Refining the assimilation of Aeolus Doppler wind LiDAR observations in NOAA/FV3GFS by adopting VarQC

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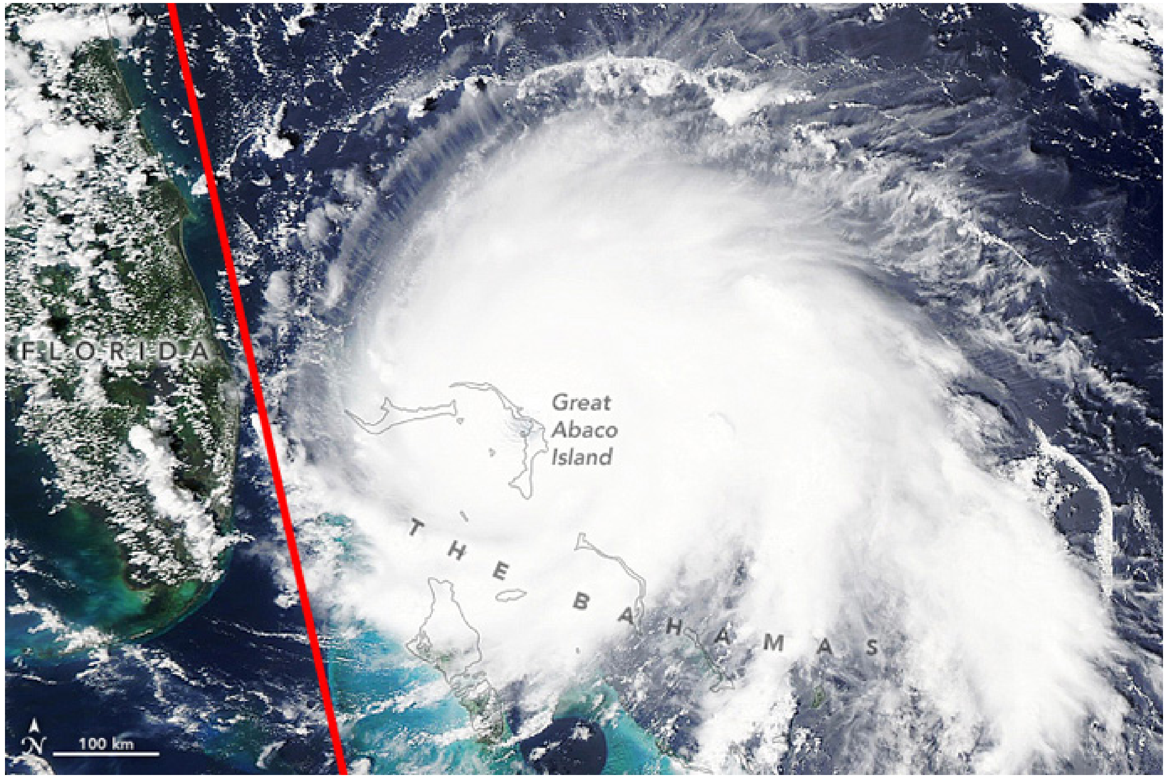
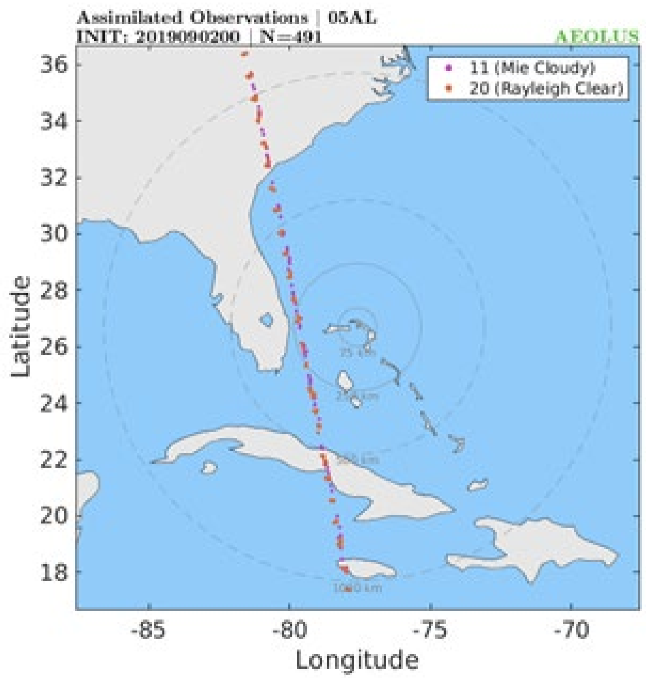


