NWC SAF Winds Intercomparison Study Report: 2021

Final Report

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1. Abstract

Three previous Atmospheric Motion Vector (AMV) intercomparison studies, conducted between 2007 to 2019, compared the operational AMV algorithms of various satellite-derived wind producers using a common set of MSG/SEVIRI and Himawari/AHI images and ancillary data. The studies assessed how the cloudy AMVs compared in terms of coverage, speed, direction, and cloud height (Genkova et al. 2008, 2010; Santek et al. 2014, Santek et al. 2018, 2019).

Main conclusions of these studies were:

- The use by all AMV processing centers of the "Common Quality Indicator (CQI)" has a quantified skill in filtering collocated AMVs, for an improved statistical agreement.
- The differences in the AMV datasets depend very much on the "AMV height assignment" used and much less on the use of a prescribed or specific configuration.
- The centers using "Cross Correlation Contribution height assignment" (EUMETSAT, NWCSAF) had in general the best validation statistics in the second AMV Intercomparison.
- JMA algorithm had the best overall performance in the third AMV Intercomparison study, mainly due to its new height assignment method: "Optimal estimation method considering the observed infrared radiances, the vertical profile of the Numerical Weather Prediction wind, and the estimated brightness temperature using a radiative transfer model".

In this continuation, AMVs calculated by the same six AMV producers with NOAA's GOES-16/ABI satellite data are compared to address three main goals:

- To consider both 11.2 mm channel Cloudy AMVs and 6.2 mm channel Clear air AMVs in the comparison. In the previous AMV Intercomparison studies only Cloudy AMVs were considered.
- To compare the different AMV datasets with additional reference wind observations, beyond those already considered in the previous AMV Intercomparison studies (Radiosounding winds, NWP analysis winds and CALIPSO satellite cloud heights). Here, aircraft wind data and ADM-Aeolus satellite lidar wind profiles are considered. Rayleigh scattering Aeolus wind profiles are compared with Clear air AMVs, and Mie scattering Aeolus wind profiles are compared with Cloudy AMVs.
- Finally, through the comparison of the different options by the different AMV processing centers for the calculation of AMVs with GOES-16 satellite, to define the best options for the calculation of AMVs with the new generation of geostationary satellites (Himawari-8/9, GOES-R, MTG-I, etc.)

2. Motivation

It is a fact that all AMV operational algorithms have changed since the time of the previous AMV Intercomparison studies and an update of results would be very beneficial for them, and also that the verification of the differences in the current processing of GOES-16 images for the calculation of AMVs by the different producers will help very much to identify the optimum options for the calculation of AMVs with the new generation of geostationary satellites.

Considering this, the performance of a new AMV Intercomparison is very beneficial for all AMV producers, to quickly detect the aspects of the AMV calculation which would benefit from further refinement.

NOAA's GOES-16/ABI satellite data are used in the processing. This way, improvements of the different AMV algorithms respect to AMVs calculated with MSG and Himawari-8 satellite data in previous AMV intercomparison studies are shown. Additionally, a verification is done of the best options available for the processing of AMVs with the new generation of geostationary satellites (Himawari-8/9, GOES-R, MTG-I, etc.), with higher spatial resolution, higher temporal resolution, and more spectral channels. The study acts as an input for the development of all AMV algorithms, for their optimal use with this new generation of geostationary satellites.

3. Case Study

The International Winds Working Group (IWWG) discussed with the International Clouds Working Group (ICWG), the desire to use similar image data for both “IWWG’s AMV intercomparison study” and “ICWG’s Cloud Intercomparison study”. This way, synergies improve between both studies.

Considering this, similar input satellite datasets from GOES-16/ABI data for 20 October 2019 are used for the AMV calculation by the different AMV producers, in six different experiments. In all of them, the “Common Quality Index” is included in the AMV calculation for the AMV comparison. A common dataset of NWP model input data and cloud input data are used for the AMV calculation.

The experiments are numbered, thusly:

Table 3-1: Experiment numbering and bands: Infrared window (IR) and water vapor (WV).

Experiment		Configuration	Time (UTC)	Participants
1	IR	Common	11:50/12:00/12:10	All
2a	IR	Own	11:20/11:30/11:40	All
2b	IR	Own	11:50/12:00/12:10	All
2c	IR	Own	18:50/19:00/19:10	All
3	WV	Own	11:20/11:30/11:40	All, except JMA
4	WV	Own	11:10/11:30/11:50	All, except JMA

In Experiments 1, 2a, 2b and 2c, Cloudy AMVs for GOES-16 11.2µm ABI channel are calculated. In Experiments 3 and 4, Clear air AMVs for GOES-16 6.2µm ABI channel are calculated. The use of two different time steps in Experiments 3 and 4, not considered in the previous AMV Intercomparison studies, is good to detect in the different AMV datasets if a different time step has different implications.

In Experiment 1, a common configuration with target box size of 16x16 pixels, search box size of 54x54 pixels, line/element separation of 16 pixels is used. This configuration is similar to the one defined in the previous AMV Intercomparison study and is interesting to see if anything has changed since then. Additionally, the use of common options for the AMV calculation attempts to remove the impact of the different configurations used by the various AMV processing centres, thus easing the optimum comparison of target selection, feature tracking, height assignment, and quality control processes used by them.

In the rest of experiments, the operational configuration with optimal specific options for the AMV configuration is used by each AMV processing centre. This tries to compare the performance of the AMV datasets generated by each AMV processing centre using their best practices.

Considering the different reference datasets used in this AMV Intercomparison:

- AMVs in Experiments 1 and 2b, with central image at 12:00 UTC are compared with radiosonde and NWP wind analysis data. This is similar to what was already done in the two previous AMV intercomparisons.
- AMVs in Experiments 2a, 3 and 4, with central image at 11:30 UTC, are compared to aircraft wind data and ADM-Aeolus satellite lidar wind profiles (using Mie scattering Aeolus wind profiles for cloudy AMVs in Experiment 2a, and Rayleigh scattering Aeolus wind profiles for clear air AMVs in Experiments 3 and 4). Both comparisons are new and did not occur in any of the previous AMV intercomparisons (considering that ADM-Aeolus is only available since 2018).
- AMVs in Experiment 2c, with central image at 19:00 UTC, are compared to CALIPSO satellite cloud height data. A similar experiment was done in the latest AMV intercomparison with limited results. A better case with more collocation pairs between AMV heights and CALIPSO heights is defined in this AMV Intercomparison for a more complete output.

Examples of GOES-16 ABI images for 20 October 2019 at 1200 UTC are shown in Figure 3-1 (11.2µm, band 14) and Figure 3-2 (6.2µm, band 14). The day was selected to agree with the International Cloud Working Group, to increase the synergies between both “AMV Intercomparison study” and “Cloud Intercomparison study”.

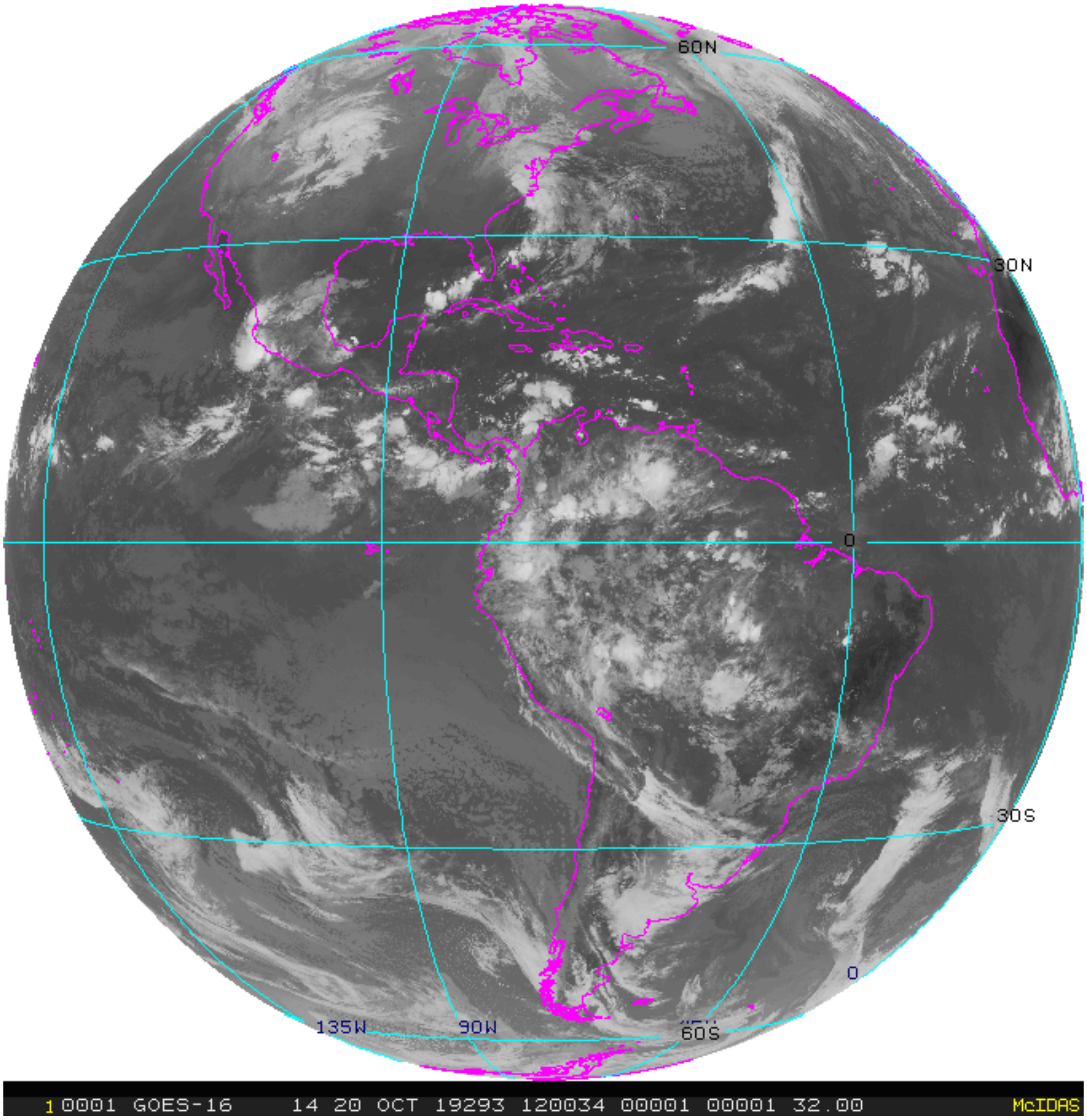

Figure 3-1: GOES-16 ABI 11.2 µm (band 14) from 20 October 2019 at 1200 UTC.

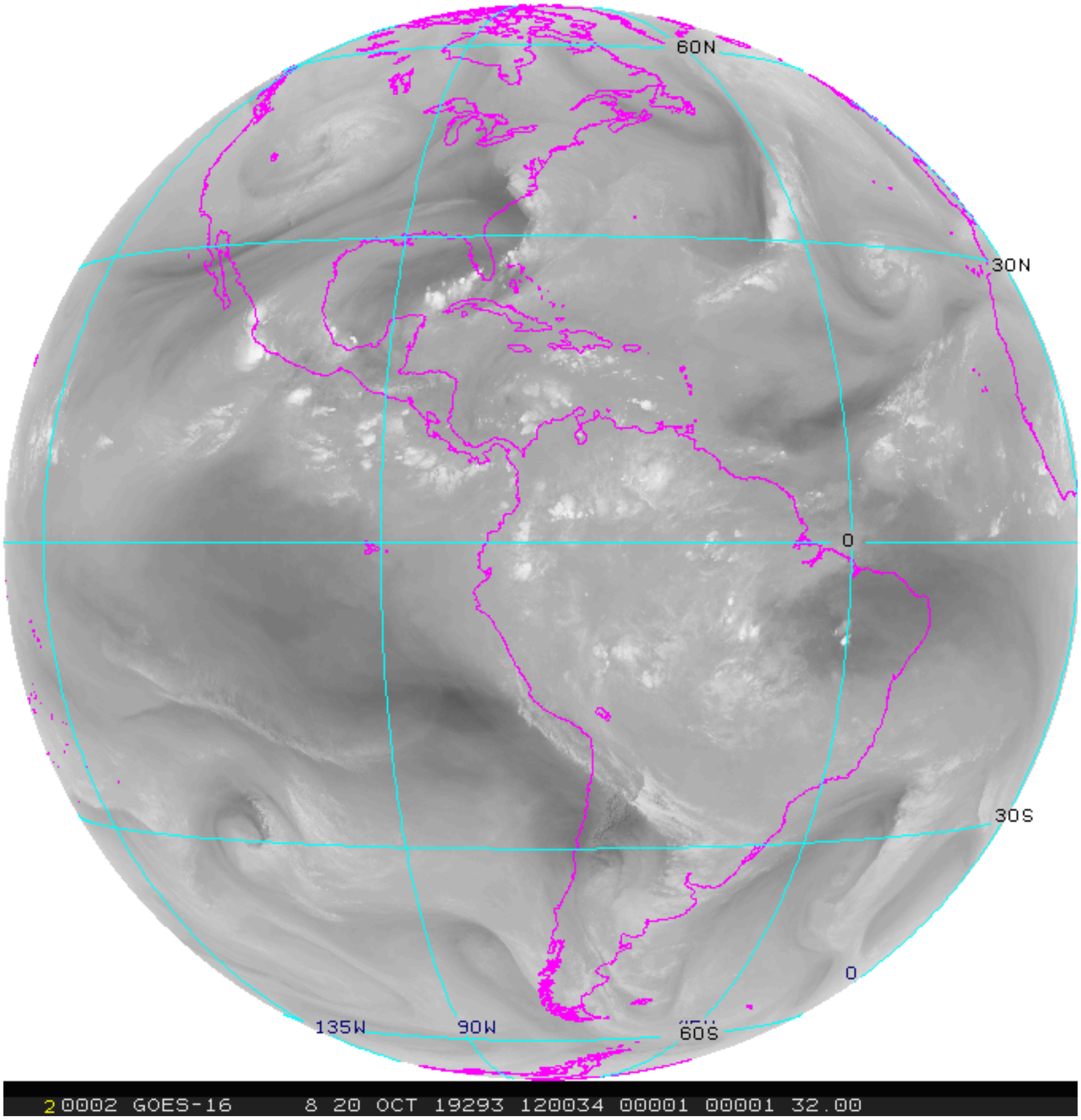

Figure 3-2: GOES-16 ABI 6.2 µm (band 8) from 20 October 2019 at 1200 UTC.

4. Overview

The output provided by the AMV producers was analyzed for six primary experiments, each of which is in a separate section, including text from the proposal describing the experiment, the approach used in the analysis, the results, and figures and tables supporting the results. Specific additional sections are later added for the specific comparisons with aircraft wind data, ADM-Aeolus wind profiles, and CALIPSO cloud heights.

The approach taken began with the scripts used in the previous intercomparison studies, resulting in plots and statistics that can be compared and contrasted with the previous work (Genkova et al. 2008, 2010; Santek et al. 2014; Santek et al. 2018, 2019).

5. Input Data Files

Each AMV producer provided files containing the AMV outputs for the different experiments with the same parameters, using a comma-separated value (CSV) text file format. The format of these input files is exactly equivalent to the ones used in the two previous AMV intercomparison studies, so that tools already used in these previous studies could be used again straightforward.

The AMV producers are:

1. BRZ: CPTEC (Brazil Weather Forecast and Climatic Studies Center)
2. EUM: EUMETSAT (European Organization for the Exploitation of Meteorological Satellites)
3. JMA: Japan Meteorological Agency
4. KMA: Korea Meteorological Administration
5. NOA: NOAA (National Oceanic and Atmospheric Administration)
6. NWC: NWC SAF (Satellite Application Facility on Support to Nowcasting & Very Short Range Forecasting)

The three-letter abbreviations above are used throughout the remainder of this report to identify the different AMV producers. The variables reported by the centers are in the same order as described by the header from NWC:

Table 5-1: Reported variables for each AMV.

