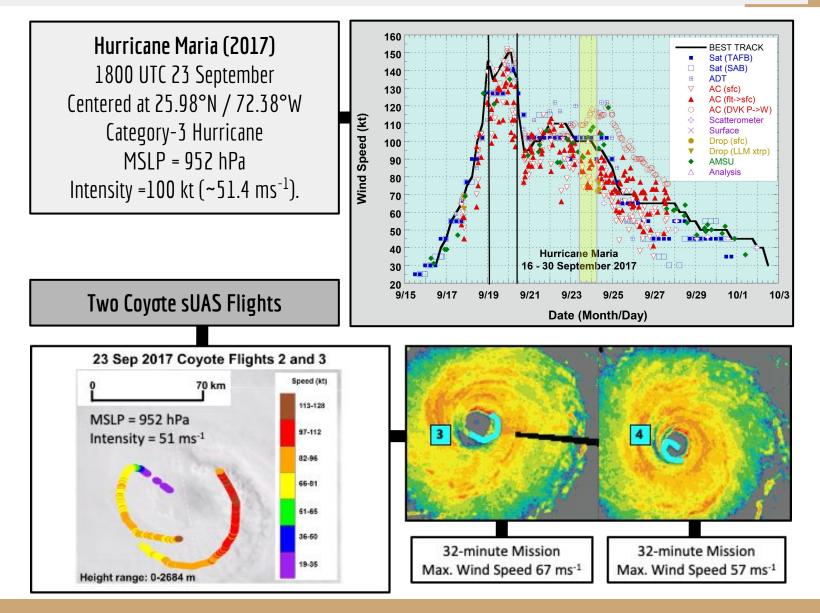
Q2 = Median of Entire Dataset Q1 = First Quartile = Median of Lower Half of Dataset Q3 = Third Quartile = Median of Upper Half of Dataset \Rightarrow Interquartile Range = IQR = Q3 - Q1 <u>Outliers:</u> X < Q1 - 1.5×IQR or X > Q3 + 1.5×IQR

Online Quality Control: A Case Study

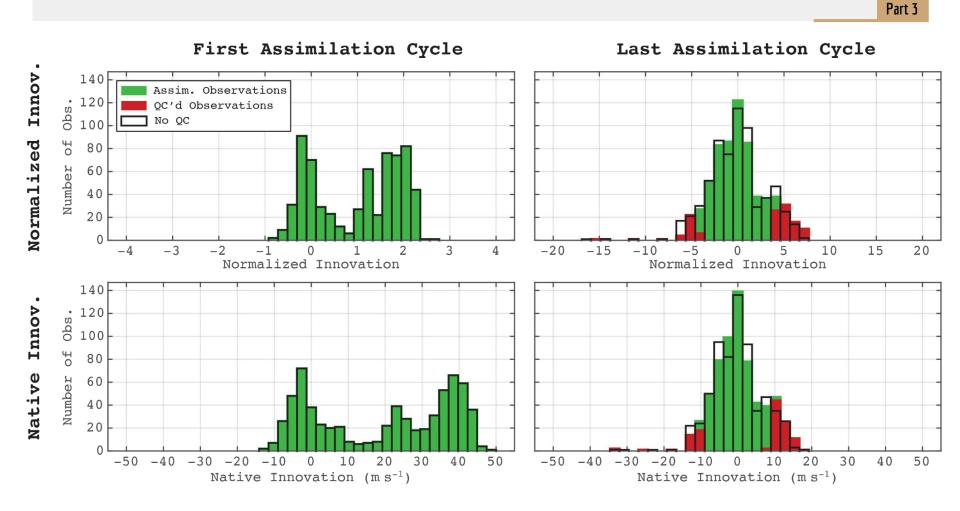
Hurricane Maria (2017) 1800 UTC 23 September Centered at 25.98°N / 72.38°W Category-3 Hurricane MSLP = 952 hPa Intensity =100 kt (~51.4 ms⁻¹).



Online Quality Control: A Case Study

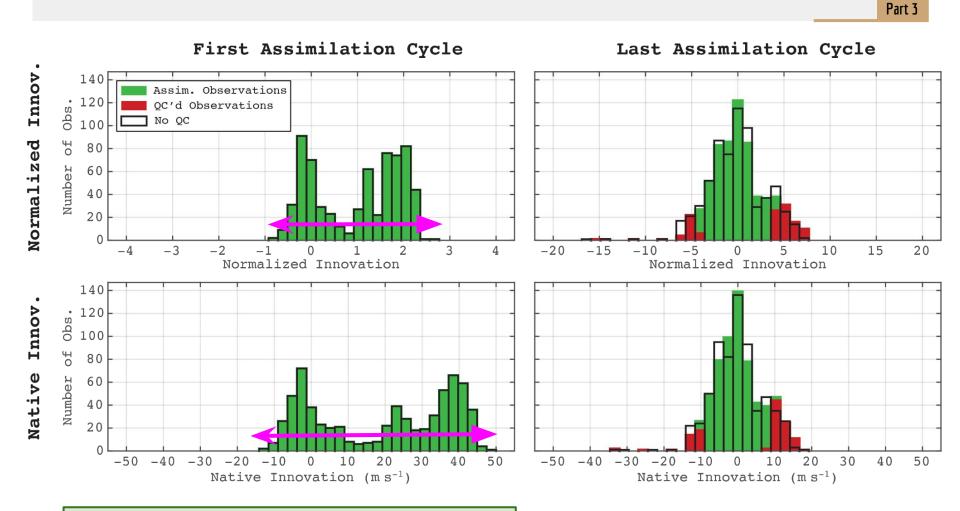


Online Quality Control: What Was Filtered Out?