Aeolus satellite track overlaid on a NASA Aqua's satellite image of hurricane Dorian at 1805 UTC on September 1, 2019. (Satellite image: NASA)

Motivation: QC of Aeolus HLOS and use tropical cyclone (TC) prediction

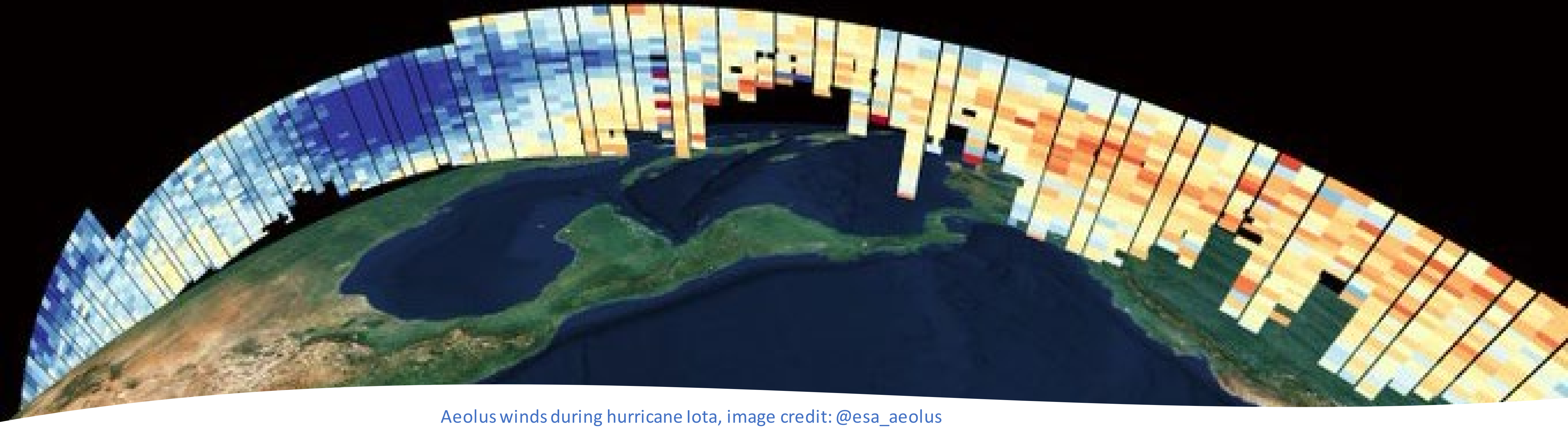
- Current assimilation of Aeolus observation in FV3GFS has shown promise with evidence of impacts to the synoptic environment
- A TC impact assessment yielded a high case-to-case variability in results prompted us to ponder… Are we rejecting observation outliers or good quality data?
- Implications for TC's: Large (O-B) departures in the TC environment can have detrimental impacts on the analysis

Valid: 20190902, during Hurricane Dorian, 2019



Assimilated observations in FV3GFS at edge of the Dorian's outer core (258 km radius)

DA in the presence of complex synoptic features in TC's with regions of strong gradients may benefit from advanced quality control



Aeolus winds during hurricane Iota, image credit: @esa_aeolus

Objective: Optimize Aeolus assimilation with an emphasis on hurricane analysis and forecast in NOAA NWP systems

- Improve the assimilation of Aeolus HLOS retrievals in global (FV3GFS) and storm-scale (HWRF) NWP to improve TC analysis and prediction
- DA refinements in collaboration with NECEP/EMC (e.g., addressing suboptimal observation weight assignment by implementing new Variational QC)
- All DA developments done in FV3GFS to improve hurricane prediction are to be ported to HWRF to quantify the impact of regional hurricane forecasts

New NCEP Variational Quality Control

Assimilate what you can, reject what you must!