Column	Variable	Description
1	ID	Identification number
2	LAT[DEG]	Latitude
3	LON[DEG]	Longitude
4	TS[PIX]	Target box size
5	SS[PIX]	Search box size
6	SPD[MPS]	AMV speed
7	DIR[DEG]	AMV direction
8	PRES[HPA]	AMV pressure
9	L	Low-level correction
10	NWSSPD[MPS]	Background guess wind speed
11	NWSDIR[DEG]	Background guess wind direction
12	ALB[%]	Albedo
13	CORR[%]	Correlation
14	T	Brightness temperature
15	PRESSERR[HPA]	AMV pressure error
16	H	Height assignment method
17	QIN[%]	QI without forecast
18	QIF[%]	QI with forecast
19	QIC[%]	Common QI

The data for the AMV processing consisted of:

- GOES-16 ABI datasets for the times given in Table 3-1, in the mission standard netCDF files, corresponding to each pixel of the ABI full disk imagery for all 16 bands, each one with its specific resolution (band 2 at ½ km resolution; bands 1/3/5 at 1 km resolution, and rest of bands at 2 km resolution). Bands to be used for the AMV calculation are band 8 (WV, 6.2μ) and band 14 (IR, 11.2μ).
- GFS GRIB2 NWP forecast fields for 19 and 20 October 2019, each one containing the 03, 06, 09 and 12 hour forecast data for each synoptic run. These files are used by the different AMV producers for the AMV calculation.
- Cloud products provided in netCDF format by NOAA/NESDIS, including the following parameters for each GOES-16 image time: land class, surface type, surface elevation, cloud probability, cloud mask, cloud type, cloud phase, cloud top pressure. They replicate the Cloud products already used in the previous AMV intercomparison.

Notes:

- To ensure consistent geographic coverage among the centres, the original CSV files were modified to retain only those winds within 6670 km from the satellite subpoint (with maximum distance from equator at 60° of latitude at satellite longitude).
- Only AMVs from 100 to 1000 hPa were considered in comparison statistics.
- JMA did not generate clear-sky AMVs for Experiments 3 and 4.
- The AMVs generated by KMA are the same for Experiments 1 and 2b, as the NOAA cloud product was not used in Experiment 1[1], and the rest of defined parameters are the same in the prescribed and operational configuration.

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[1] Email received from Kim Hee-ae of NMSC/KMA on 21 December 2021.

6. Wind Retrieval Algorithms

Please refer to the paper summarizing the result of the latest AMV intercomparison study (Santek et al. 2019) to check the specifications and differences between the AMV algorithms for each one of the producers, as defined at that time.

The few changes in the AMV processing by the different centres for this new Intercomparison study, defined by the different producers, are as follows:

1. BRZ reports the AMV height assignment process has improved with inclusion of the CO_2 slicing method; the tracking routine has been fixed correcting an issue found in the previous intercomparison; the NWP first guess has also been tuned to filter bad AMVs.
2. EUM reports their algorithm is essentially the same, but it has been adapted to be in line with the operational MTG-FCI AMV processor for a more meaningful comparison and validation. The main changes are:
    - The AMV latitude and longitude is now calculated as the weighted average of the pixels used by the CCC method (much like the pressure, temperature, etc. are calculated); this aims at locating the AMV at the tracked feature, rather than at the centre of the target area.
    - Different target area sizes are used for cloudy and clear-sky (32x32 and 48x48 pixels respectively).
    - The threshold for the application of the low-level inversion correction has been changed from 700 hPa to 600 hPa.
3. JMA reports there are no changes that affect quality or characteristics.
4. KMA reports the height assignment method has changed from “EBBT” and “IR/WV intercept” to “CCC method”.
5. NOA reports significant changes in the cloud products used by the AMVs. A satellite zenith angle cutoff of 62 degrees has also been added. “Mixed” cloud type is now screened out. And some cloud top pressure limits have also been added based on the cloud type: AMVs related to “thick ice” or “cirrus” clouds are removed for cloud top pressure > 500 hPa; AMVs related to “liquid” or “supercooled” clouds are removed for cloud top pressure < 500 hPa.
6. NWC reports NWC/GEO-HRW v2018 algorithm was used in the previous AMV intercomparison while NWC/GEO-HRW v2021 is used in current AMV intercomparison. Main differences between both are a better distribution of AMVs in high/medium/low levels of the troposphere for a better characterization of wind in all levels; an optimization of the running time of the algorithm (approximately 30%); an extension of the AMV processing to GOES-16/17 satellites.

A second question was also made to the AMV producers to check if the AMV algorithm used in this intercomparison is exactly the operational one or has any difference with respect to it. Considering this:

1. BRZ reports it differs a little because the change in the AMV height assignment has not been implemented operationally yet, and the NWP model used in the AMV processing is not the GFS model defined for the intercomparison. The algorithm used in the AMV intercomparison can be considered an updated version of the operational one that can replace it in the very near future.
2. EUM reports the algorithm used in the AMV intercomparison is based on the MTG-I/FCI AMV processor, which is not yet operational.
3. KMA reports their operational algorithm still uses “EBBT” and “IR/WV intercept” methods in the height assignment, but they plan to change that to the “CCC method” used in this intercomparison.
4. NOA reports the AMV algorithm used in this intercomparison is different from the operational one, without giving more details on this.
5. JMA and NWC report the AMV algorithms used in this intercomparison are exactly the operational ones (the corresponding NWC algorithm was released to users in April 2022).

A final question was also made to the AMV producers regarding filtering of the AMV data they provide for the AMV intercomparison, or if they provide all AMVs such as they are produced. Considering this:

1. BRZ reports all AMVs with issues (image with low contrast, too low correlation, very high viewing angles, etc.) are removed before the quality control. Additionally, there is an NWP consistency check through which the AMV is rejected if the difference with the NWP wind at the same level is greater than 10 ms^{-1} in speed or 60° in direction. They understand this consistency check can hide errors in the AMV calculation process.
2. NOA reports that beyond the filterings already mentioned in the first question of this chapter, any other filtering is related to gross error checks (in speed, direction, etc.) and is present in the operational algorithm.
3. NWC reports there are two main parts of the AMV process in which this can have an impact:
    - In the tracer selection. Many tracers are defined as invalid, and so all corresponding AMVs are removed in the process. The conditions so that tracers are kept as good are defined in the NWC/GEO-HRW ATBD[2] where both tracer selection methods are explained in detail: “Gradient method” and “Tracer characteristics method.”
    - In the quality control process, in which several filterings are defined: AMVs are only valid if correlation >= 80%; if pressure

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[2] https://www.nwcsaf.org/aemetRest/downloadAttachment/6474

  error <= 150 hPa; if not affected by any Orographic influence; if at least another AMV is found in the same latitude/longitude 5° box with a similar speed and direction.

  - Additionally, cloudy AMVs are only valid inside the 100-1000 hPa layer, and with a minimum of 2.5% cloudy pixels inside the tracer. Clear air AMVs are only valid inside the 100-400 hPa layer. Finally, the two subAMVs in the same AMV must use the same height assignment and be within limits of speed difference (10 ms^{-1}), direction difference (20°), and pressure difference (50 hPa).

4. EUM, JMA and KMA report they apply no filtering in the provided AMV outputs.

7. Experiment 1

a) Approach

AMV producers extract cloudy AMVs with GOES-16/ABI 11.2µm infrared channel, using a prescribed configuration with target box size of 16x16 pixels, search box size of 54x54 pixels, and a line/element separation of 16 pixels. There was also an option to use outputs from NOAA/NESDIS Cloud product in the height assignment, for a better comparison of results. However, only EUM, NOA and NWC used this Cloud product in the height assignment, so limiting partially the comparison of the results.

As already said, this configuration is similar to the one defined in the previous AMV Intercomparison studies and is interesting to see if anything has changed since then for the same experiment. Additionally, the use of common options for the AMV calculation attempts to remove the impact of the different configurations used by the various AMV processing centres, thus easing the comparison of them.

Remembering conclusions from previous AMV intercomparison studies with this configuration:

- In the first study (Genkova et al. 2008 & 2010) it was found that: *Winds datasets retrieved using common target and search box sizes reveal that each producer's algorithm is finely tuned to a specific imagery temporal and spatial resolution, as well as target and search box sizes.*
- In the second study (Santek et al. 2014):
  The number of collocated vectors is small (in the hundreds), due to the lower overall numbers of AMVs when using the prescribed target and search box sizes. Considering this configuration, there are more similarities between centers: speed and direction differences are not statistically different, although pressure and QI values are significantly different.
- In the third study (Santek et al. 2018 & 2019):
  Generally there are more AMVs, compared to the equivalent experiments in the previous AMV intercomparisons, due to the higher resolution of AHI imager (2km) vs SEVIRI (3 km), more oceanic regions, and fewer deserts.
  Secondly, only a part of AMV centres used the prescribed NOAA/NESDIS Cloud product in the height assignment, having as consequence a larger variability in collocated AMV vectors than in the previous AMV intercomparisons, and so indicating that the height assignment is the main driver in variability, over prescribed versus operational configuration of algorithm running parameters.

> *Finally, the use of the "Common Quality Control (CQI)" results in better statistical agreement for collocated AMVs from the different centres, especially for CQI >= 80%.*

For each one of the AMV datasets, an initial comparison of AMV quantities, AMV distribution in layers, and distribution of AMV speed and pressure values for the different centres are evaluated in Subchapter 7b). Later, an evaluation of differences in the AMV speed, direction, pressure and Quality Index values for collocated AMVs is evaluated in Subchapter 7c). Comparisons against Radiosounding winds and NWP analysis winds are later evaluated in Subchapters 7d) and 7e) respectively. A verification of the height assignment for the different centres is done using NWP model best-fit pressure in Subchapter 7f). And finally, an evaluation of the quality of the AMVs with respect to the "Common Quality Control (CQI)" is done in Subchapter 7g).

b) Parameter distributions

For each one of the AMV datasets a summary of the different AMV parameters (number of AMVs, distribution in high/medium/low layer, speed and pressure distributions in the whole atmosphere and in the three layers) is shown here. Four different tables are shown for each AMV dataset, related to four different Quality index thresholds: Quality index without forecast (QINF) >= 50% and >= 80%, and Common Quality Index (CQI) >= 50% and >= 80%.

Considering the values of the different parameters in Table 7-1 to Table 7-4:

- The total number of AMVs ranges between 32,000 for NOA and 113,000 for JMA considering all AMVs, and between 25,000 for BRZ and NOA and 105,000 for JMA considering CQI >= 80%, with differences of up to 4 times in the number of AMVs in spite of the prescribed configuration.
- Considering CQI >= 80%, the maximum speed has a very small range between 65 and 70 ms^{-1} for all centres except BRZ (with a value of 45 ms^{-1}). The mean speed has also a very small range between 12 and 14 ms^{-1} for all centres except BRZ (with a value of 9 ms^{-1}).
- Considering CQI >= 80%, the minimum pressure has also a small range between 103 and 125 hPa for all centres. The maximum pressure ranges between 966 hPa for KMA and 1050 hPa for EUM. The mean pressure ranges between 509 and 594 hPa (except for BRZ, who shows again a different value of 722 hPa).
- Related to this, the distribution of AMVs in the different layers has also small differences, with 39-52% of AMVs in the high layer, 7-15% of AMVs in the medium layer, and 37-47% of AMVs in the low layer for all centres except again BRZ (which has different AMV percentages of 16%/21%/63% respectively in the high/medium/low layer).
- With all this, the AMV parameter distributions using the prescribed configuration show relatively small differences between the different centres except BRZ, which shows a significantly different behaviour. No clear explanation appears here about why this happens.

Comparing with results for the Experiment with prescribed configuration in the previous AMV intercomparison (Experiment 1):

- Increases in the amount of AMVs are seen in half of the centres (EUM, JMA, NWC) and decreases are seen in the other half of the centres (BRZ, NOA, KMA), so reflecting differences in the AMV algorithm in this period of time.
- Speed and pressure ranges are slightly smaller than those presented in the previous intercomparison, so showing some additional homogenization between the AMVs from different centres.
- BRZ was also four years ago the most different dataset.
- Comparing values in this prescribed experiment, four years ago with AHI radiometer and now with ABI radiometer, the main difference is the mean

pressure, which has significantly fallen to lower levels from approximately 430 hPa to 550 hPa, so showing a larger proportion of low level AMVs. This might not only be related to the geographical characteristics of the region seen by Himawari-8 and GOES-16 satellites (proportion and location of oceanic areas, of deserts, etc), but also on the specific cases used in both intercomparisons.

The “AMV parameter distribution histograms” in Chapter 17 (shown for Experiment 1 in Figure 17-1 to Figure 17-12) complement this information, with histograms showing the distribution of AMV speed, direction, pressure and Quality index values using both Quality index thresholds. In all cases, a map is also included showing the geographical coverage of each AMV dataset, using three color codes: green for AMVs with Quality index >= 80%, blue for AMVs with Quality index >= 50% and red for AMVs with Quality index < 50%.

Major observations in the variable histograms for the different centres show:

- Considering the speed, the histogram maxima are at slowest speeds, and the proportion of data reduces progressively for higher speeds in all centres. The main difference is related to the maximum speeds in the histogram, showing again the fact indicated previously: the maximum speed is between 65 and 70 ms^{-1} for all centres except BRZ, with a value of 45 ms^{-1}.
- Considering the direction histogram, all centres show two maximums for easterly and westerly winds, being the main difference a pair of smaller submaximums around the westerly direction, which are more pronounced for BRZ and NOA.
- Considering the pressure histogram, all centres show two maximums at high levels (250-300 hPa) and low levels (900-950 hPa) except BRZ, which only shows a maximum at low levels.
- Considering the Common Quality Control histogram, all centres show a maximum near 100% with smaller frequencies for progressively smaller CQI values. The maximum is however less noticeable for BRZ.
- Considering the specific Quality Control without forecast histogram, a similar distribution is shown with another maximum near 100%. The maximum is here less noticeable for BRZ, KMA and NWC.

Table 7-1: Experiment 1 statistical summary of AMV datasets for QINF>=50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63411	45668	113614	32925	52605	99906
QI>=50	48127	38107	110976	31117	41602	85457
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	101.45	44.30	67.16	67.55	78.61	70.22
SPD_mean	12.83	9.10	13.95	12.11	13.73	13.86
P_min	109.44	104.78	125.00	101.52	102.74	120.00
P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
P_mean	569.72	709.65	594.07	567.50	509.71	535.01
Low_winds	44.75	60.22	45.68	44.00	36.67	42.30
Mid_winds	9.17	23.81	15.80	8.74	11.63	8.26
High_winds	46.08	15.97	38.52	47.26	51.69	49.43
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	47.78	31.17	31.23	30.35	78.61	33.13
Low_SPD_mean	8.42	8.37	9.05	8.49	8.84	8.73
Low_P_min	700.02	700.08	700.00	700.13	700.00	700.00
Low_P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
Low_P_mean	896.88	882.37	901.72	899.10	850.63	859.21
Mid_SPD_min	2.50	3.75	2.50	3.01	2.51	2.54
Mid_SPD_max	73.75	41.52	49.83	56.69	58.86	61.91
Mid_SPD_mean	13.60	9.76	11.79	11.90	13.43	14.79
Mid_P_min	400.07	400.04	400.10	400.05	400.01	401.00
Mid_P_max	699.82	699.94	699.90	699.99	699.91	699.00
Mid_P_mean	508.13	553.95	521.13	541.57	520.01	517.69
High_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
High_SPD_max	101.45	44.30	67.16	67.55	75.12	70.22
High_SPD_mean	16.95	10.89	20.65	15.52	17.26	18.09
High_P_min	109.44	104.78	125.00	101.52	102.74	120.00
High_P_max	399.97	399.99	400.00	399.98	399.95	400.00
High_P_mean	264.25	290.58	259.16	263.58	265.53	260.45

Table 7-2: Experiment 1 statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63411	45668	113614	32925	52605	99906
QI>=50	55066	41422	111656	31117	47112	99408
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	124.56	44.92	67.16	67.55	82.85	70.22
SPD_mean	12.66	9.56	13.93	12.11	13.24	13.29
P_min	108.95	104.26	125.00	101.52	102.44	120.00
P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
P_mean	580.06	706.38	593.95	567.50	507.62	540.00
Low_winds	45.93	59.43	45.64	44.00	36.17	42.90
Mid_winds	10.43	24.56	15.86	8.74	12.24	8.85
High_winds	43.63	16.01	38.50	47.26	51.59	48.25
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	81.65	31.17	31.23	30.35	49.81	34.47
Low_SPD_mean	8.80	8.69	9.03	8.49	8.74	8.56
Low_P_min	700.02	700.01	700.00	700.13	700.00	700.00
Low_P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
Low_P_mean	893.57	881.14	901.69	899.10	848.93	858.24
Mid_SPD_min	2.51	3.75	2.50	3.01	2.51	2.50
Mid_SPD_max	73.75	41.52	49.83	56.69	64.34	61.91
Mid_SPD_mean	13.66	10.42	11.78	11.90	13.07	14.14
Mid_P_min	400.06	400.04	400.10	400.05	400.01	401.00
Mid_P_max	699.82	699.94	699.90	699.99	699.91	699.00
Mid_P_mean	519.62	553.10	520.93	541.57	522.08	522.89
High_SPD_min	2.50	3.76	2.50	3.00	2.50	2.50
High_SPD_max	124.56	44.92	67.16	67.55	82.85	70.22
High_SPD_mean	16.48	11.51	20.62	15.52	16.45	17.34
High_P_min	108.95	104.26	125.00	101.52	102.44	120.00
High_P_max	399.97	399.99	400.00	399.98	399.95	400.00
High_P_mean	264.48	292.74	259.21	263.58	264.89	260.21