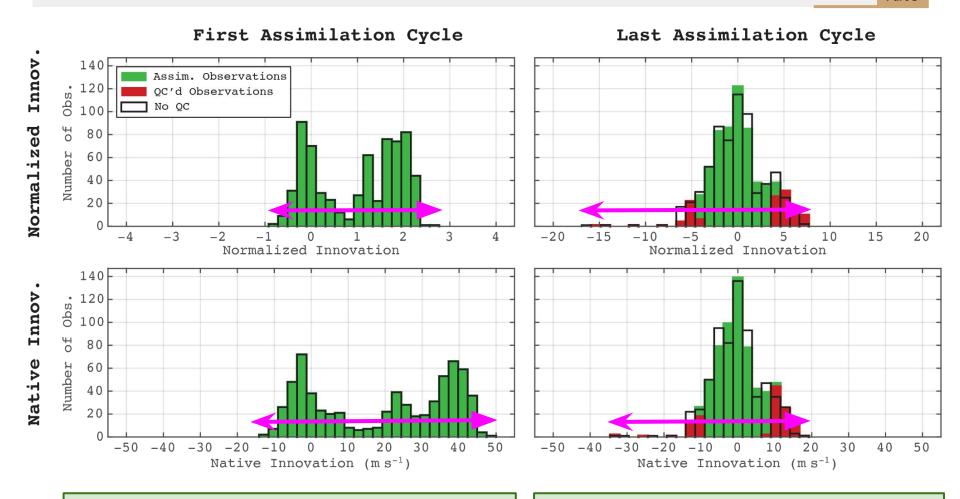
4

Online Quality Control: What Was Filtered Out?



- Small Normalized Innov. Despite Large Actual Innov.
- Robust To Allow Observations Despite Bimodal Dist.

Online Quality Control: What Was Filtered Out?

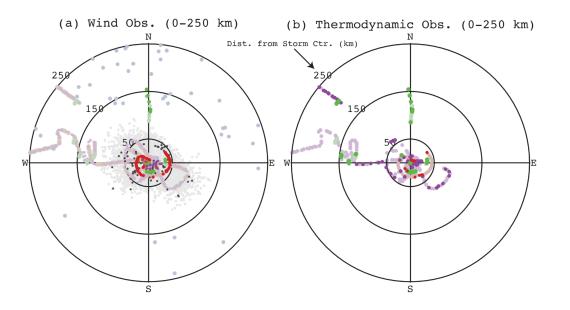


- Small Normalized Innov. Despite Large Actual Innov.
- Robust To Allow Observations Despite Bimodal Dist.
- Large Norm. Innov. Despite Smaller Actual Innov.

Part 3

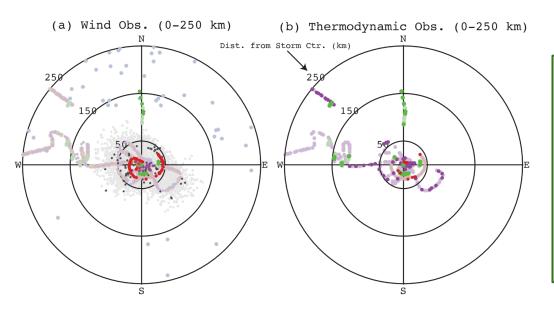
More Restrictive In The Tails

4



5

Colors:		Dimming:
Coyote Flight Level	Dropsonde	Assimilated Obs.
SFMR Tail Doppler Radar	AMV	∎QC'd Obs.



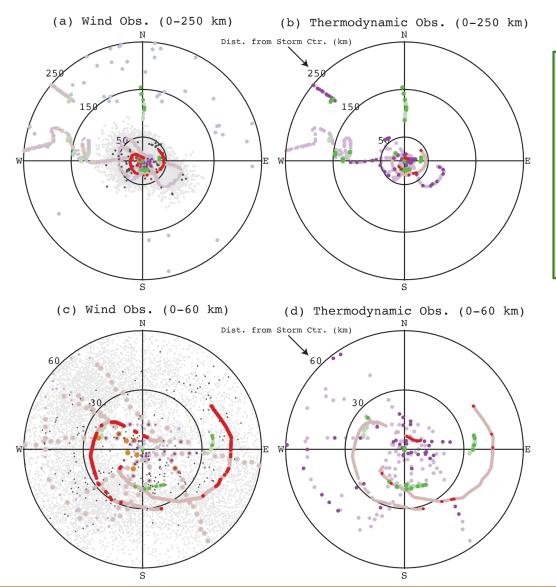
5

• Filtered-Out Wind Observations Concentrated Further Toward The Center, Suggesting Higher Normalized Errors In That Region (Due To Both Position & Intensity Errors)

Part 3

• Filtered-Out Thermodynamic Observations Spread Further Out From The Center

Colors:	Dimming:	
Coyote Flight Level	Dropsonde	Assimilated Obs.
SFMR Tail Doppler Radar	AMV	QC'd Obs.