Power of Assimilation: St. John Henry Newman

- Even good quality data show significant departures from the pure Gaussian form
- Current Gaussian-based operational data assimilation may not be sufficient
- Adopted a new VarQC scheme implemented in the 2021 operational NCEP/GFS (Purser et al., 2019) to improve the assimilation of Aeolus
- For observations whose departures fall into super-logistic (Chevron-type) family whose PDF is shaped by modulating parameters
- The VarQC scheme is capable of assigning adaptive weights to observations

Mathematical formalism of VarQC

- The VarQC component of the incremental VAR observational cost function in GSI is given as:

$$J_o = \sum_i -g(\alpha_i, \beta_i, \kappa_i; z_i)$$

- where α, β, κ are PDF modulating parameters (asymmetry, broadness, convexity) and z is the probability of gross error
- The modulating parameters are based on skewness, variance, and kurtosis
- $z_i = \frac{x}{\sigma}$, the z PDF is a non-dimensional error variable, x is the observation error, σ is a small departure from the measurement

Mathematical notation of VarQC

- Thus, the weight $W_i(z_i)$ given to an observation by the VarQC algorithm is related to the probability of the shaping parameters and the probability of the gross error
- $W_i(z_i)$ is obtained during the inner minimization loop when taking the gradient of J_o
- VarQC assigns adaptive weights as a function of observation increment and the probability of gross error

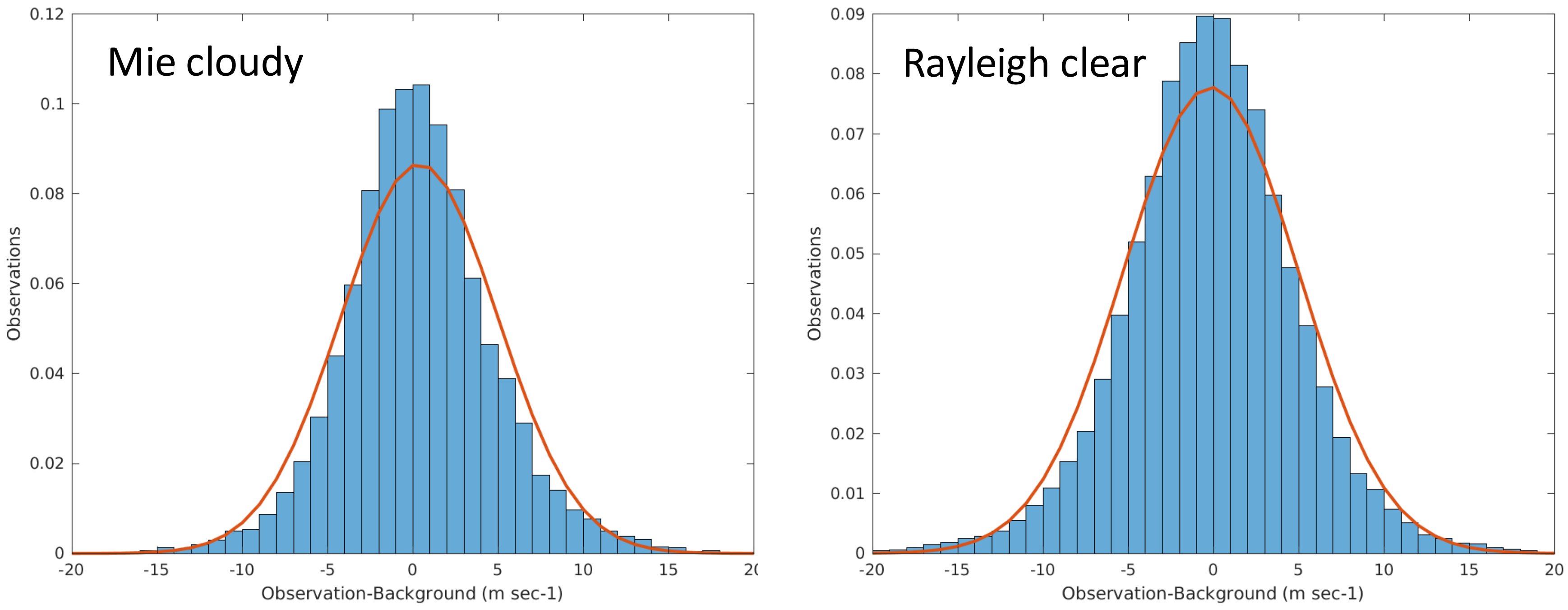
$$W_i(z_i)=\begin{Bmatrix} 1 & : z_i = 0 \\ \frac{-1}{z_i}\frac{dg_i(\alpha_i,\beta_i,\kappa_i;z_i)}{dz_i} & : z_i \neq 0 \end{Bmatrix}$$