Table 7-3: Experiment 1 statistical summary of AMV datasets for QINF>=80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63411	45668	113614	32925	52605	99906
QI>=80	37371	22821	100655	25944	25369	55606
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	67.59	40.72	67.16	67.55	65.30	70.22
SPD_mean	13.75	8.57	14.40	12.82	16.12	15.58
P_min	121.96	106.35	125.00	104.62	102.74	120.00
P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
P_mean	574.84	721.82	594.23	572.25	524.70	534.42
Low_winds	45.80	62.77	45.90	44.92	39.56	42.24
Mid_winds	8.05	21.49	15.10	7.51	9.33	7.55
High_winds	46.15	15.74	39.00	47.57	51.11	50.21
Low_SPD_min	2.50	3.75	2.50	3.01	2.50	2.50
Low_SPD_max	47.78	31.17	31.23	30.35	28.17	29.92
Low_SPD_mean	8.69	8.07	9.25	8.78	9.36	9.38
Low_P_min	700.05	700.08	700.00	700.13	700.00	700.00
Low_P_max	1050.00	1000.00	1001.10	998.75	971.79	974.00
Low_P_mean	900.53	888.58	902.55	904.72	856.99	862.34
Mid_SPD_min	2.52	3.75	2.51	3.05	2.53	2.59
Mid_SPD_max	63.85	36.51	49.83	56.69	48.99	61.91
Mid_SPD_mean	15.03	8.96	12.24	12.71	16.03	16.66
Mid_P_min	400.07	400.04	400.10	400.05	400.07	401.00
Mid_P_max	699.78	699.85	699.90	699.96	699.85	699.00
Mid_P_mean	504.33	554.18	523.08	540.91	513.37	513.08
High_SPD_min	2.50	3.76	2.50	3.00	2.50	2.51
High_SPD_max	67.59	40.72	67.16	67.55	65.30	70.22
High_SPD_mean	18.55	10.00	21.29	16.64	21.36	20.63
High_P_min	121.96	106.35	125.00	104.62	102.74	120.00
High_P_max	399.97	399.99	400.00	399.98	399.95	400.00
High_P_mean	263.96	285.75	258.94	263.20	269.58	261.73

Table 7-4: Experiment 1 statistical summary of AMV datasets for CQI>=80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63411	45668	113614	32925	52605	99906
QI>=80	45287	25626	105062	25944	39551	92663
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	67.59	44.92	67.16	67.55	65.30	70.22
SPD_mean	13.16	8.99	14.21	12.82	13.91	13.54
P_min	112.13	106.35	125.00	104.62	102.74	120.00
P_max	1050.00	1000.00	1001.10	998.75	965.96	974.00
P_mean	585.91	722.11	594.01	572.25	509.09	540.89
Low_winds	47.30	62.83	45.78	44.92	37.08	43.22
Mid_winds	8.90	21.31	15.42	7.51	10.72	8.50
High_winds	43.80	15.85	38.81	47.57	52.21	48.29
Low_SPD_min	2.50	3.75	2.50	3.01	2.50	2.50
Low_SPD_max	53.56	31.17	31.23	30.35	49.75	34.47
Low_SPD_mean	8.93	8.24	9.18	8.78	8.94	8.64
Low_P_min	700.02	700.08	700.00	700.13	700.00	700.00
Low_P_max	1050.00	1000.00	1001.10	998.75	965.96	974.00
Low_P_mean	897.75	889.54	902.09	904.72	851.86	858.66
Mid_SPD_min	2.51	3.75	2.51	3.05	2.52	2.53
Mid_SPD_max	66.44	39.15	49.83	56.69	48.99	61.91
Mid_SPD_mean	14.42	9.68	12.04	12.71	13.72	14.59
Mid_P_min	400.07	400.04	400.10	400.05	400.06	401.00
Mid_P_max	699.82	699.85	699.90	699.96	699.91	699.00
Mid_P_mean	516.65	552.55	522.22	540.91	517.10	521.60
High_SPD_min	2.50	3.76	2.50	3.00	2.50	2.50
High_SPD_max	67.59	44.92	67.16	67.55	65.30	70.22
High_SPD_mean	17.48	11.04	21.01	16.64	17.47	17.74
High_P_min	112.13	106.35	125.00	104.62	102.74	120.00
High_P_max	399.97	399.99	400.00	399.98	399.95	400.00
High_P_mean	263.22	286.40	259.12	263.20	264.00	259.87

c) Collocation plots

Plots of collocated AMV parameters from the different algorithms are shown in Figure 7-1 and Figure 7-3 to measure the respective differences (from top to bottom: speed, direction, pressure, and quality control). AMV pressure scatter plots comparing the EUM AMV pressure with the pressure of all other collocated AMVs are also shown in Figures 7-2 and 7-4 to detect better the differences in the different AMV height assignment processes.

In both cases, a distance threshold of 55 km between AMVs and two quality control thresholds are used for this: "Quality index without forecast (QINF)" >= 50% and "Common Quality Index (CQI)" >= 50%. The thresholds are kept low to still detect the variability of the parameters in the different AMV datasets.

There are around 27000 collocated AMVs considering the QINF threshold, and around 33000 collocated AMVs considering the CQI threshold. The plots of collocated parameters (Figures 7-1 and 7-3) show:

- The big number of collocations acts as an obstacle here, especially considering the direction and quality control plots, in which the large amount of data avoids to find any significant information. This can be compared to what happens in chapters 9) and 10), in which the smaller amount of collocations permits there to extract more conclusions.
- Considering the speed plot, some higher-speed outliers are found, mostly related to JMA (yellow dots), but also occurring in KMA (red dots) and NOA (black dots). For the higher speeds, lower-speed outliers from BRZ are also found (green dots); considering also the previously shown smaller BRZ highest speed values, this might show the inability of BRZ algorithm to find very high speed values (maybe related to not using "tracking areas" of enough size?).
- Considering the pressure dots, the only informations that can be extracted is that BRZ and EUM can reach lower levels (blue dots and green dots), that the frequency of BRZ AMVs is higher at mid-levels, and that NOA has also some higher-level outliers.

Considering the AMV pressure scatter plots (Figure 7-2 and Figure 7-4), AMV pressures related to EUM and NWC relate very well to each other, due to the fact of both using "CCC method height assignment" and using here the same Cloud product for the calculations. The low level correction, which EUM applies but NWC does not apply, can also be seen below 900 hPa (where EUM pressure values are lower than those of NWC).

Pressure values for KMA and NOA have a smaller correspondence with the previous ones, although still not too different. KMA also applies "CCC method height assignment", but its results are noisier, with more values outside the diagonal, because of using its specific Cloud product in the calculations. NOA

uses a different method, which defines more AMVs near the ground when EUM defines a high or medium level AMV, but also defines higher AMVs when EUM defines a low level AMV.
The most different height assignments are related to BRZ, which in general shows lower levels than EUM (although some low level AMVs are higher), and to JMA, which shows a much more random distribution of AMVs, especially with many AMVs which are located in high levels while the rest of centres locate them at low levels below 800 hPa. A good exercise here would be to check visually these JMA AMVs and the clouds they are related to, and see in the corresponding satellite image if there are very high clouds or low clouds (such as defined by the other AMV centres) in these locations.

Finally, considering all elements together, the height assignment procedure and the AMV pressure it defines keep on being the main driver in variability, over any other option defined in the AMV algorithms. In spite of this, a homogenization process has occurred in the different AMV algorithm since the AMV intercomparisons started, and now for example layer distribution, speed and pressure ranges are smaller than in previous AMV intercomparison, and the comparisons against rawinsondes and NWP analysis winds also show that differences in errors betwen the different AMV datasets are also smaller.

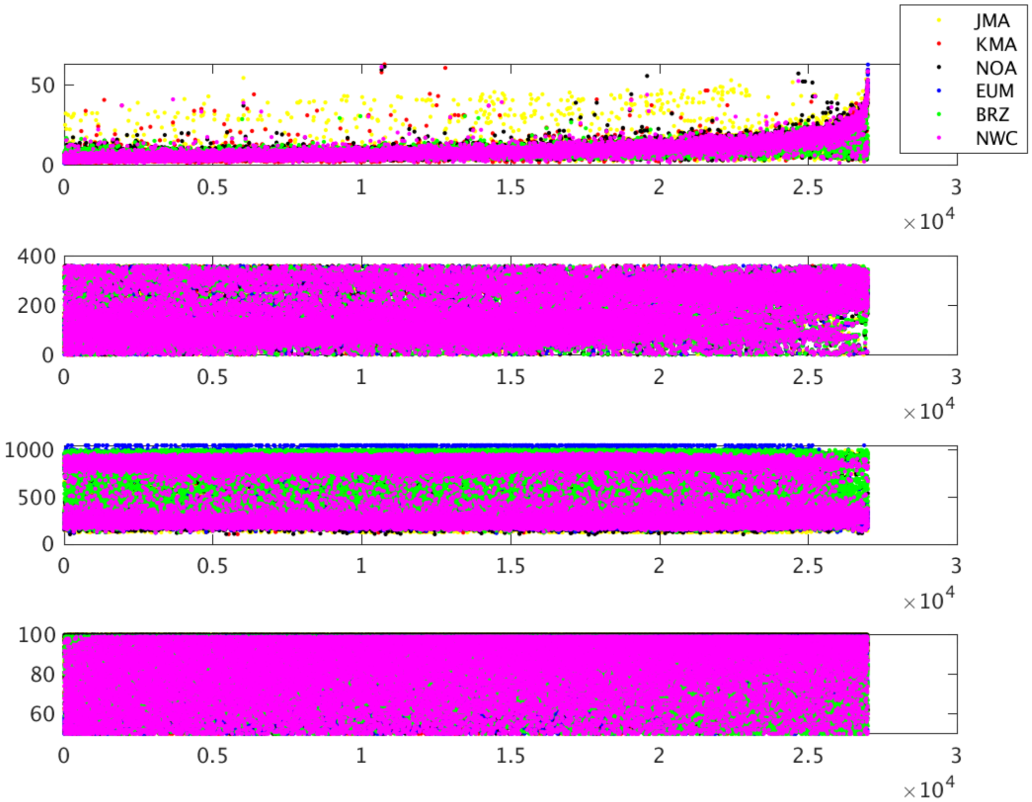

Figure 7-1: Experiment 1 (QINF >= 50) Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

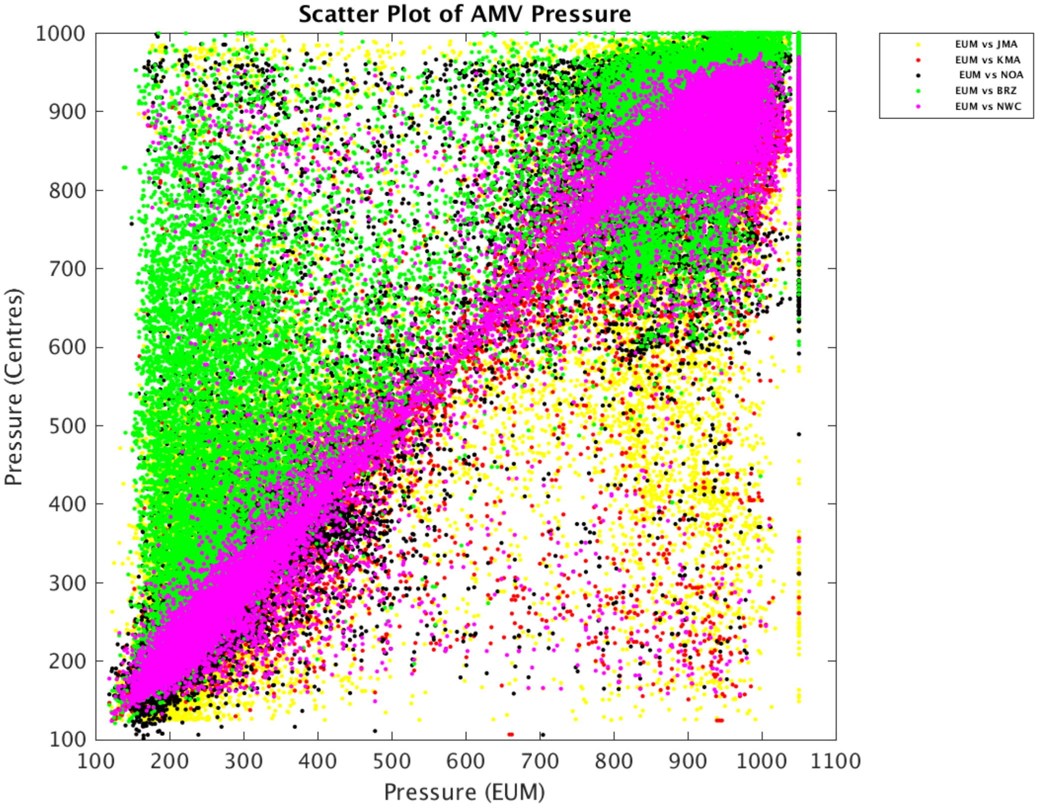

Figure 7-2: Experiment 1 (QINF >= 50) Scatter plot of AMV pressure for each center vs. EUM pressure.

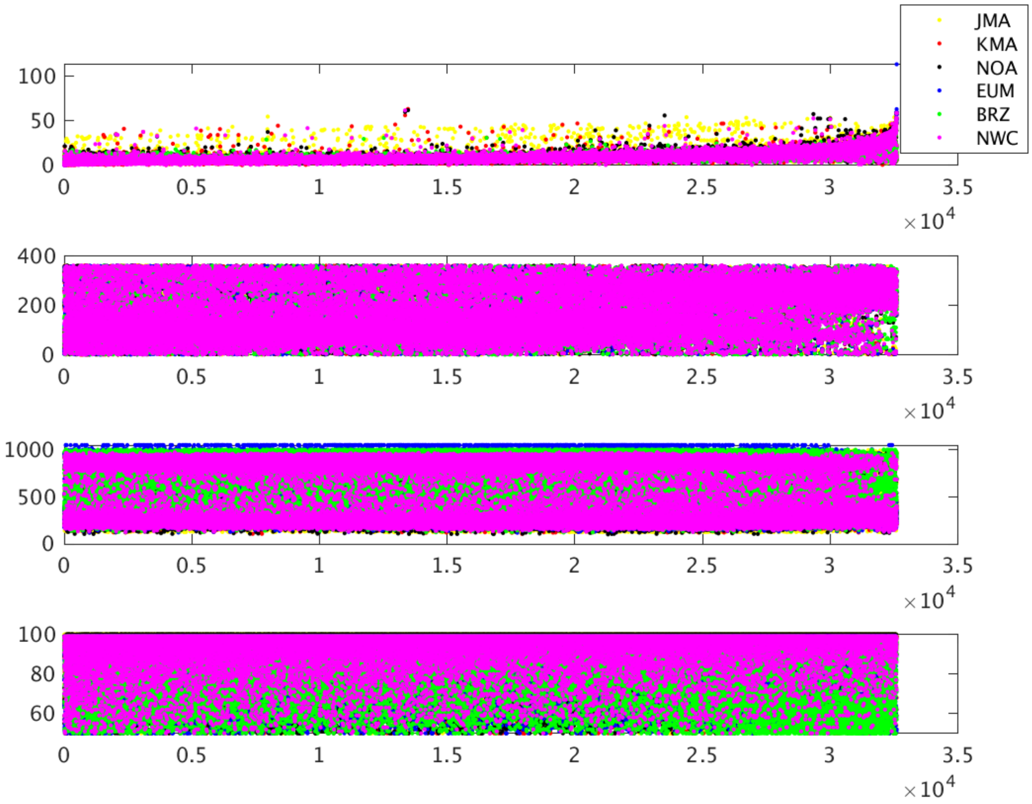

Figure 7-3: Experiment 1 (CQI >= 50) Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

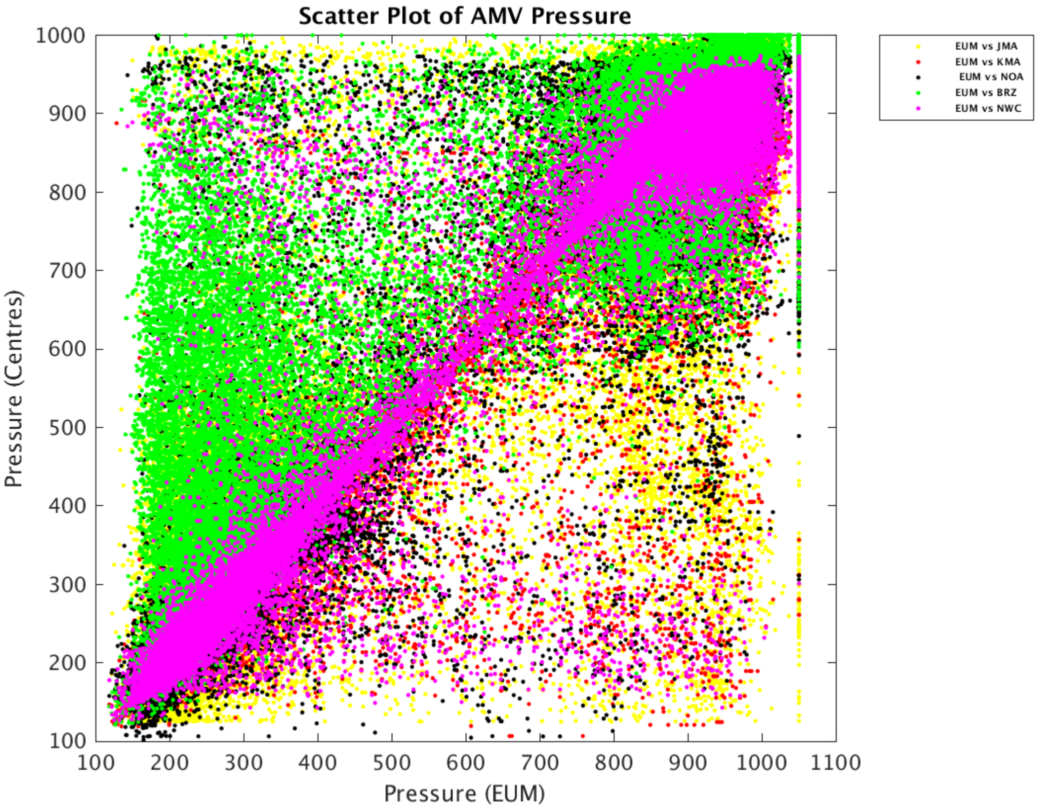

Figure 7-4: Experiment 1 (CQI >= 50) Scatter plot of AMV pressure for each center vs. EUM pressure.

d) Rawinsonde comparison

The comparison of all AMVs to nearby rawinsondes is summarized in the following tables for QINF, CQI >= 50% and QINF, CQI >= 80% (the same thresholds as used in the previous Intercomparison study). Collocated AMVs for all levels have also been compared for QINF, CQI >= 50%.