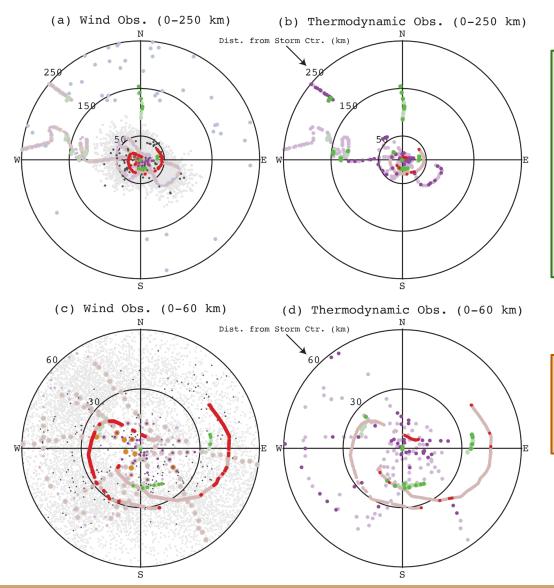
5

• Filtered-Out Wind Observations Concentrated Further Toward The Center, Suggesting Higher Normalized Errors In That Region (Due To Both Position & Intensity Errors)

Part 3

• Filtered-Out Thermodynamic Observations Spread Further Out From The Center

Colors:		Dimming:	
Coyote Flight Level	Dropsonde	Assimilated	Obs.
SFMR Tail Doppler Radar	AMV	QC'd Obs.	



5

• Filtered-Out Wind Observations Concentrated Further Toward The Center, Suggesting Higher Normalized Errors In That Region (Due To Both Position & Intensity Errors)

Part 3

• Filtered-Out Thermodynamic Observations Spread Further Out From The Center

• Closer To The Center, Relatively Homogeneous Spatial Distribution Of Both Wind & Thermodynamic Observations

Colors:	Dimming:	
Coyote Flight Level	Dropsonde	Assimilated Obs.
SFMR Tail Doppler Rada	ar AMV	QC'd Obs.

6 Online Quality Control: Observation-Space Impact Part 3

1 - >

	(a)	Wind O	oservat:	lons			
	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	I	Error mprov. (m s ⁻¹)	SprRat Improv. (rat.)
Coyote U/V	+55.1%	+64.1%	+57.0%	+35.6%		+6.0	+0.172
TDR Superobs	+23.1%	+29.2%	+23.6%	+15.0%	-	+2.0	+0.057
AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	-	0.0	
Other U/V	+22.0%	+36.7%	+24.8%	+9.0%	-	-2.0	-0.057
SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%		-4.0 -6.0	-0.115

Wind Observations

(b) Thermodynamic Observations

	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv (K, $g kg^{-1}$) +1.5	Improv. (rat.)
Coyote T	+28.3%	+84.2%	+51.6%	+16.9%	+1.5	
Other T	+50.4%	+20.8%	+43.8%	+44.0%	- +0.5	+0.1
Coyote Q	+45.1%	+65.4%	+57.6%	+39.0%	- 0.0 0.5	-0.1
Other Q	+66.0%	+55.5%	+64.2%	+78.0%	-1.0	

Online Quality Control: Observation-Space Impact Part 3

ict		RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv. (m s ⁻¹)	SprRat Improv. (rat.)
II	Coyote U/V	+55.1%	+64.1%	+57.0%	+35.6%	+6.0	+0.172
	TDR Superobs	+23.1%	+29.2%	+23.6%	+15.0%	- +2.0	+0.057
	AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	- 0.0	
	Other U/V	+22.0%	+36.7%	+24.8%	+9.0%	2.0	-0.057
	SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%	-4.0	-0.115

	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	II	Error mprov. g kg ⁻¹)	SprRat Improv. (rat.)
()	b) Ther	modynam	ic Obse	rvatio	. — າຣ		
SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%		-4.0 -6.0	-0.115
Other U/V	+22.0%	+36.7%	+24.8%	+9.0%		-2.0	-0.057
AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	-	0.0	
						+2.0	+0.057

(a) Wind Observations

(b) Thermodynamic Observations							
Er	RMS Bias rror Improv prov.	Error	Spread Ratio Improv.	Error Improv. (K, g kg ⁻¹) +1.5	SprRat Improv. (rat.) +0.3		
Coyote T +2	8.3% +84.2	8 +51.68	+16.9%	- +1.0	+0.2		
Other T +5	0.4% +20.8	8 +43.88	+44.0%	- +0.5	+0.1		
Coyote Q +4	5.1% +65.4	8 +57.68	+39.0%	0.5	-0.1		
Other Q +6	6.0% +55.5	8 +64.28	+78.0%	1.0	-0.2		