- For the symmetric case and closer to Gaussian realm, the modulating weight goes to unity since alpha = 0

(O-B) Statistical Assessment and non-Gaussianity

- Accurate probability model for the Aeolus observation errors (Mie-cloudy and Rayleigh-clear)
- Observed departures from the pure Gaussian form

Innovation Statistics: valid: 2019082018



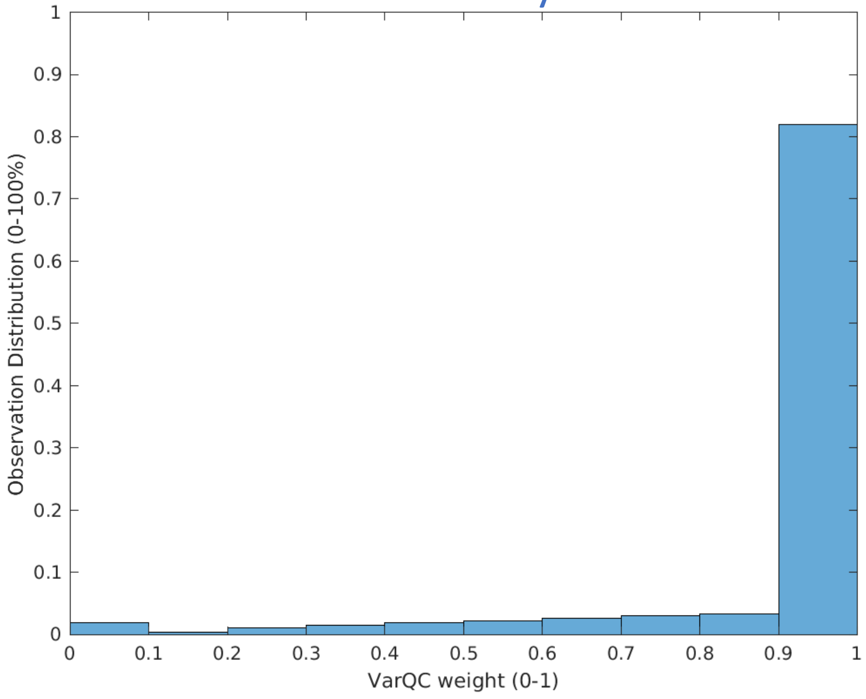
- Innovation statistics indicate departures from the pure Gaussian form
- Unimodal and leptokurtic distributions, with some asymmetry
- Aeolus assimilation may benefit from advanced QC by assigning adaptive weights to observation outliers and not rejecting them

Adaptive weight distribution for Aeolus after VarQC

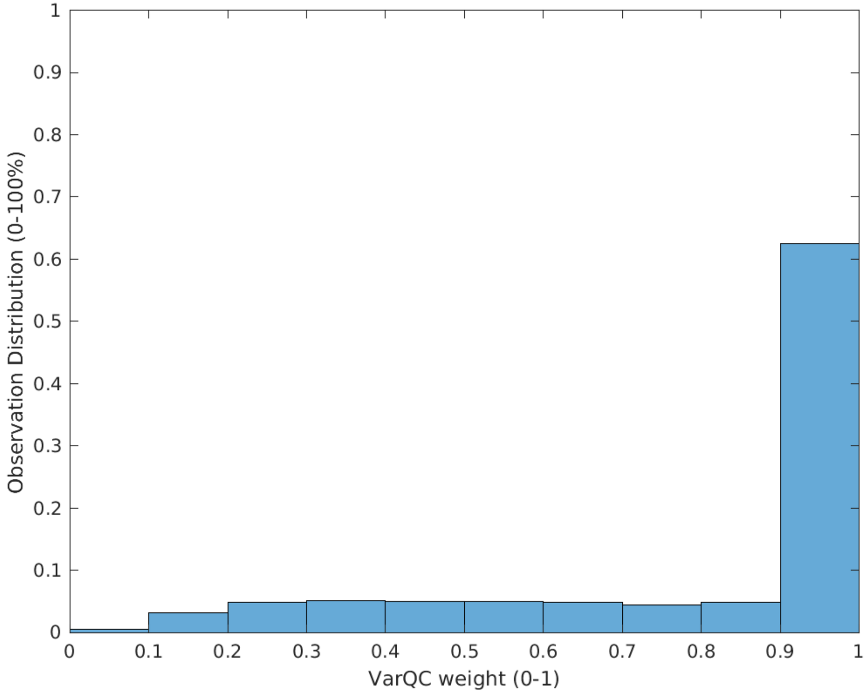
- VarQC deals with rejection limits outside of the Gaussian
- Not discarding observations that lead to large departures, but assigning less weight during the final analysis