The QINF >=50% (Table 7-5) vector RMS ranges from 5.6 ms^{-1} (BRZ) to 6.2 – 7.4 ms^{-1} (NOA, JMA, NWC) to greater than 8 ms^{-1} (EUM, KMA). In Table 7-6 (QINF threshold increased to 80%) the statistics are slightly improved for BRZ with the vector RMS of 5.3 ms^{-1} and the RMS for KMA, EUM decreasing to less than 8 ms^{-1}. The statistics were about the same for NOA, JMA, NWC with the RMS ranging from 6.2 – 7.6 ms^{-1}. The large RMS differences are probably due to the substantial variation in height assignment methods used. However, the variability is reduced compared to what was observed in Experiment 1 in the previous Study, partly due to improved height assignment methods and a larger sample of AMV/rawinsonde matches.

Table 7-8 summarizes the statistics for the CQI >=50%, where vector RMS ranges from 6.2 – 7.4 ms^{-1} (NOA, BRZ, JMA, NWC) to approximately 9 ms^{-1} (KMA, EUM). For the CQI > = 80% (Table 7-9) the statistics are about the same for NOA, BRZ, JMA, NWC, with an improvement for KMA, EUM as the RMS dropped below 8 ms^{-1}.

Considering only collocated AMVs as compared to rawinsondes, the number of matched observations is reduced to approximately 1600 for each centre, however, that is more than an order of magnitude greater than the previous intercomparison study with only 100 matches. For QINF > =50%, the vector RMS is improved with less variability between centres (Table 7-7): Vector RMS ranges from 4.50 (JMA) to 6.33 (EUM). Results are similar for CQI >= 50% (Table 7-10).

Table 7-5: Experiment 1: All AMVs (QINF >= 50) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS= speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	2191	0.63	15.78	0.29	3.44	-1.17	5.63
EUM	3162	-0.03	13.41	-1.65	6.39	-1.36	8.10
JMA	5635	0.37	14.53	-0.10	4.63	2.45	6.68
KMA	2716	0.33	12.67	-2.00	6.64	-1.61	8.58
NOA	2143	0.81	13.49	-0.04	4.39	-0.56	6.20
NWC	5479	0.31	11.99	-1.56	5.77	-1.03	7.43

Table 7-6: Experiment 1: All AMVs (QINF >= 80) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS= speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1201	1.16	15.52	0.16	2.94	-2.31	5.30
EUM	2304	-0.17	13.35	-1.39	6.11	-1.37	7.63
JMA	5055	0.46	14.52	-0.07	4.64	2.07	6.72
KMA	1580	0.44	12.18	-1.85	5.77	-1.87	7.24
NOA	1760	1.06	13.33	-0.00	4.38	-1.19	6.18
NWC	3541	0.49	12.17	-1.54	5.91	-1.64	7.63

Table 7-7: Experiment 1: Collocated AMVs (QINF >= 50) comparison to rawinsondes within 150 km. N = number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS = speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1584	0.94	16.55	0.66	3.72	1.87	5.91
EUM	1632	-0.30	13.64	-1.04	4.79	-1.72	6.33
JMA	1657	0.23	14.87	-0.28	3.17	0.54	4.50
KMA	1657	-0.36	12.92	-0.99	4.92	-2.32	6.25
NOA	1647	0.39	14.14	-0.27	3.85	-2.87	5.38
NWC	1666	-0.48	12.81	-0.98	4.55	-1.37	5.84

Table 7-8: Experiment 1: All AMVs (CQI >= 50) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS= speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	3972	-0.21	12.63	-0.45	4.66	-0.57	6.40
EUM	4147	0.03	13.56	-1.70	7.15	1.63	9.04
JMA	5675	0.36	14.53	-0.10	4.64	2.48	6.68
KMA	3370	0.33	12.80	-2.12	7.23	0.11	8.85
NOA	2143	0.81	13.49	-0.04	4.39	-0.56	6.20
NWC	6748	0.23	12.09	-1.65	5.80	0.16	7.42

Table 7-9: Experiment 1: All AMVs (CQI >= 80) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS= speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	3110	-0.13	12.53	-0.45	4.60	-1.41	6.31
EUM	3110	0.01	13.44	-1.41	6.64	0.98	8.35
JMA	5313	0.43	14.48	-0.08	4.64	2.06	6.70
KMA	2653	0.23	12.41	-1.82	6.53	-0.73	8.11
NOA	1760	1.06	13.33	-0.00	4.38	-1.19	6.18
NWC	6187	0.16	12.00	-1.57	5.72	-0.42	7.36

Table 7-10: Experiment 1: Collocated AMVs (CQI >= 50) comparison to rawinsondes within 150 km. N = number of matches; P bias = pressure bias; P RMS = pressure RMS; Spd bias = speed bias; Spd RMS = speed RMS; Dir bias = wind direction bias; Vec RMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1998	1.25	16.58	0.53	3.83	0.71	6.04
EUM	2075	-0.09	13.96	-1.01	4.99	-2.40	6.79
JMA	2109	0.07	14.59	-0.42	3.33	0.82	4.71
KMA	2088	-0.49	13.38	-1.25	5.29	-2.00	6.87
NOA	2086	0.32	13.99	-0.26	3.92	-2.72	5.56
NWC	2099	-0.10	12.69	-0.97	4.50	-1.77	5.91

e) Model Grid comparison

The Python scripts used to determine the Best fit height analysis also define the comparison of all AMVs to the NWP background model grid winds. This comparison was based on ECMWF ERA5 analysis using QINF, CQI >= 80%. The tables below are for all AMVs and AMVs by pressure range (high, medium, and low).

The AMV/ERA5 RMS statistics are reduced over what was computed with rawinsonde comparisons (previous section); this trend is analogous to what was found in Experiment 1 of the 2018 Study, with the following notable exceptions:

- In the 2018 Study, BRZ had the largest deviation from the background grid, except for the low-level AMVs where KMA and EUM had the largest deviations. In this current Study, BRZ shows a significant improvement in RMSE that is comparable to the sites with the best statistics (NOA, NWC). This is due to improvements in the height assignment, including the addition of a CO_2 technique, updates to the tracking algorithm, and the new "NWP consistency" filtering, whose impact should be however reduced (or removed completely) to reduce also the dependency on the NWP model.
- In the 2018 Study, the RMSE for individual centres is approximately the same when considering all AMVs for QINF >= 80% and CQI >= 80%. However, that is not the case in the current study for EUM and KMA. For QINF >= 80% (Table 7-11), the RMSE for EUM is 5.22 ms^{-1}, while for CQI >= 80% (Table 7-15) it is 6.24 ms^{-1}. Similarly, the RMSE for KMA is 4.01 ms^{-1} (QINF >= 80%) and 5.93 ms^{-1} (CQI >= 80%). The other centres do not exhibit this variability. We can not offer an explanation as this is also observed in Experiment 2.

The AMV/ERA5 RMS values for all levels for QINF >= 50% range from 3.9 to 5.5 ms^{-1} (Table 7-11), which is substantially better than the AMV/rawinsonde comparison, with an RMS range of 5.3 to 7.6 ms^{-1} (Table 7-6). This improvement in the statistics is related to the fact that AMV winds relate better to the NWP winds than to the Rawinsonde winds. This can be seen in general in other AMV comparison studies.

When the AMVs are binned into three levels (High: 100-400 hPa, Middle: 400-700 hPa, Low: 700-1000 hPa), the middle level AMVs have the poorest RMS ranging from 5.2 to 7.5 ms^{-1}. The best winds are in the low levels with an RMS ranging from 2.3 to 3.5. ms^{-1}, due to the generally slower winds in the low levels.

Table 7-11: Experiment 1: All AMVs (QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	22821	4416	3.20	4.09	2.83	3.75
EUM	36482	12800	3.69	5.22	2.91	4.52
JMA	100651	32693	3.55	5.46	3.15	5.22
KMA	25440	9692	3.04	4.01	2.32	3.33
NOA	25944	8788	3.09	3.94	2.46	3.36
NWC	55738	20339	3.15	4.16	2.45	3.48

Table 7-12: Experiment 1: High level AMVs (100-400 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	3592	1250	4.24	4.97	3.24	4.04
EUM	17329	7976	4.62	6.00	3.47	4.98
JMA	39256	17628	4.98	6.90	4.29	6.52
KMA	13002	6641	3.72	4.73	2.74	3.84
NOA	12341	6192	3.78	4.51	2.75	3.61
NWC	27984	14396	3.96	4.95	2.93	4.03

Table 7-13: Experiment 1: Mid level AMVs (400-700 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	4860	478	4.58	5.36	4.30	5.15
EUM	2992	492	5.36	7.52	4.80	7.11
JMA	15103	2356	4.11	6.32	3.86	6.17
KMA	2342	383	3.97	5.17	3.49	4.77
NOA	1923	272	4.97	5.81	4.58	5.56
NWC	4203	694	4.50	5.70	3.92	5.19

Table 7-14: Experiment 1: Low level AMVs (700-1000 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	14324	2683	2.47	3.25	2.22	3.04
EUM	16139	4328	2.37	3.52	1.94	3.17
JMA	46195	12697	2.14	3.36	1.95	3.25
KMA	10069	2663	1.94	2.32	1.50	1.91
NOA	11655	2319	2.04	2.72	1.80	2.49
NWC	23551	5249	1.95	2.45	1.62	2.13

Table 7-15: Experiment 1: All AMVs (CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	25626	5099	3.21	4.11	2.82	3.75
EUM	45874	14522	4.19	6.24	3.47	5.72
JMA	105057	33858	3.54	5.43	3.14	5.18
KMA	40954	13816	4.11	5.93	3.30	5.32
NOA	25944	8788	3.09	3.94	2.46	3.36
NWC	95461	31020	3.36	4.37	2.70	3.75

Table 7-16: Experiment 1: High level AMVs (100-400 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	4062	1484	4.27	5.02	3.25	4.08
EUM	20531	8772	4.75	6.24	3.67	5.33
JMA	40771	18171	4.96	6.87	4.27	6.49
KMA	21408	9156	4.61	6.11	3.57	5.22
NOA	12341	6192	3.78	4.51	2.75	3.61
NWC	45968	20662	4.12	5.12	3.18	4.30

Table 7-17: Experiment 1: Mid level AMVs (400-700 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	5411	617	4.63	5.42	4.28	5.16
EUM	4206	600	6.17	8.85	5.69	8.56
JMA	16097	2487	4.07	6.22	3.83	6.08
KMA	4319	626	5.73	8.12	5.21	7.79
NOA	1923	272	4.97	5.81	4.58	5.56
NWC	8050	1348	4.58	5.81	3.99	5.29

Table 7-18: Experiment 1: Low level AMVs (700-1000 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	16102	2993	2.46	3.24	2.21	3.03
EUM	21102	5146	3.24	5.58	2.82	5.35
JMA	48088	13188	2.15	3.35	1.95	3.23
KMA	15180	4027	2.94	4.83	2.38	4.50
NOA	11655	2319	2.04	2.72	1.80	2.49
NWC	41443	9010	2.28	2.89	1.93	2.55

f) Best fit height

The Best Fit height analysis was completed for each wind producer according to the method described by Salonen et al. (2012). This technique finds the background model best-fit pressure associated with the AMV, which is where the vector difference between the observed AMV and NWP model analysis wind is at a minimum.

It does this by first determining the model pressure level of the minimum vector difference between the AMV and the model background. Then, the actual minimum is calculated by using a parabolic fit to the vector difference for this model level and the levels directly above and below, which must be both less than or equal to 4 ms^{-1} and at least 2 ms^{-1} smaller than the vector differences +/- 100 hPa from the best-fit pressure level. Therefore, this method is dependent on the model vertical resolution. It is possible using a requirement of at least 2 ms^{-1} smaller than the vector differences +/- 100 hPa from the best-fit pressure level is too demanding of a requirement.
Similar to previous studies, the number of best-fit matches was generally about 30% of the AMVs (Salonen et al. 2012).

The following figures show for all AMV centres, for QINF >= 80% and CQI >= 80%:

- Distribution of "Best Fit minus AMV pressure" differences, color-coded by low, medium, and high clouds (upper-left),
- Spatial distribution with same color coding (upper-right),
- Relationship between AMV pressure and latitude, color-coded to indicate if the Best fit moved the AMV higher (red) or lower (blue) (lower-left),
- Relationship between AMV pressure and speed, color-coded to indicate if the Best fit moved the AMV higher (red) or lower (blue) (lower-right).

Most of the plots are in agreement for the following: throughout the middle portion of the image high-level clouds are adjusted, and in the eastern Pacific low-level clouds are adjusted due to the best fit.
The distribution of high, mid, and low-level clouds (upper left plots) are similar between the different centers with a spread of +/- 200 hPa for the high clouds, except JMA (Figure 7-9) with a much tighter and smoother distribution (+/- 100 hPa). This means that the JMA AMVs vary little from the ECMWF ERA5 analysis compared to the other AMV producers.
Also, the histograms for the low-level clouds (blue) are centered to the right of zero (for EUM, KMA, NWC)[3] which implies that low-level clouds are

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[3] See Figure 7-7, Figure 7-11, Figure 7-15, respectively.

primarily adjusted downward (increasing pressure). An exception to this downward trend is NOAA AMVs (Figure 7-13), where low-level clouds are usually adjusted upward.

An additional set of figures for all AMV centres, for QINF >= 80% and CQI >= 80% (beginning with Figure 7-17) depicts the distribution of Best Fit statistics. Depending on the site, 32% to 38% of AMVs are adjusted to a Best Fit pressure (lower-left in each figure). However, the BRZ AMVs with QINF >= 80% (Figure 7-17) is an exception with only 19% of the AMVs adjusted.