Almost All Positive Impac **On Error Statistics For All Observation Types** Assimilated

Online Quality Control: Observation-Space Impact

	(4)					
	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv. (m s ⁻¹)	SprRat Improv. (rat.)
Coyote U/V	+55.1%	+64.1%	+57.0%	+35.6%	+6.0	+0.172
TDR Superobs	+23.1%	+29.2%	+23.6%	+15.0%	- +2.0	+0.057
AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	- 0.0	
Other U/V	+22.0%	+36.7%	+24.8%	+9.0%	2.0	-0.057
SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%	-4.0	-0.115

(a) Wind Observations

- Almost All Positive Impact On Error Statistics For All Observation Types Assimilated
- Positive Impact Even In Observation Types Other Than The Coyote sUAS (Indirect Impact)

(b) Thermodynamic Observations

	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.		g kg ⁻¹)	SprRat Improv. (rat.) +0.3
Coyote T	+28.3%	+84.2%	+51.6%	+16.9%		+1.0	+0.2
Other T	+50.4%	+20.8%	+43.8%	+44.0%		+0.5	+0.1
Coyote Q	+45.1%	+65.4%	+57.6%	+39.0%		-0.5	-0.1
Other Q	+66.0%	+55.5%	+64.2%	+78.0%		-1.0	-0.2
	Other T Coyote Q	Error Improv. Coyote T +28.3% Other T +50.4% Coyote Q +45.1%	Error Bias Improv. Improv. Coyote T +28.3% +84.2% Other T +50.4% +20.8% Coyote Q +45.1% +65.4%	Bias Bias Error Improv. Improv. Improv. Coyote T +28.3% +84.2% +51.6% Other T +50.4% +20.8% +43.8% Coyote Q +45.1% +65.4% +57.6%	Bias Error Ratio Improv. Improv. Fror Ratio Coyote T +28.3% +84.2% +51.6% +16.9% Other T +50.4% +20.8% +43.8% +44.0% Coyote Q +45.1% +65.4% +57.6% +39.0%	Bias Improv. Bias Improv. Error Improv. Ratio Improv. Ratio Improv. Coyote T +28.3% +84.2% +51.6% +16.9% Other T +50.4% +20.8% +43.8% +44.0% Coyote Q +45.1% +65.4% +57.6% +39.0%	Bias Error Ratio Improv. Improv. Improv. Improv. Improv. +28.3% +84.2% +51.6% +16.9% +1.0 Other T +50.4% +20.8% +43.8% +44.0% +0.5 Coyote Q +45.1% +65.4% +57.6% +39.0% -0.5

Online Quality Control: Observation-Space Impact

t		RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv. (m s ⁻¹)	SprRat Improv. (rat.)
	Coyote U/V	+55.1%	+64.1%		+35.6%	+6.0	+0.172
	TDR Superobs	+23.1%	+29.2%	+23.6%	+15.0%	- +2.0	+0.057
	AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	- 0.0	
	Other U/V	+22.0%	+36.7%	+24.8%	+9.0%	2.0	-0.057
	SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%	-4.0	-0.115

(a) Wind Observations

- Almost All Positive Impact On Error Statistics For All Observation Types Assimilated
- Positive Impact Even In Observation Types Other Than The Coyote sUAS (Indirect Impact)
- Largest Positive Impact On Thermodynamic Observations, Which Are Usually Hard To Obtain In The PBL

(b) Thermodynamic Observations

RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv. (K, g kg ⁻¹)	SprRat Improv. (rat.) +0.3
+28.3%	+84.2%	+51.6%	+16.9%	+1.0	+0.2
+50.4%	+20.8%	+43.8%	+44.0%	- +0.5	+0.1
+45.1%	+65.4%	+57.6%	+39.0%	0.5	-0.1
+66.0%	+55.5%	+64.2%	+78.0%	1.0	-0.2
	Error Improv. +28.3% +50.4% +45.1%	Bias Bias Error Improv. +28.3% +84.2% +50.4% +20.8% +45.1% +65.4%	Bias Error Improv. Improv. +28.3% +84.2% +50.4% +20.8% +45.1% +65.4%	Bias Improv. Error Improv. Ratio Improv. +28.3% +84.2% +51.6% +16.9% +50.4% +20.8% +43.8% +44.0% +45.1% +65.4% +57.6% +39.0%	Bias Improv. Bias Improv. Error Improv. Ratio Improv. Error Improv. +28.3% +84.2% +51.6% +16.9% +1.5 +50.4% +20.8% +43.8% +44.0% +0.5 +45.1% +65.4% +57.6% +39.0% -0.5