Adaptive weight distribution valid: 2019082018

Mie cloudy

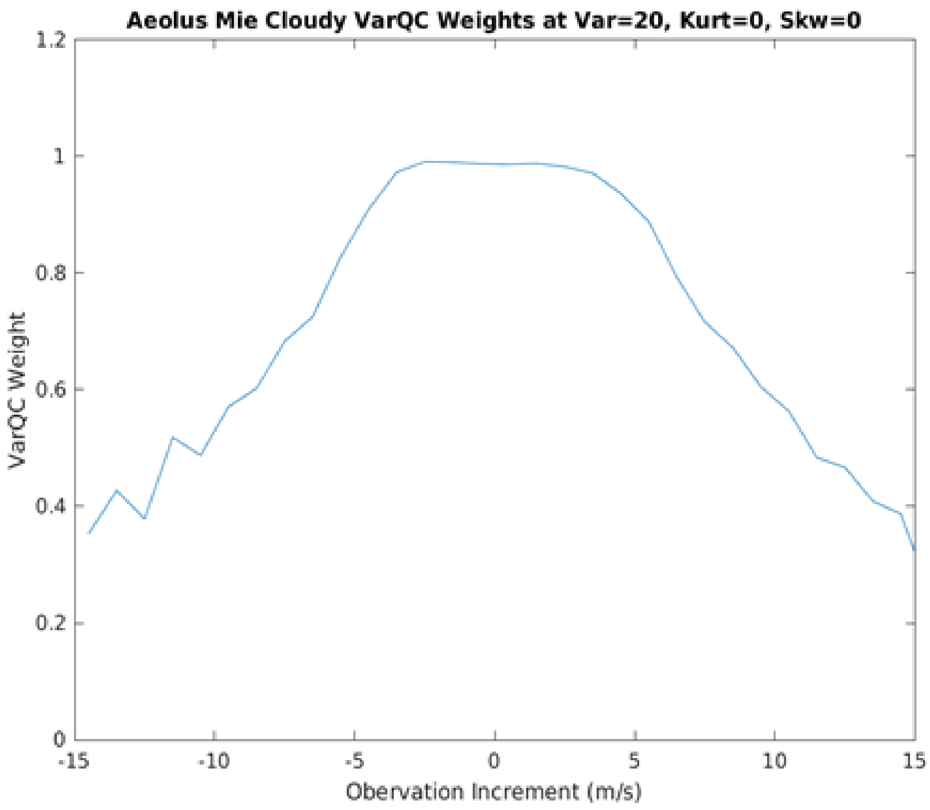


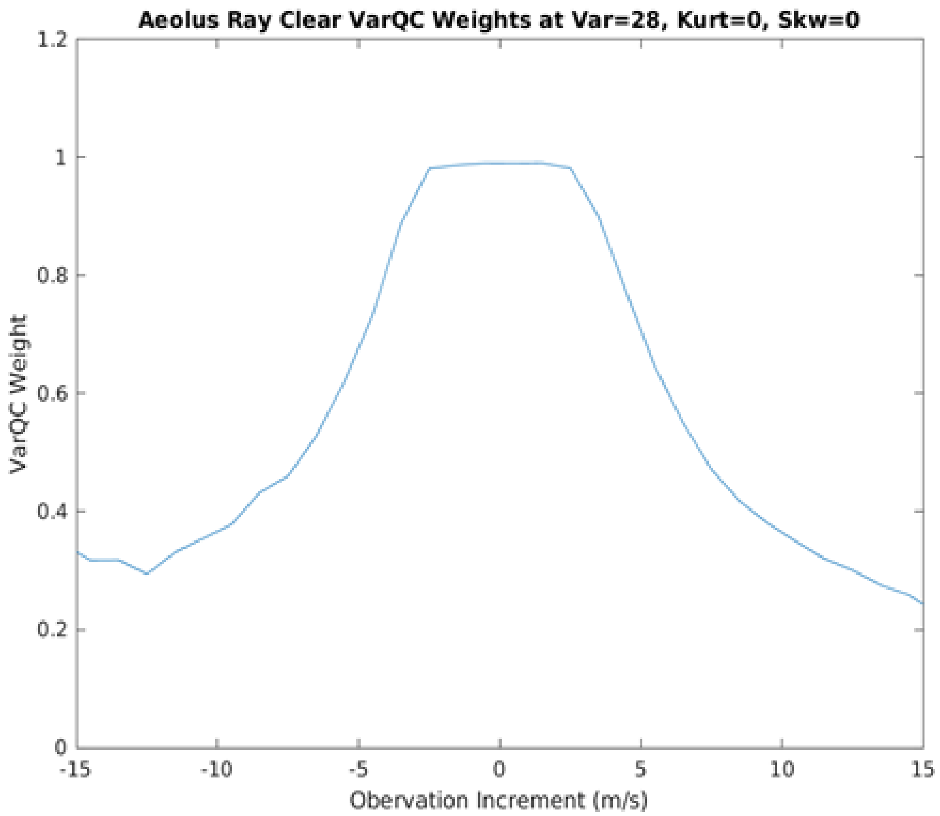
Rayleigh clear