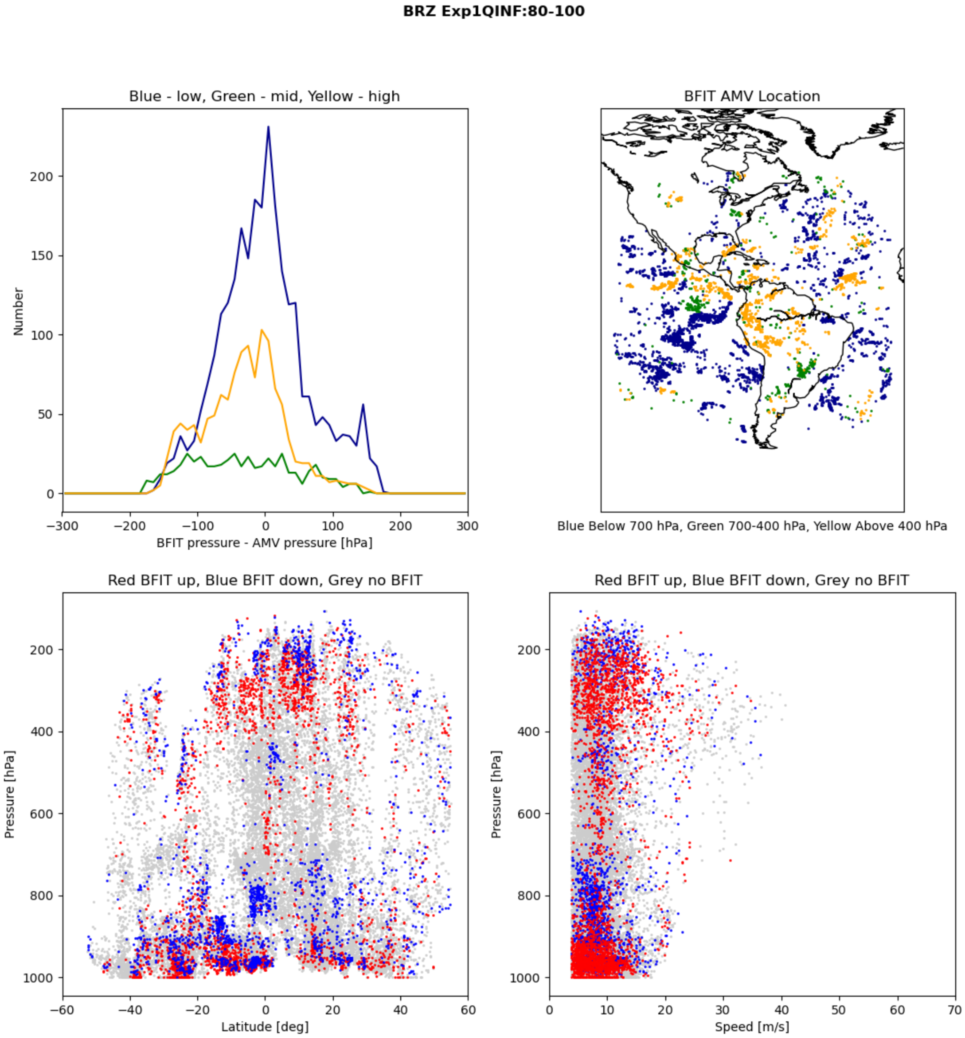

Figure 7-5: Experiment 1 BRZ (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

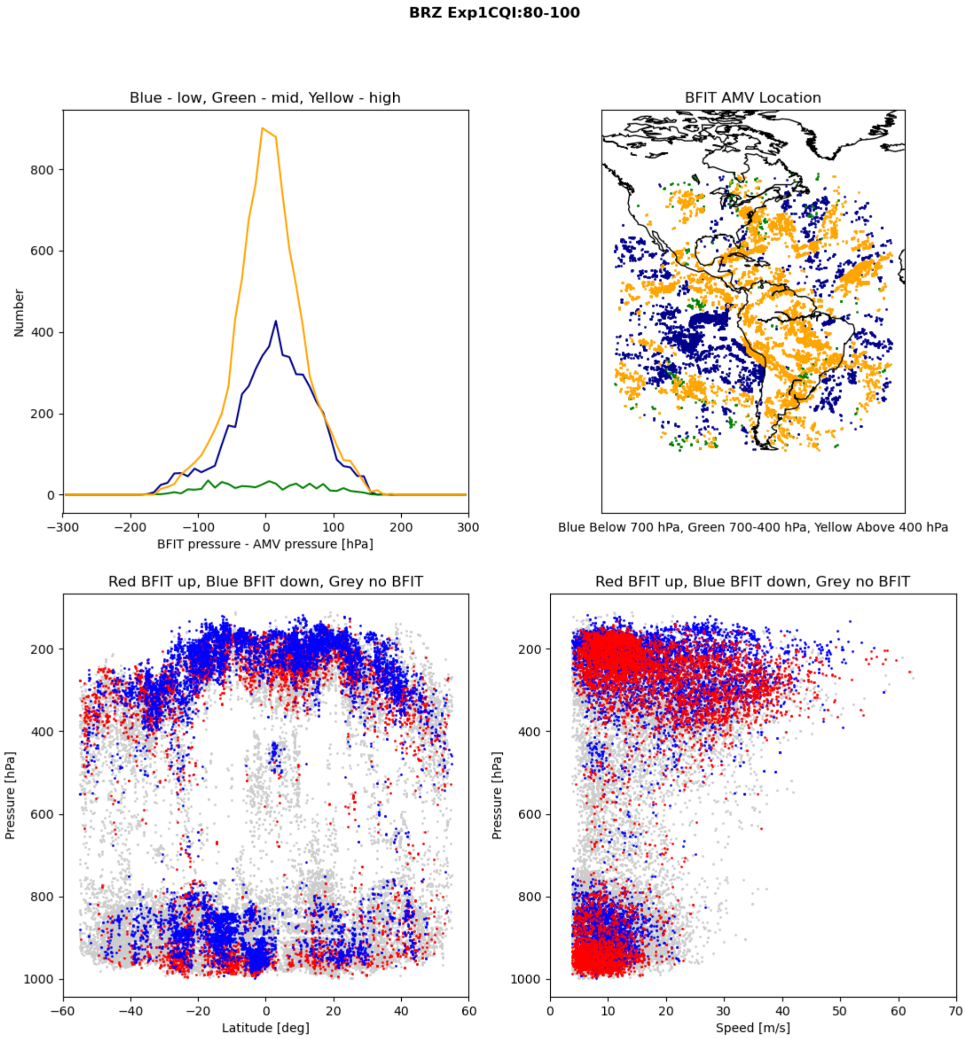

Figure 7-6: Experiment 1 BRZ (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

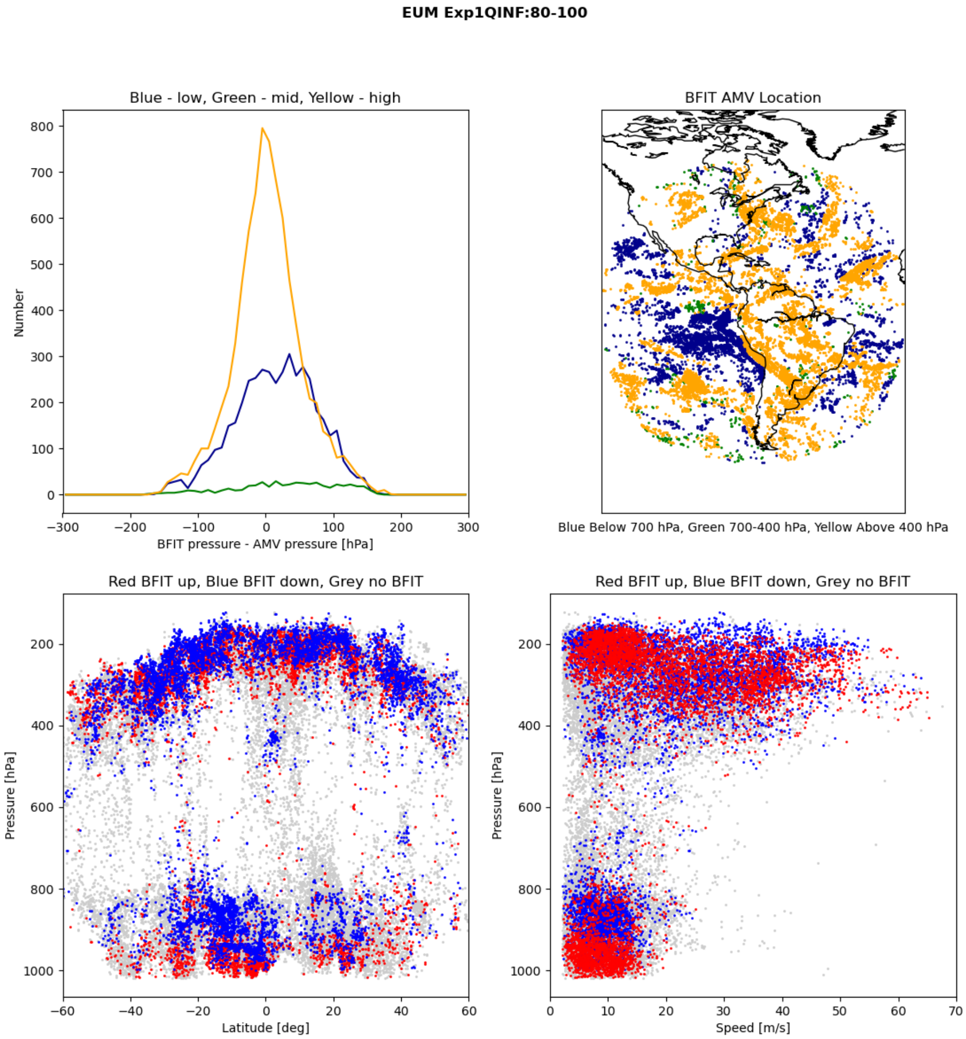

Figure 7-7: Experiment 1 EUM (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

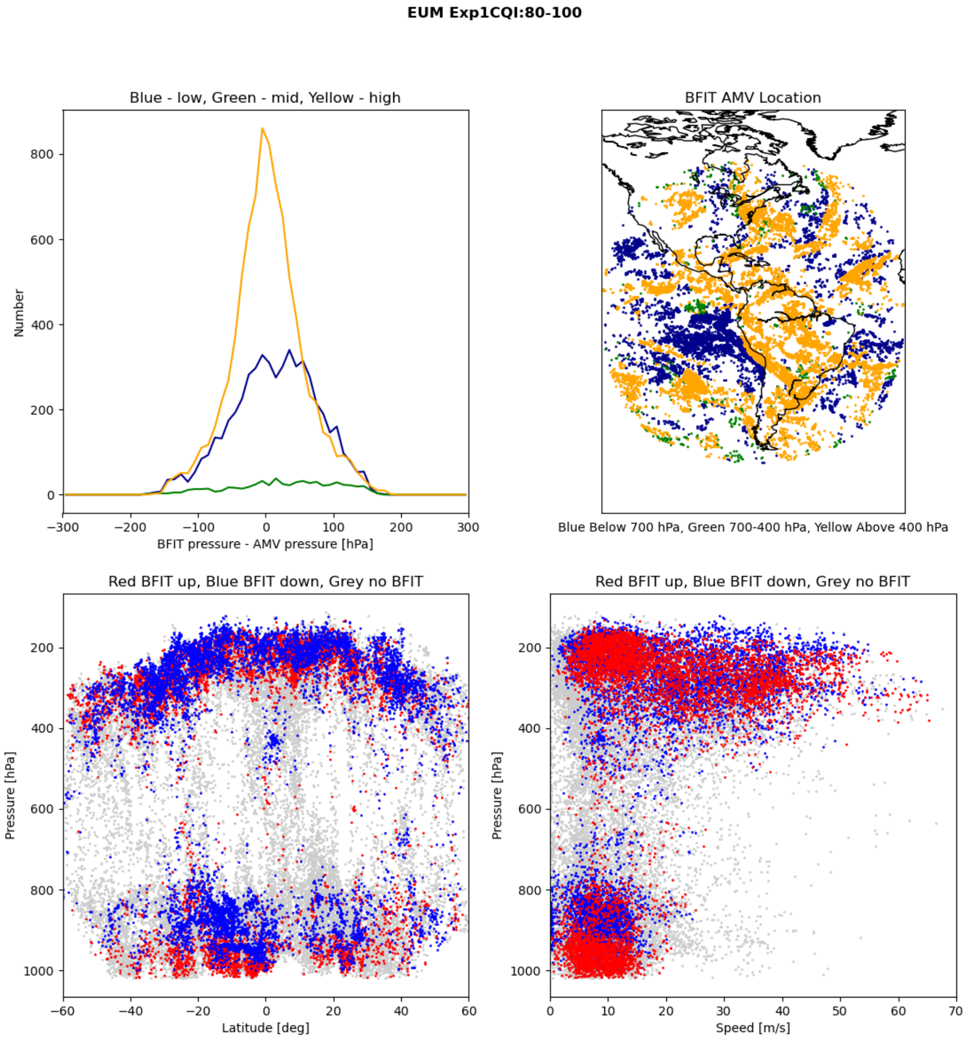

Figure 7-8: Experiment 1 EUM (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

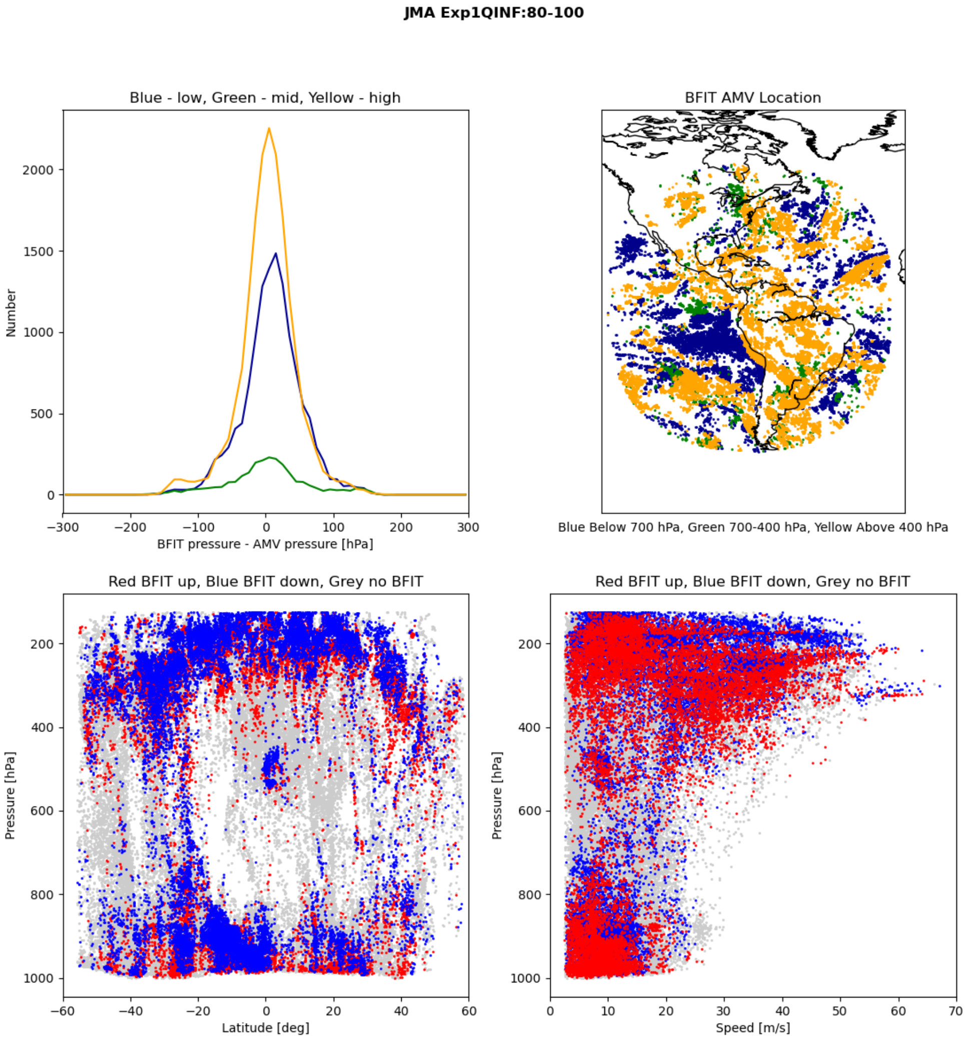

Figure 7-9: : Experiment 1 JMA (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