Online Quality Control: Observation-Space Impact

- Almost All Positive Impact On Error Statistics For All Observation Types Assimilated
- Positive Impact Even In Observation Types Other Than The Coyote sUAS (Indirect Impact)
- Largest Positive Impact On Thermodynamic Observations, Which Are Usually Hard To Obtain In The PBL
- Further Improvements In The Optimality Of Ensemble Spread

	(a)						
	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Err Impr (m s	ov.	SprRat Improv. (rat.)
Coyote U/V	+55.1%	+64.1%	+57.0%	+35.6%		6.0 4.0	+0.172
TDR Superobs	+23.1%	+29.2%	+23.6%	+15.0%	- +:	2.0	+0.057
AMV U/V	+4.6%	-35.6%	-0.5%	-6.8%	- 0	.0	
Other U/V	+22.0%	+36.7%	+24.8%	+9.0%		2.0	-0.057
SFMR Wind Speed	+15.7%	-72.0%	-0.6%	-10.4%		4.0 6.0	-0.115 -0.172

(a) Wind Observations

(b) Thermodynamic Observations

	RMS Error Improv.	Bias Improv.	Total Error Improv.	Spread Ratio Improv.	Error Improv. $(K, g kg^{-1})$ +1.5	SprRat Improv. (rat.) +0.3
Coyote T	+28.3%	+84.2%	+51.6%	+16.9%	+1.0	+0.2
Other T	+50.4%	+20.8%	+43.8%	+44.0%	- +0.5	+0.1
Coyote Q	+45.1%	+65.4%	+57.6%	+39.0%	0.5	-0.1
Other Q	+66.0%	+55.5%	+64.2%	+78.0%	-1.0	-0.2

6

Part 3

Important To Remember That Normalized Online QC Only Works In Observation Space: $\Delta y' = OMB / [\sigma^{b2} + y^{O2}]^{1/2}$

Important To Remember That Normalized Online QC Only Works In Observation Space: $\Delta y' = OMB / [\sigma^{b2} + y^{O2}]^{1/2}$

Part 3

Therefore, This Approach Can Only Be Implemented In The EnKF Part Of The HAFS-DA System, But Regardless Of Its Being A Pure EnKF Or EnVar Application

Important To Remember That Normalized Online QC Only Works In Observation Space: $\Delta y' = OMB / [\sigma^{b^2} + y^{o^2}]^{1/2}$

Part 3

Therefore, This Approach Can Only Be Implemented In The EnKF Part Of The HAFS-DA System,

But Regardless Of Its Being A Pure EnKF Or EnVar Application

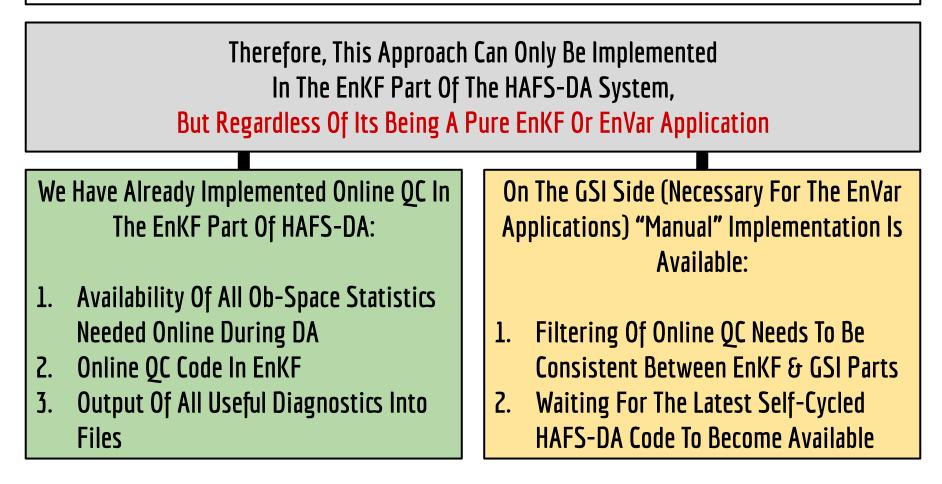
We Have Already Implemented Online QC In The EnKF Part Of HAFS-DA:

- 1. Availability Of All Ob-Space Statistics Needed Online During DA
- 2. Online QC Code In EnKF
- 3. Output Of All Useful Diagnostics Into Files

Important To Remember That Normalized Online QC Only Works In Observation Space:

Part 3

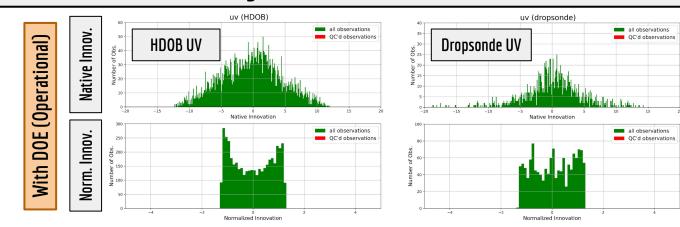
 $\Delta y' = OMB / [\sigma^{b2} + y^{o2}]^{1/2}$