VarQC adaptive weights 0 to 1 range
- 0 least impact to the analysis
- 1 most impact to the analysis

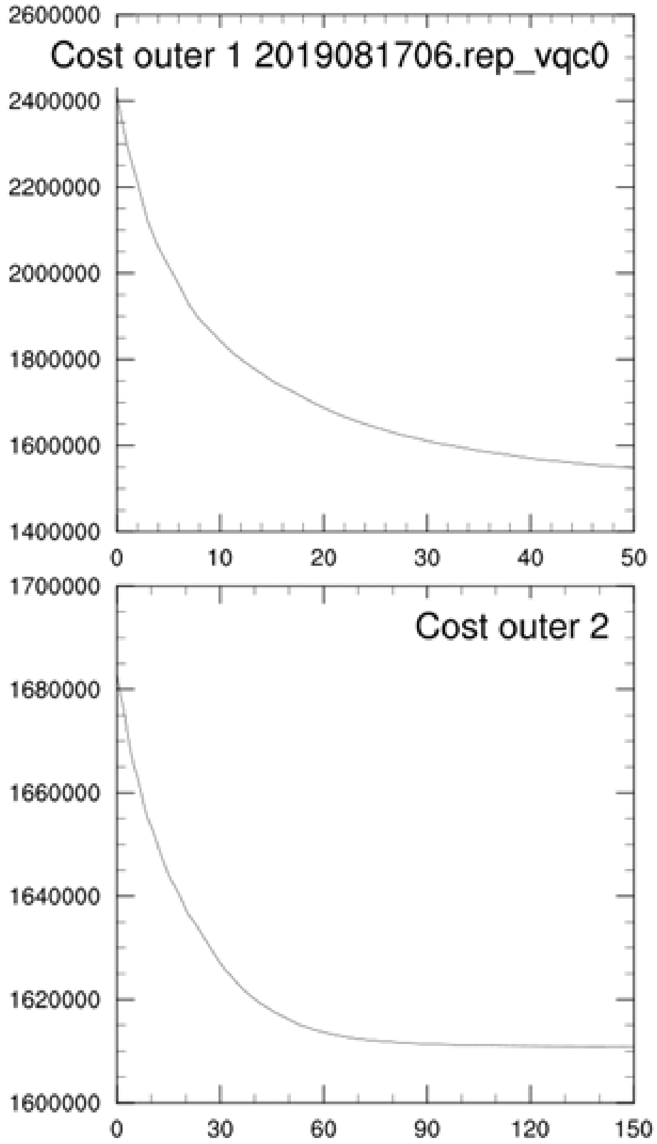
Dynamical Weight Assignment for Observation