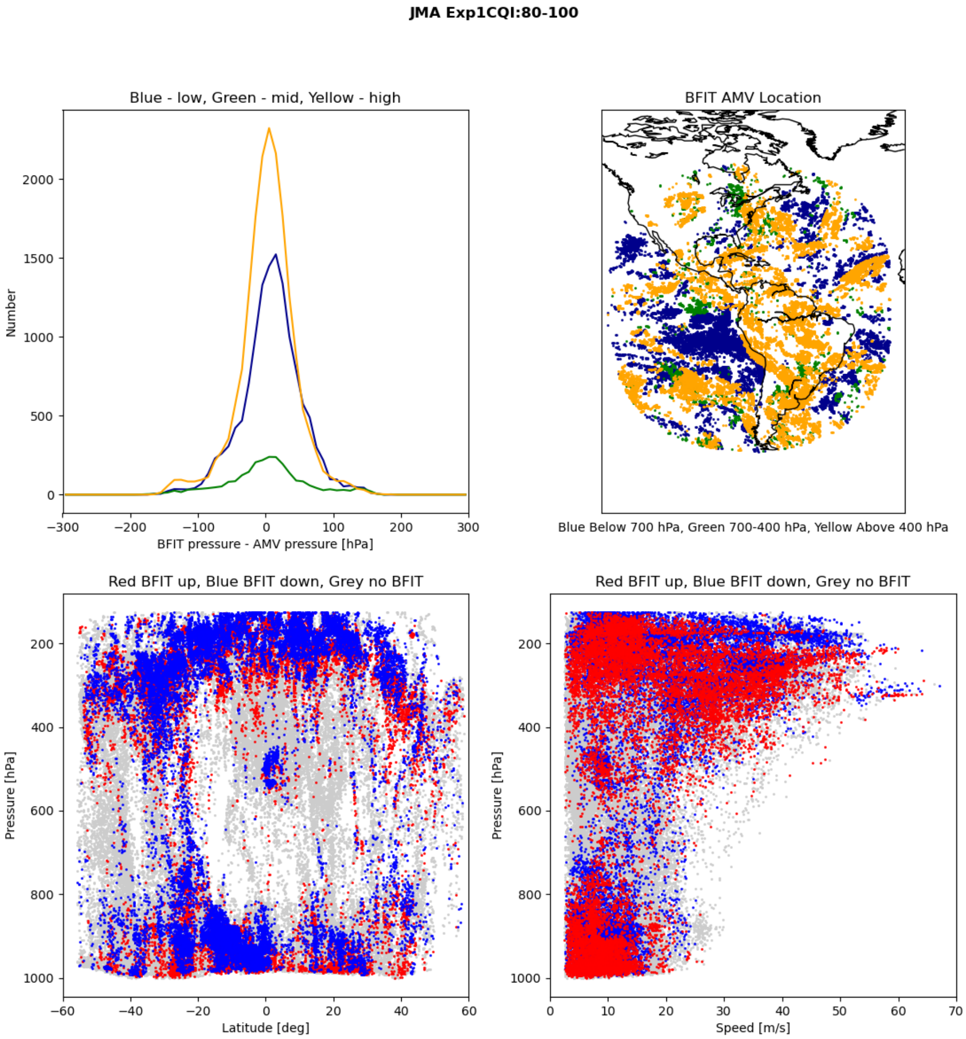

Figure 7-10: Experiment 1 JMA (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

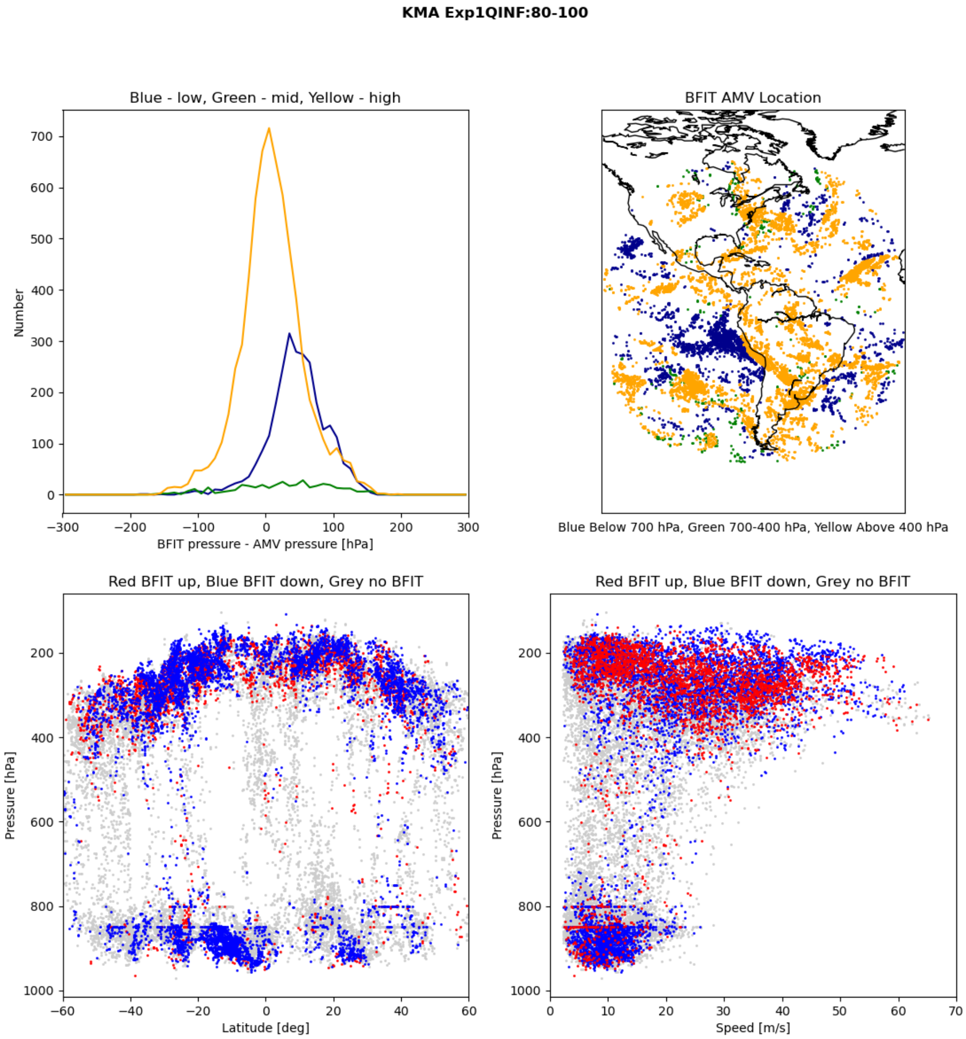

Figure 7-11: Experiment 1 KMA (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

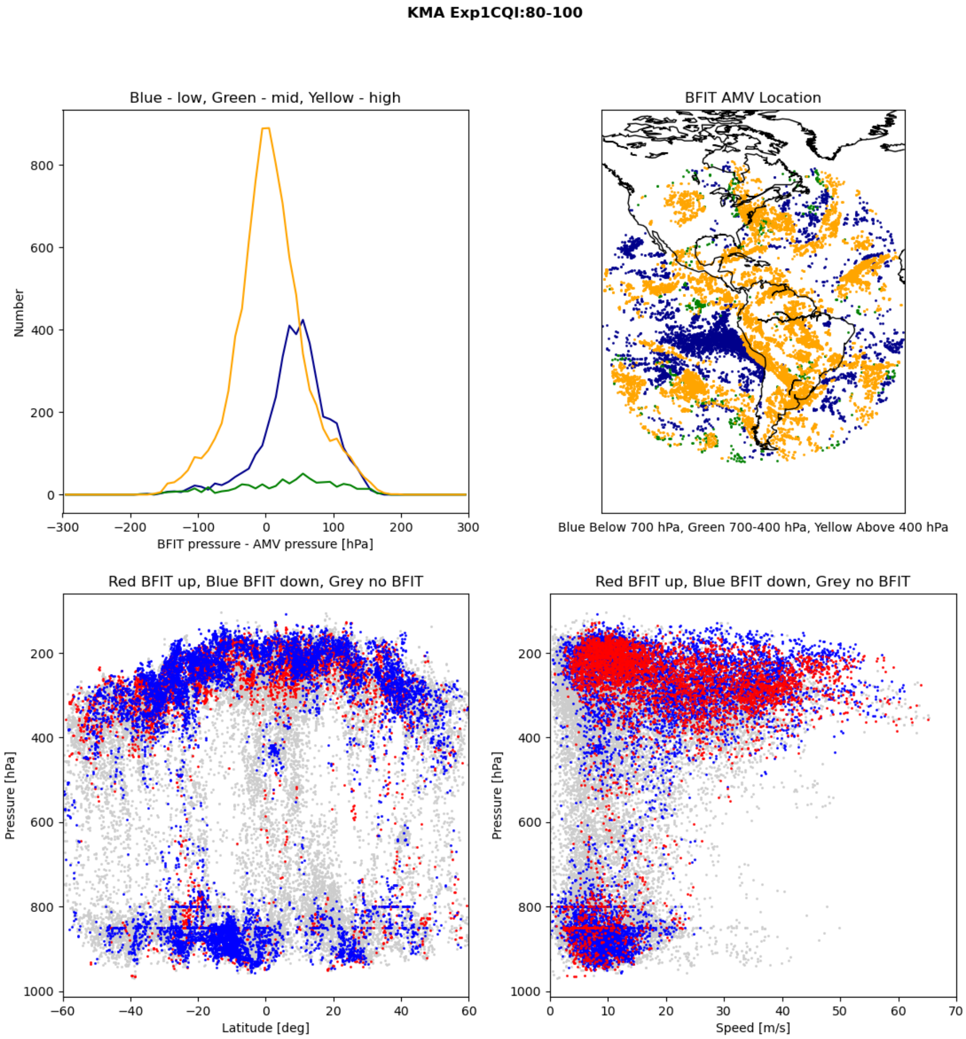

Figure 7-12: Experiment 1 KMA (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

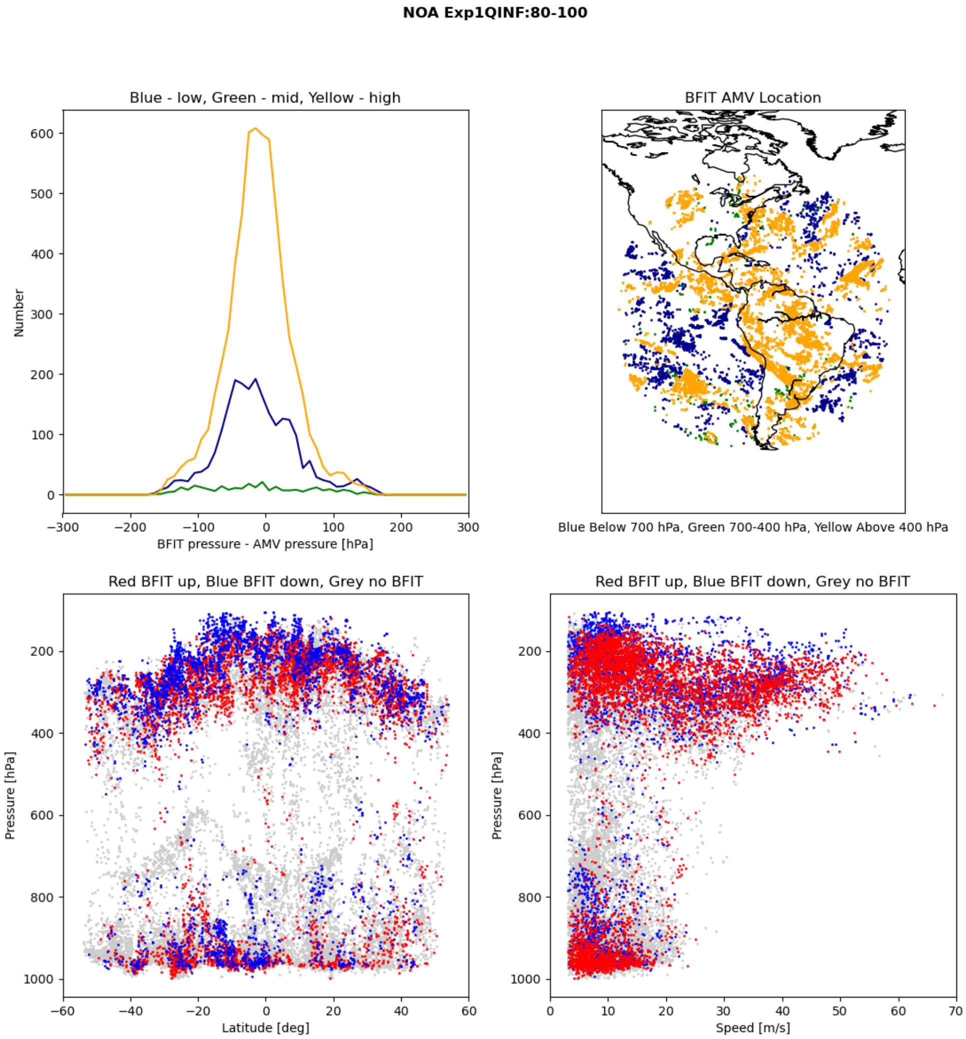

Figure 7-13: Experiment 1 NOA (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

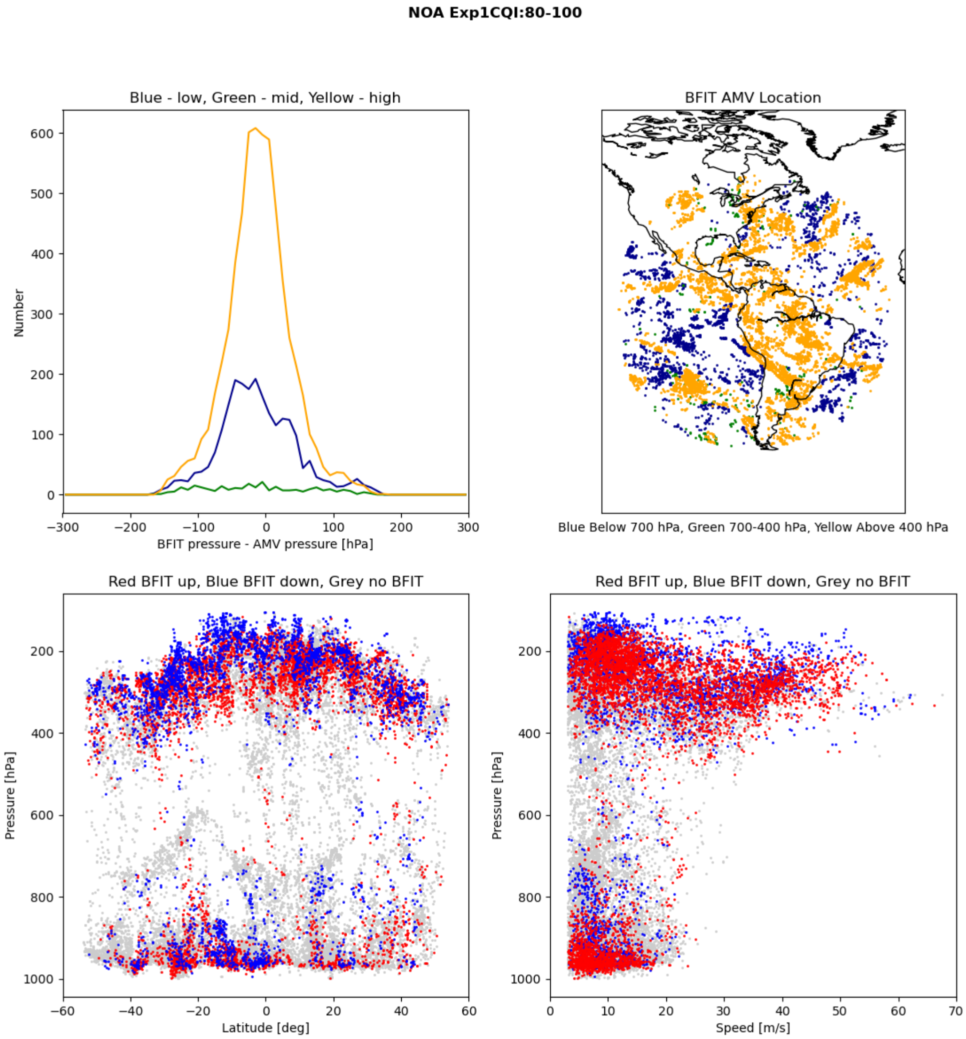

Figure 7-14: Experiment 1 NOA (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