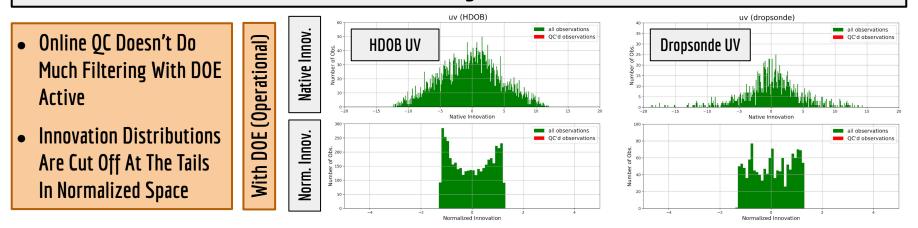
Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms

Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms

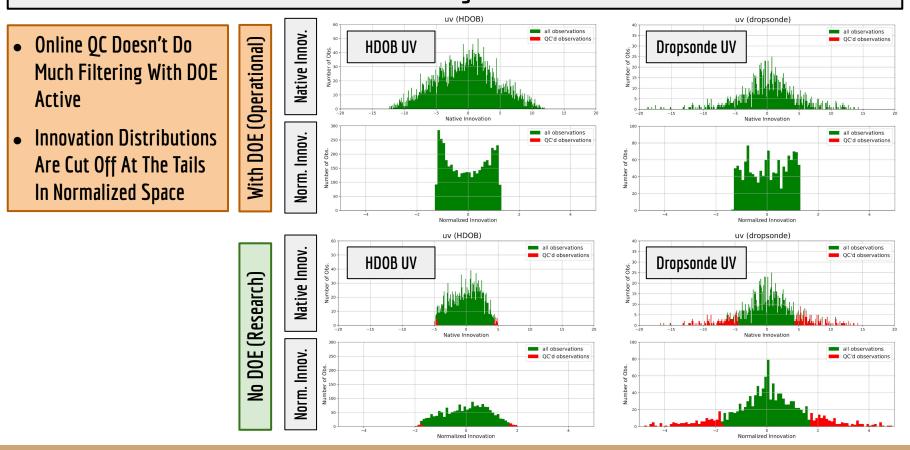
Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms



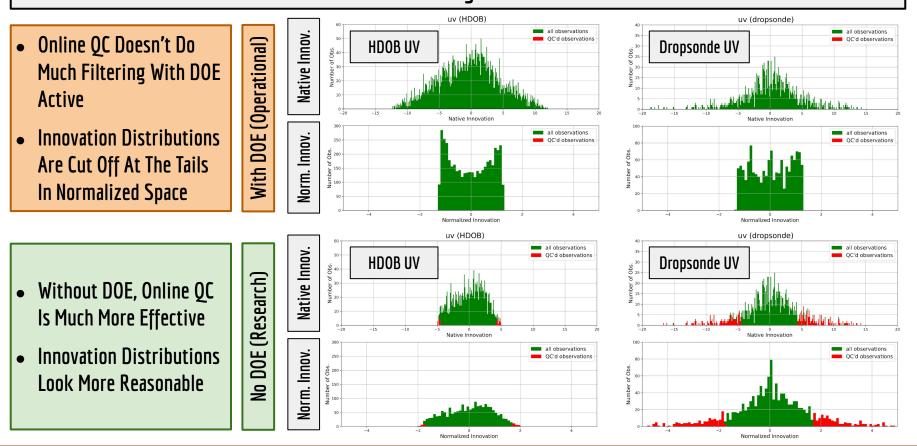
Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms



Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms



Complication 1: Impact On Performance Of Online QC With Existing QC Mechanisms



Complication 2: Need For Retuning Of Observation Errors

Complication 2: Need For Retuning Of Observation Errors

Complication 2: Need For Retuning Of Observation Errors

Experimental Design								
		Exp1: Default	Exp2: No DOE	Exp3a	Exp 3b	Exp 3c	Exp 3d	
GSI Namelist	tdrerr_inflate	Т	F	F F		F	F	
Parameter	aircraft_recon	Т	F	F	F	F	F	
	Flight-level U+V (m/s)	2.5	2.5	4.0	3.0	2.0	4.0	
	Flight-levelT(K)		0.75	0.9	0.75	0.6	0.6	
Obs Error	Flight-level Q(RH)	0.7	0.7	double	0.7	0.7	0.7	
ODS EITOI	Dropsonde U+V (m/s)	2.5	2.5	4.0	2.5	2.0	2.0	
	Dropsonde T(K)	0.75	0.75	0.9	0.75	0.6	0.6	
	Dropsonde Q(RH)	0.7	0.7	20% increase	0.7	0.7	0.7	