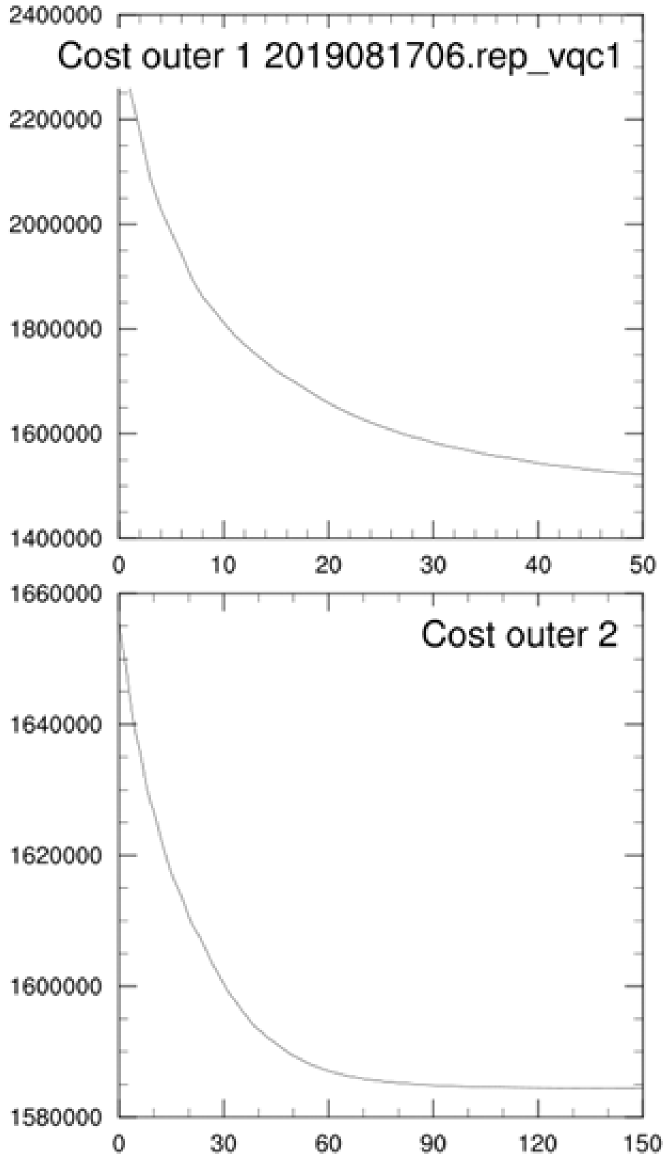


- More weight in the middle of the distribution
- Non-zero weight in the tails (places with large departures)
- More influence of data with large departures