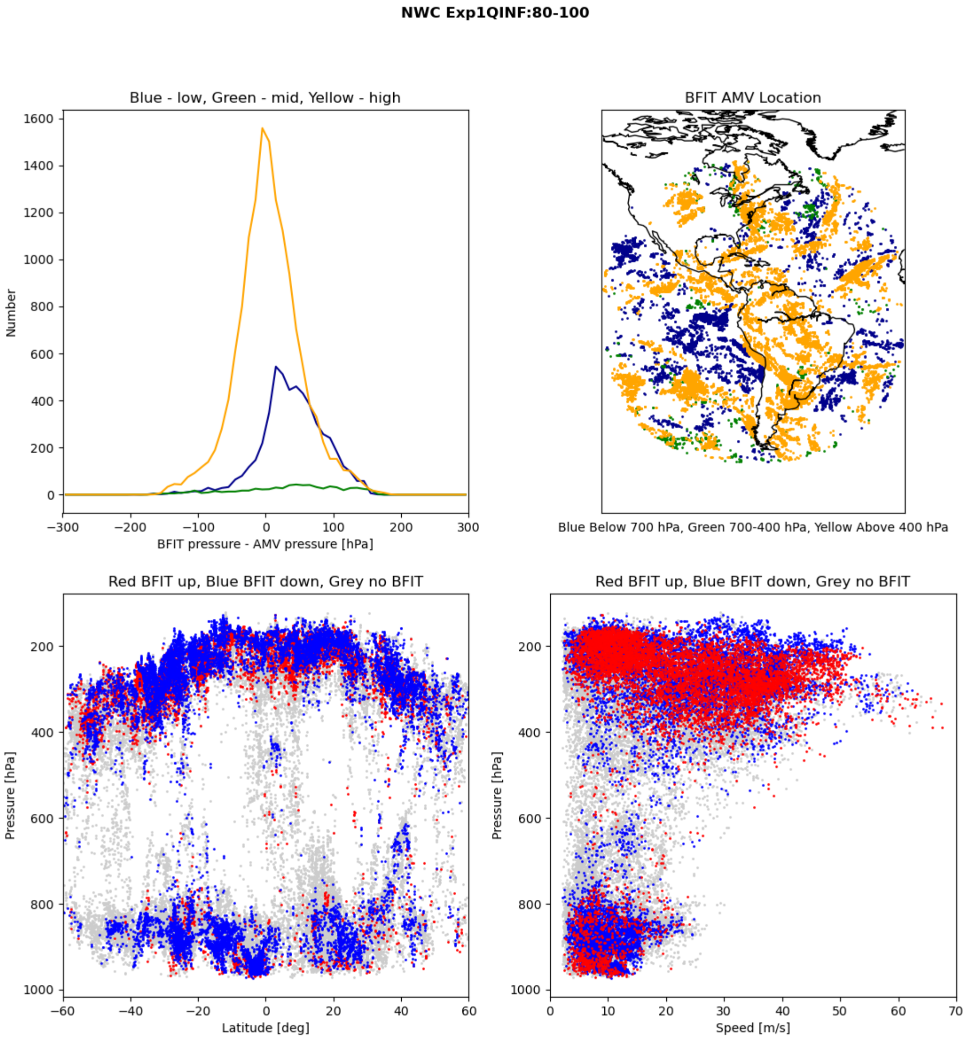

Figure 7-15: Experiment 1 NWC (QINF): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

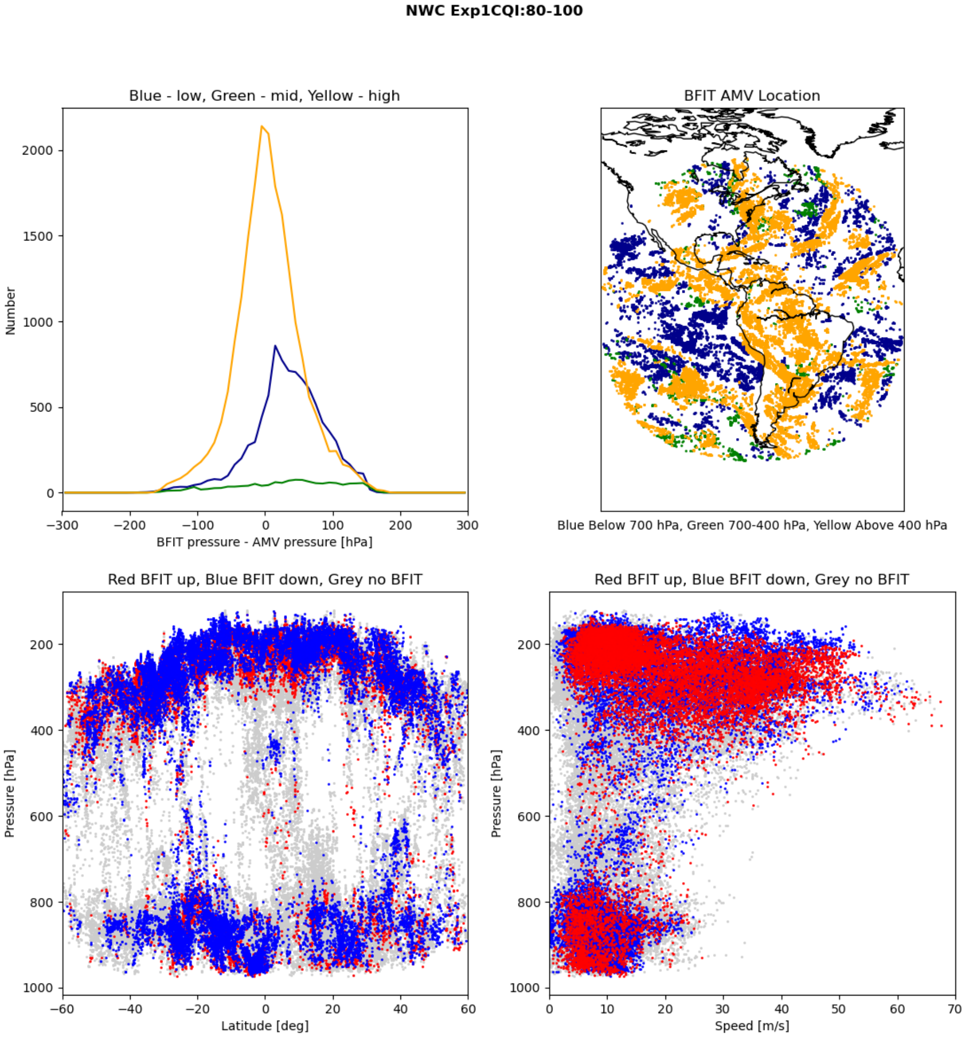

Figure 7-16: Experiment 1 NWC (CQI): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

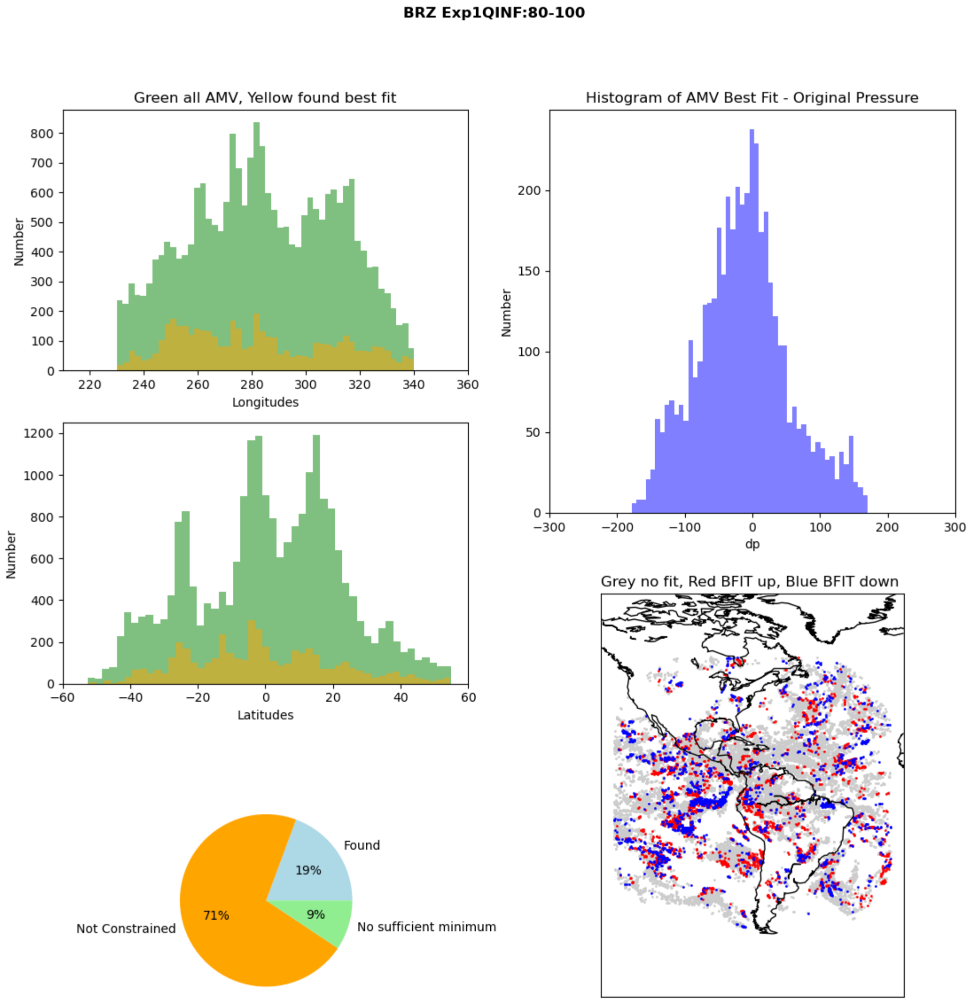

Figure 7-17: Experiment 1 BRZ (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

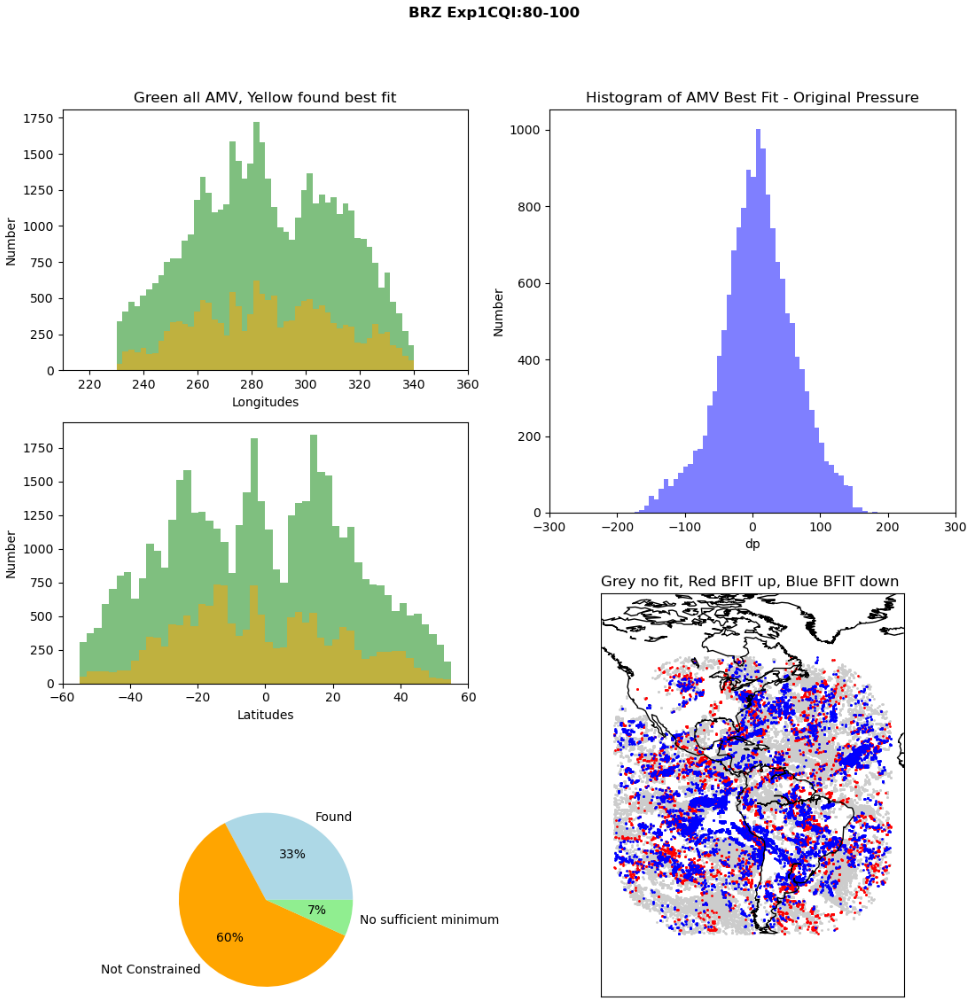

Figure 7-18: Experiment 1 BRZ (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

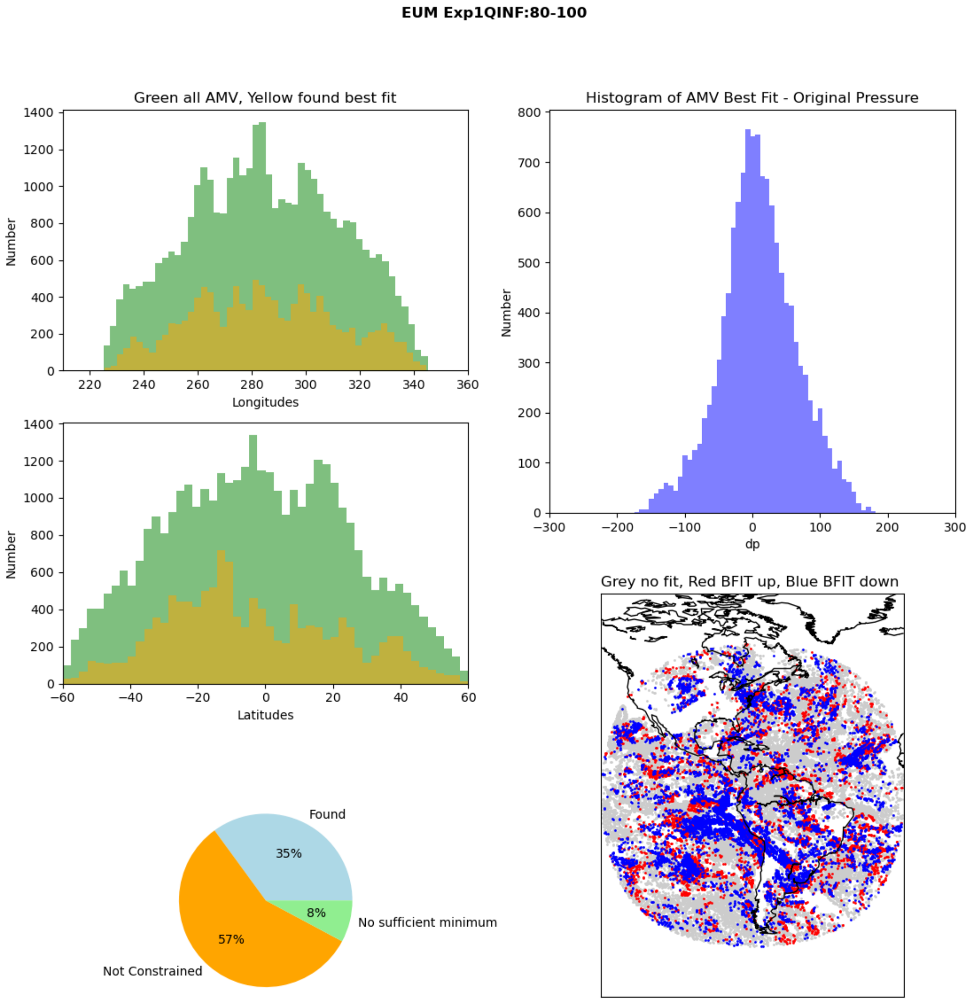

Figure 7-19: Experiment 1 EUM (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference, "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

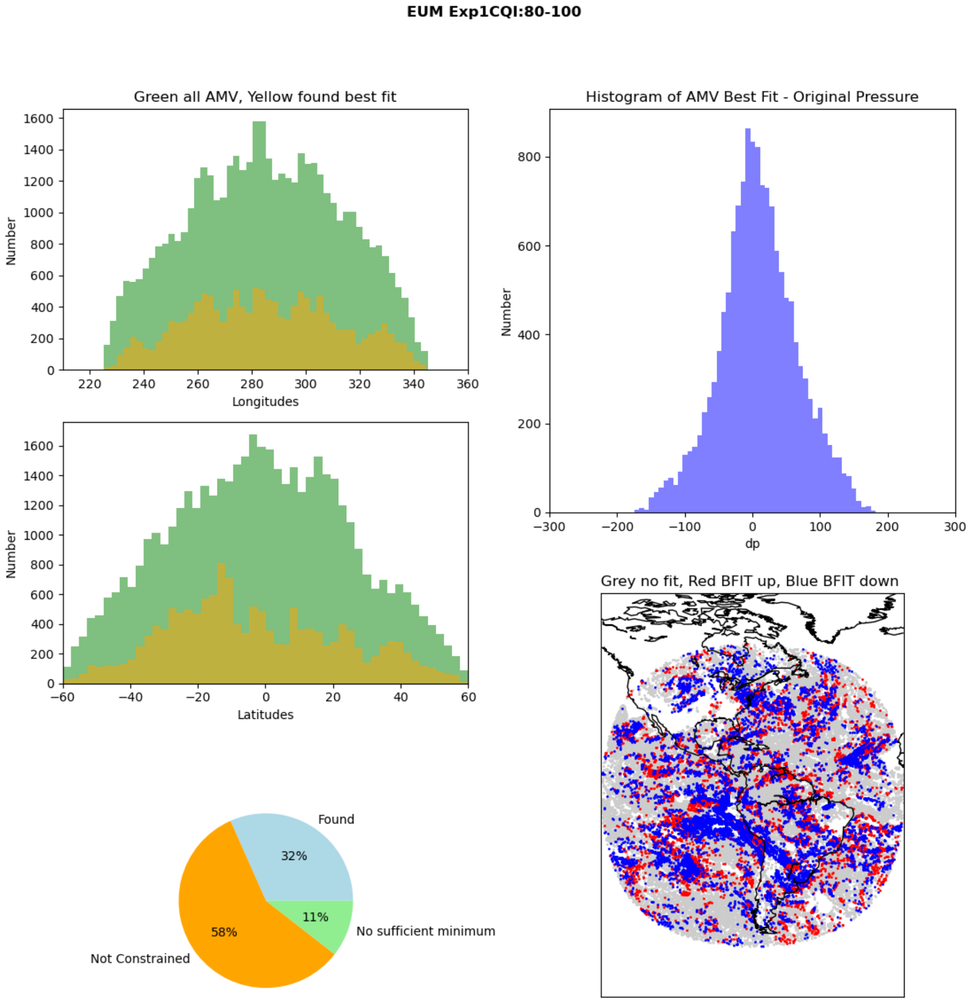

Figure 7-20: Experiment 1 EUM (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