Complication 2: Need For Retuning Of Observation Errors

			Experimen	tai Desigii			
		Exp1: Default	Exp2: No DOE	Exp3a	Exp 3b	Ехр 3с	Exp 3d
GSI Namelist	tdrerr_inflate	Т	F	F	F	F	F
Parameter	aircraft_recon	Т	F	F	F	F	F
	Flight-level U+V (m/s)	2.5	2.5	4.0	3.0	2.0	4.0
	Flight-level T(K)	0.75	0.75	0.9	0.75	0.6	0.6
Obs Error	Flight-level Q(RH)	0.7	0.7	double	0.7	0.7	0.7
ODS EITO	Dropsonde U+V (m/s)	2.5	2.5	4.0	2.5	2.0	2.0
	Dropsonde T(K)	0.75	0.75	0.9	0.75	0.6	0.6
	Dropsonde Q(RH)	0.7	0.7	20% increase	0.7	0.7	0.7

Complication 2: Need For Retuning Of Observation Errors

Experimental Design									
		Exp1: Default	Exp2: No DOE	Exp3a	Exp 3b	Ехр 3с	Exp 3d		
GSI Namelist	tdrerr_inflate	Т	F	F	F	F	F		
Parameter	aircraft_recon	T,	F	F	F	F	F		
	Flight-level U+V (m/s)	2.5	2.5	4.0	3.0	2.0	4.0		
	Flight-level 0.75 0.7	0.75	0.9	0.75	0.6	0.6			
Obs Error	Flight-level Q(RH)			double	0.7	0.7	0.7		
ODS EITOI	Dropsonde U+V (m/s)	2.5	2.5	4.0	2.5	2.0	2.0		
	Dropsonde T(K)	0.75	0.75	0.9	0.75	0.6	0.6		
	Dropsonde Q(RH)	0.7	0.7	20% increase	0.7	0.7	0.7		

Complication 2: Need For Retuning Of Observation Errors

Experimental Design									
		Exp1: Default	Exp2: No DOE	Exp3a	Exp 3b	Ехр 3с	Exp 3d		
GSI Namelist	tdrerr_inflate	Т	F	F	F	F	F.		
Parameter	aircraft_recon	т	F	F	F	F	F		
	Flight-level U+V (m/s)	2.5	2.5	4.0	3.0	2.0	4.0		
	Flight-level T(K)	vel 0.75 0.75		0.9	0.75	0.6	0.6		
Obs Error	Flight-level Q(RH)	0.7	0.7	double	0.7	0.7	0.7		
ODS EITO	Dropsonde U+V (m/s)	2.5	2.5	4.0	2.5	2.0	2.0		
	Dropsonde T(K)	0.75	0.75	0.9	0.75	0.6	0.6		
	Dropsonde Q(RH)	0.7	0.7	20% increase	0.7	0.7	0.7		

Complication 2: Need For Retuning Of Observation Errors

Complication 2: Need For Retuning Of Observation Errors

Consistency Exp1: Exp2: Exp 3a Exp 3b Exp 3c Exp 3d Ratio Default No DOE platform 2.07 / 0.87 2.12 1.87 1.54 Т 1.53 1.52 0.5 1.34 1.19 1.19 1.19 Dropsonde Q U+V 1.38 0.39 1.85 1.45 1.34 1.35 Т 2.19 0.79 1.79 1.57 1.40 1.40 2.78 1.45 2.13 1.57 HDOB 1.57 1.57 Q U+V 1.45 1.40 1.58 1.60 1.55 1.58

Observation-Space Diagnostics

Complication 2: Need For Retuning Of Observation Errors

platform	onsistency Ratio		Exp2: No DOE	Exp 3a	Exp 3b	Exp 3c	Exp 3d	
	Т	2.07 /	0.87	2.12	1.87	1.54	1.53	
Dropsonde	Q	1.52	0.5	1.34	1.19	1.19	1.19	
	U+V	1.38	0.39	1.85	1.45	1.34	1.35	
	Т	2.19	0.79	1.79	1.57	1.40	1.40	
HDOB	Q	2.78	1.45	2.13	1.57	1.57	1.57	
	U+V	1.45	1.40	1.58	1.60	1.55	1.58	

Observation-Space Diagnostics

Spread Consistency Becomes More Optimal (Closer To 1)

Complication 2: Need For Retuning Of Observation Errors

platform	Consistency atform		Exp2: No DOE	Exp 3a	Exp 3b	Exp 3c	Exp 3d
	Т	2.07 /	0.87	2.12	1.87	1.54	1.53
Dropsonde	Q	1.52	0.5	1.34	1.19	1.19	1.19
	U+V	1.38	0.39	1.85	1.45	1.34	1.35
	Ţ	2.19	0.79	1.79	1.57	1.40	1.40
HDOB	Q	2.78	1.45	2.13	1.57	1.57	1.57
	U+V	1.45	1.40	1.58	1.60	1.55	1.58

Observation-Space Diagnostics

Spread Consistency Becomes More Optimal (Closer To 1)

		Average O-min-A						
Description	Average O-Min-F	Exp. 1	Exp 3a	Exp 3b	Exp 3c	Exp 3d		
T / Q (dropsonde)	0.68 / 0.37	0.72 / 0.32	0.33 / 0.27	0.24 / 0.27	0.18 / 0.27	0.18 / 0.27		
U+V (dropsonde)	-0.141	-0.116	0.20	0.11	0.06	0.05		
T / Q (HDOB)	0.74 / 0.079	0.62 / 0.076	0.18 / 0.01	0.12 / -0.036	0.08 / -0.04	0.07 / -0.04		
U+V (HDOB)	-0.398	-0.23	0.033	0.085	0.176	-0.04		