Aeolus DA No VarQC



Aeolus DA with VarQC



Minimization statistics

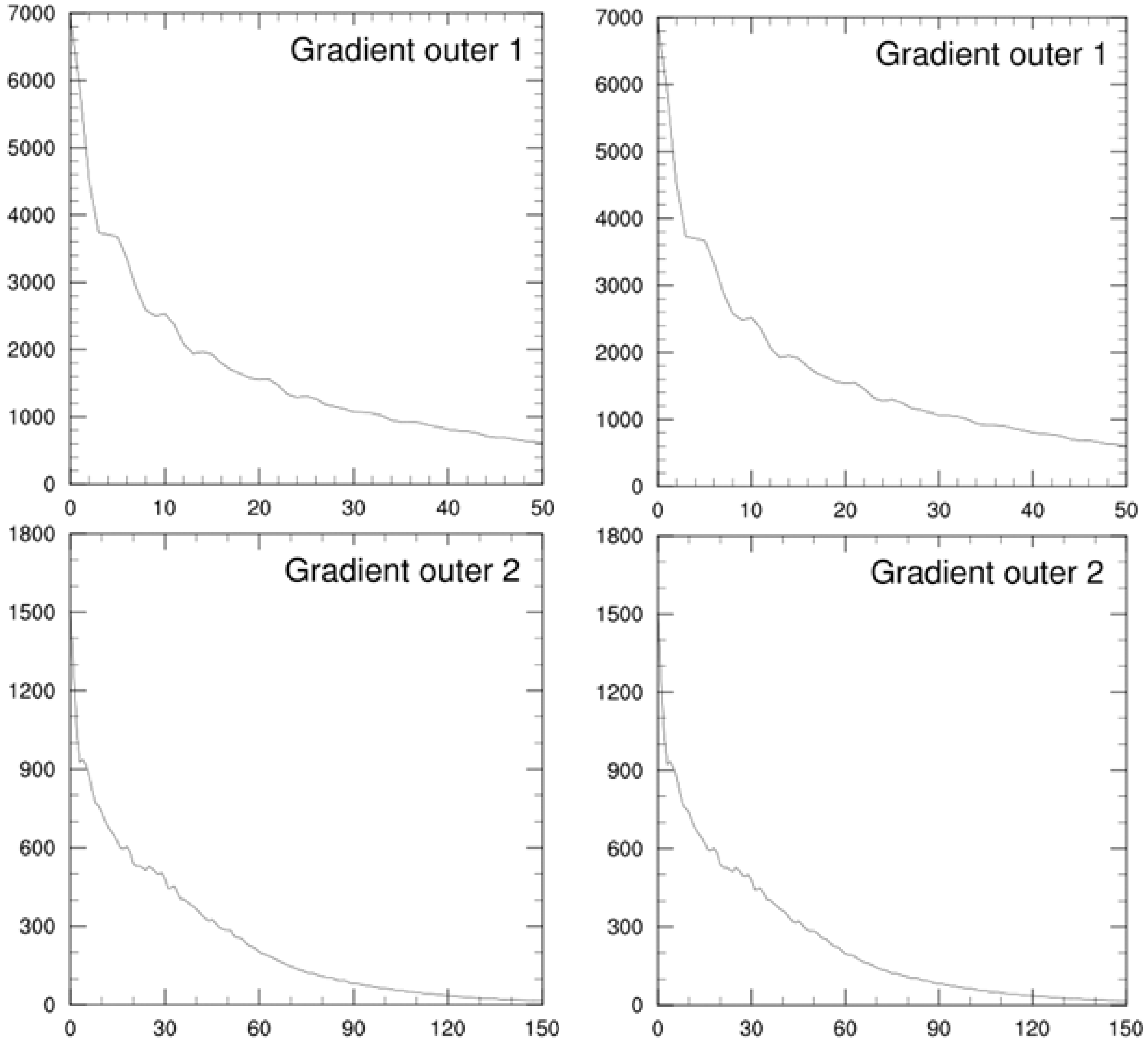
valid: 2019081706-2019082018

Further cost function reduction after second outer loop minimization for Aeolus with VarQC (left)

Gradient statistics

Aeolus DA No VarQC

Aeolus DA with VarQC



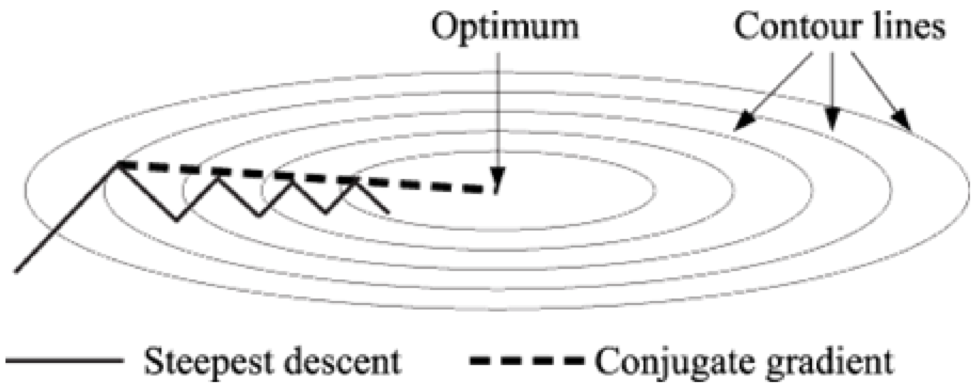
valid: 2019081706-2019082018

-More zigzagging with VarQC, but reaches convergence

- VarQC on top of steepest descent algorithm within the conjugate gradient minimization method

- Treatment of large innovations resulting in large gradient norm spikes

Minimization in GSI



Summary and next steps

- The new VarQC scheme in FV3GFS is capable of assigning adaptive weights to observations
- Initial tuning tests have shown that observations with large departures are included in the analysis with less weight
- Conduct an TC impact assessment on FV3GFS of Aeolus observations with the inclusion on VarQC
- Provide initial and lateral boundary conditions from FV3GFS_v16 with Aeolus DA + VarQC to initialize regional hurricane forecasts (NCEP/HWRF)

Thank you for your attention!

Any questions?