Complication 2: Need For Retuning Of Observation Errors

platform	onsistency Ratio		Exp2: No DOE	Exp 3a	Exp 3b	Exp 3c	Exp 3d	
	Т	2.07 /	0.87	2.12	1.87	1.54	1.53	
Dropsonde	Q	1.52	0.5	1.34	1.19	1.19	1.19	Spi
	U+V	1.38	0.39	1.85	1.45	1.34	1.35	Bec
	Т	2.19	0.79	1.79	1.57	1.40	1.40	0p ⁻
HDOB	Q	2.78	1.45	2.13	1.57	1.57	1.57	
	U+V	1.45	1.40	1.58	1.60	1.55	1.58	

Observation-Space Diagnostics

Spread Consistency Becomes More Optimal (Closer To 1)

			Average O-min-A						
Description	Average O-Min-F	Exp. 1	Exp 3a	Exp 3b	Ехр Зс	Exp 3d			
T / Q (dropsonde)	0.68 / 0.37	0.72 / 0.32	0.33 / 0.27	0.24 / 0.27	0.18 / 0.27	0.18 / 0.27			
U+V (dropsonde)	-0.141	-0.116	0.20	0.11	0.06	0.05			
T / Q (HDOB)	0.74 / 0.079	0.62 / 0.076	0.18 / 0.01	0.12 / -0.036	0.08 / -0.04	0.07 / -0.04			
U+V (HDOB)	-0.398	-0.23	0.033	0.085	0.176	-0.04			

Analysis Errors (Distance From Observations, OMA) Become Smallest

Complication 2: Need For Retuning Of Observation Errors

C platform	onsistenc Rati	- LAPII	Exp2: No DOE	Exp 3a	Exp 3b	Exp 3c	Exp 3d				
	Т	2.07 /	0.87	2.12	1.87	1.54	1.53				
Dropsonde	Q	1.52	0.5	1.34	1.19	1.19	1.19	Spread Consistency			
	<u>+</u>	1 38	0 39	1 85	1 4 5	1 34	1.35	Becomes More			
HDOB		1.40 1.57 1.58	Optimal (Closer To 1)								
Descriptio T / Q (dropso	 The Latest Self-Cycled HAFS-DA Code With EnVar Using A Large Number Of Cases 										
		0.0070.37	0.7270.32	0.5570.27	0.2470.27	0.1070.27	0. 18 / 0.27	(Distance From			
U+V (dropso	nde)	-0.141	-0.116	0.20	0.11	0.06	0.05	Observations, OMA)			
T / Q (HDO	9B)	0.74 / 0.079	0.62 / 0.076	0.18 / 0.01	0.12 / -0.036	0.08 / -0.04	0.07 / -0.04	Become Smallest			
U+V (HDO	B)	-0.398	-0.23	0.033	0.085	0.176	-0.04				

Observation-Space Diagnostics

Summary / Final Thoughts



2

Collaboration between AOML/HRD and University of Miami allows for expertise and research applications ranging from collection of observations to assimilation in operational models

Expertise with the depth and technical details of available inner-core observing platforms allows improvements with implications up to NHC operations

New DA research being conducted with experimental observing platforms such as sUAS and
 CYGNSS has potential to improve operational models

Research is actively being carried out with both operational HAFS-A and HAFS-B systems and
 the experimental self-cycled HAFS system to test assimilation of new observations as well as implementation of new DA techniques



Publications Of Note

Wu, D., A. Aksoy, et al., 2023: Improvements in the Assimilation of Tropical Cyclone Inner-core Observations in NOAA's Next-Generation Hurricane Analysis and Forecast System (HAFS). Fifth Special Symposium on Tropical Meteorology and Tropical Cyclones, January 2023, Denver, Colorado, American Meteorological Society.

Sellwood, K. J., J. A. Sippel, and A. Aksoy, 2023: Assimilation of Coyote Small Uncrewed Aircraft System Observations in Hurricane Maria (2017) using Operational HWRF. *Weather and Forecasting*, Early Online Release, https://doi.org/10.1175/WAF-D-22-0214.1.

Aksoy, A., J. J. Cione, B. A. Dahl, and P. D. Reasor, 2022: Tropical cyclone data assimilation with Coyote Uncrewed Aircraft System observations, very frequent cycling, and a new online quality control technique. *Monthly Weather Review*, **150**, 797-820, https://doi.org/10.1175/MWR-D-21-0124.1.

Cione, J. J., G. H. Bryan, R. Dobosy, J. A. Zhang, G. de Boer, A. Aksoy, et al., 2020: Eye of the storm: Observing hurricanes with a Small Unmanned Aircraft System. *Bulletin of the American Meteorological Society*, **101**, E186–E205, https://doi.org/10.1175/BAMS-D-19-0169.1.