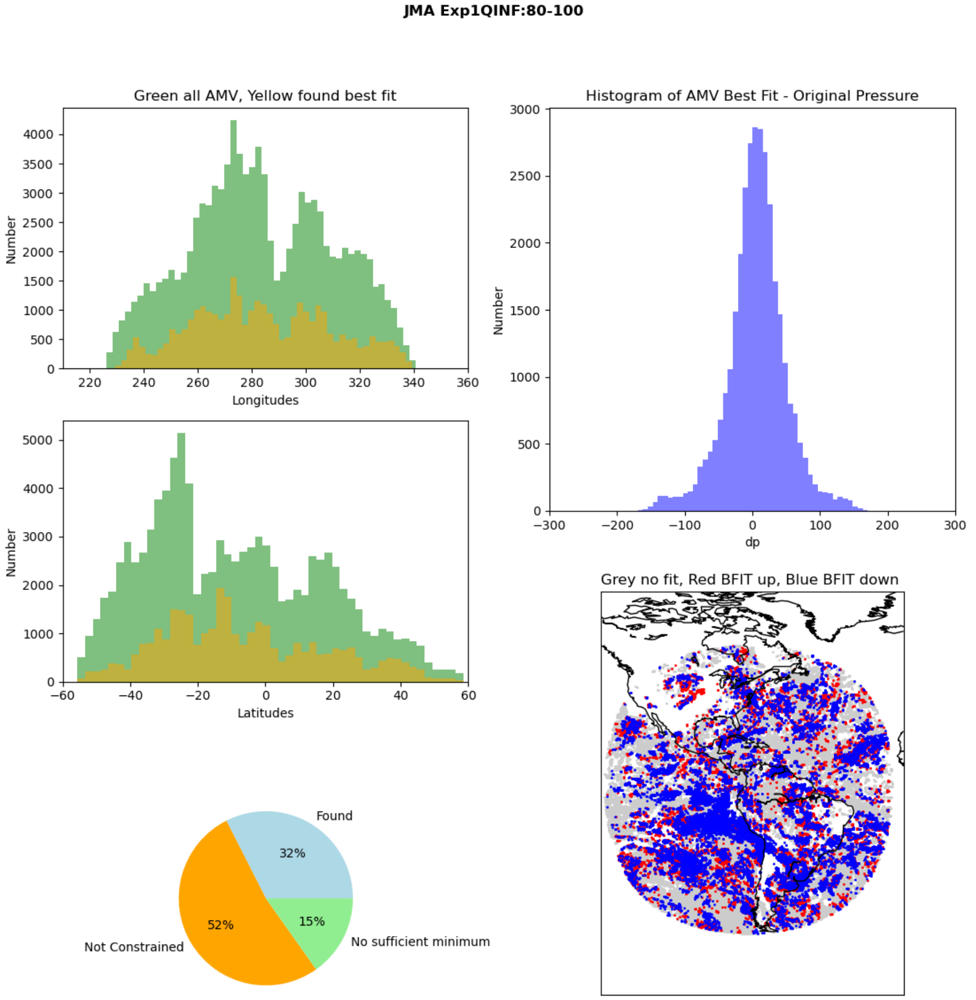

Figure 7-21: Experiment 1 JMA (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference, "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

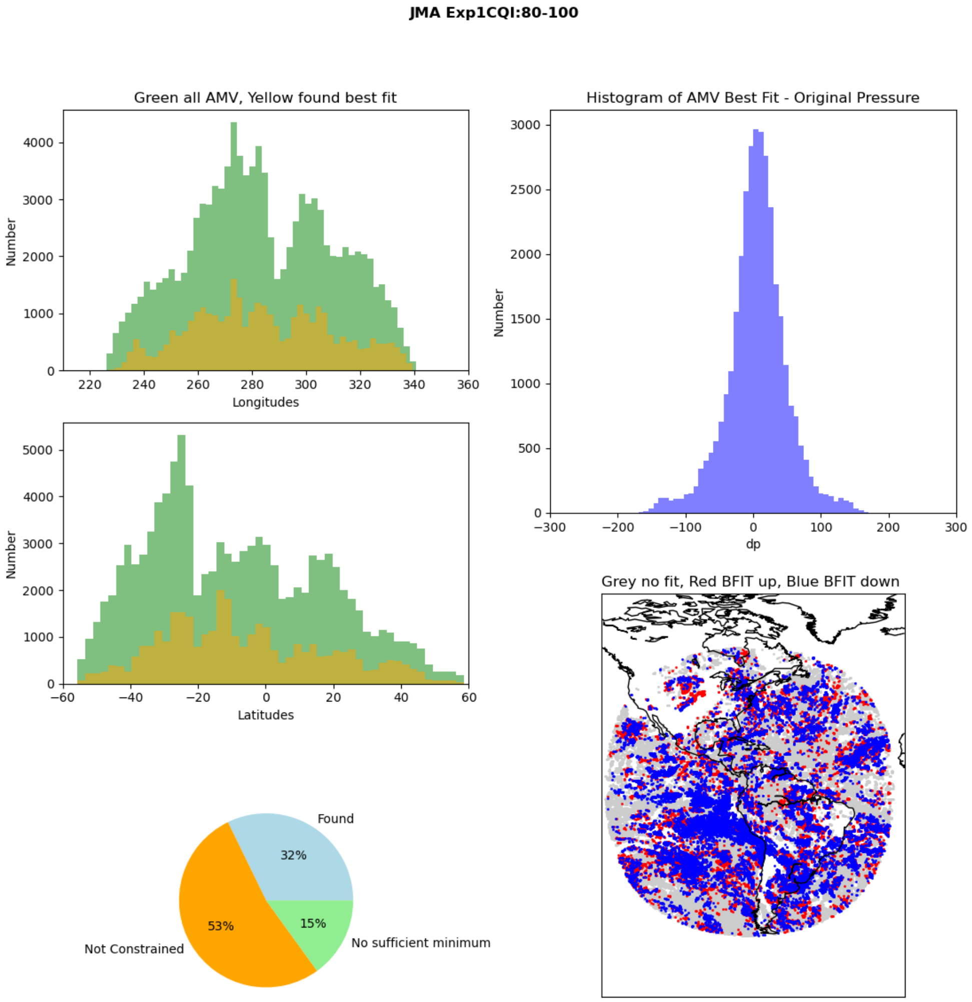

Figure 7-22: Experiment 1 JMA (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

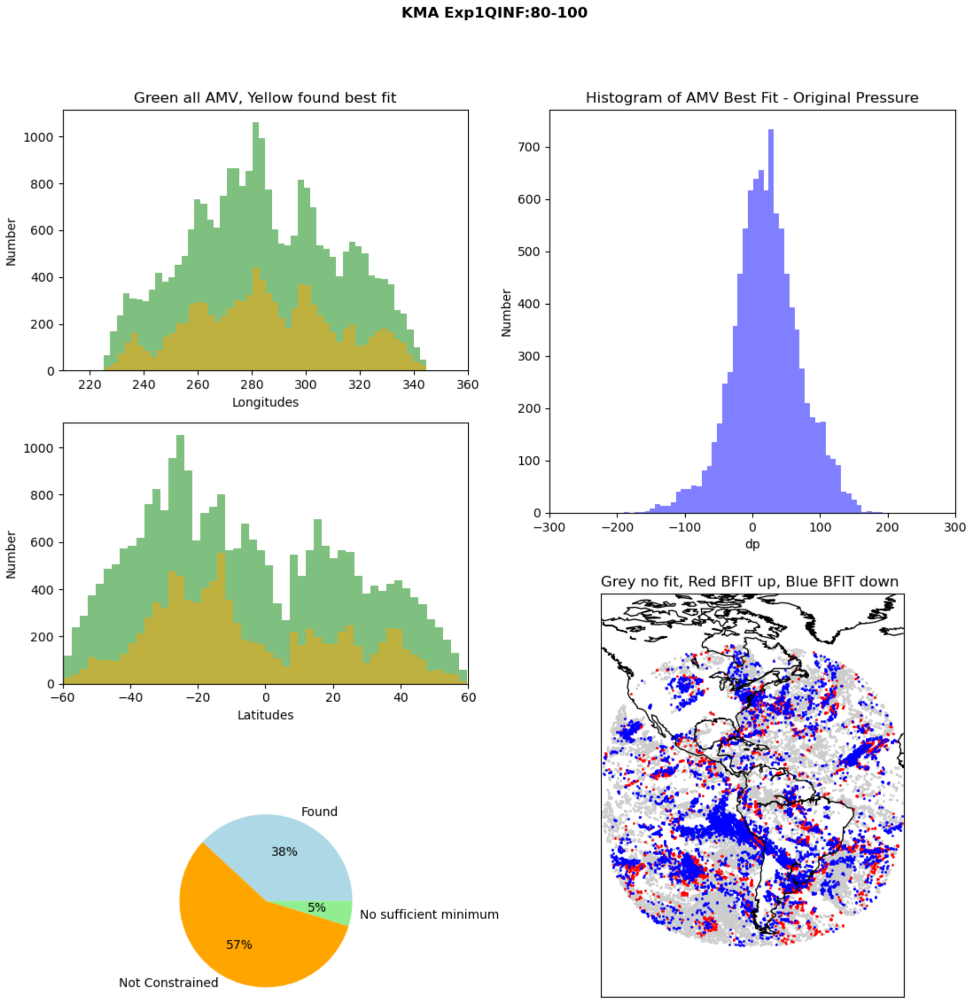

Figure 7-23: Experiment 1 KMA (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

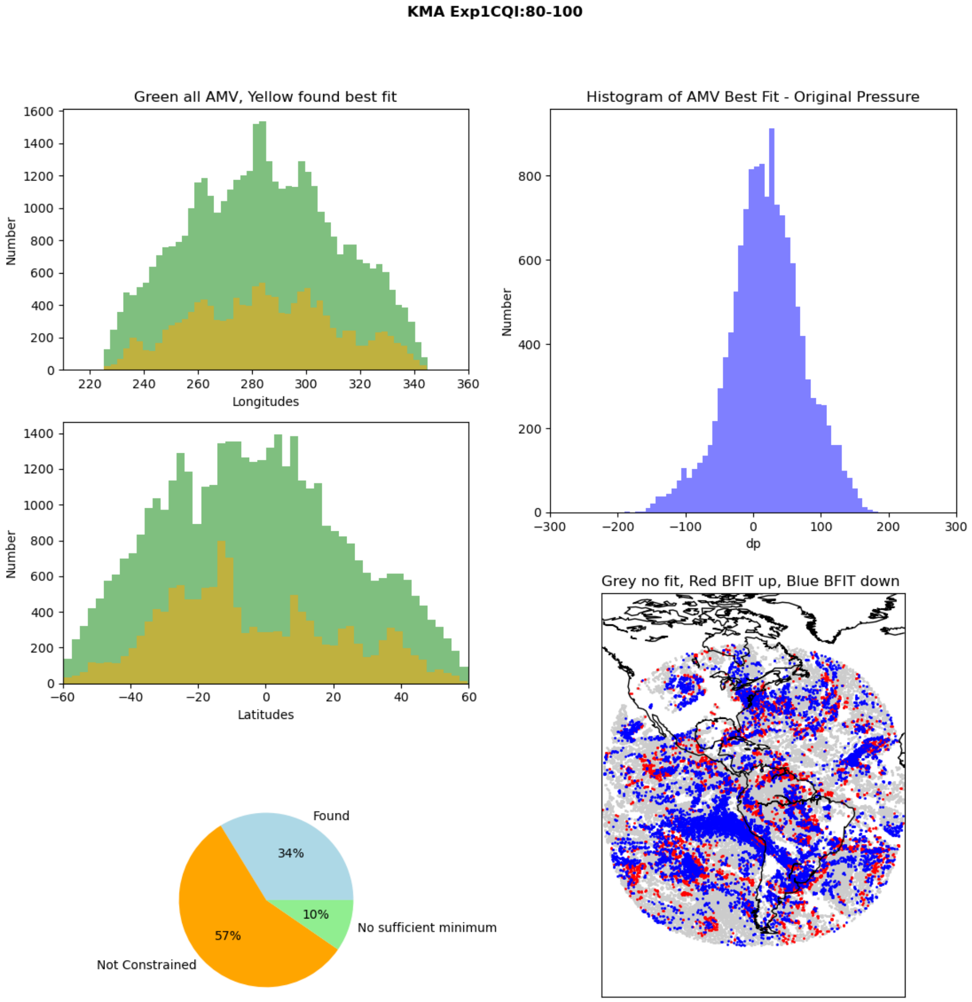

Figure 7-24: Experiment 1 KMA (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

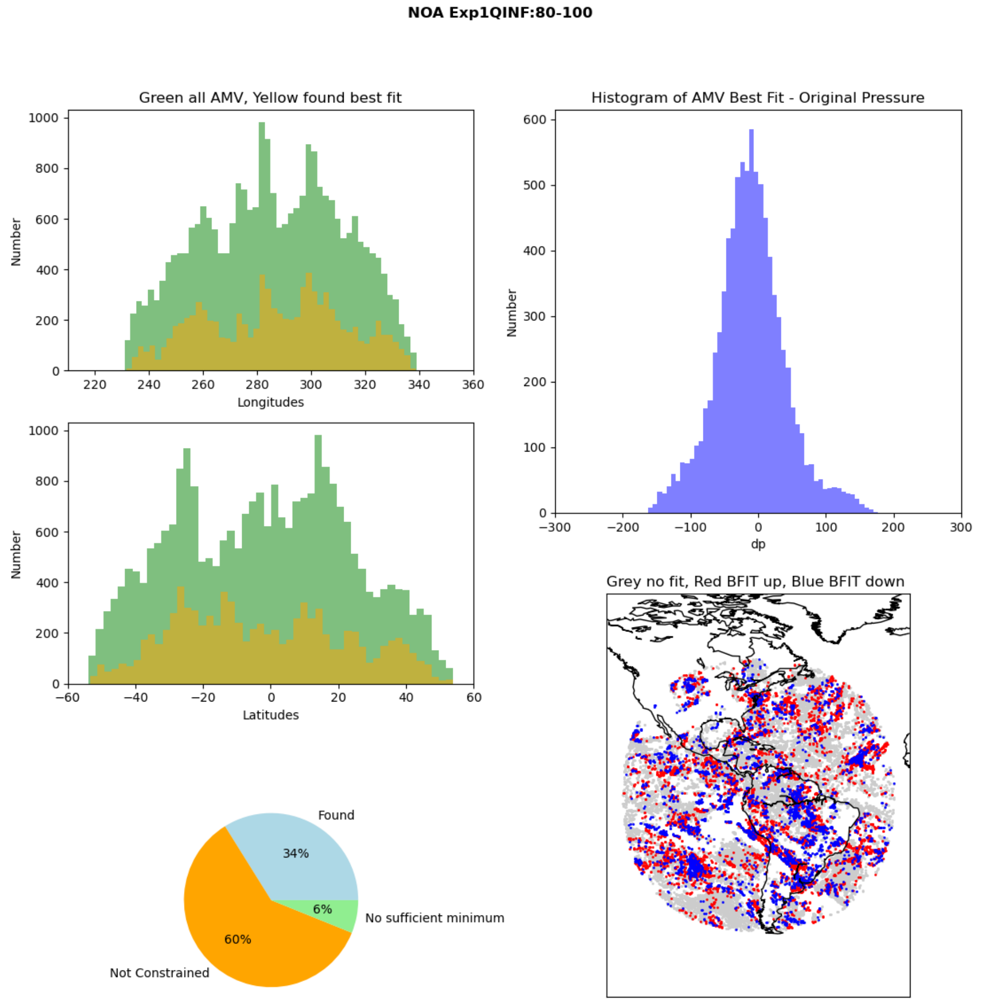

Figure 7-25: Experiment 1 NOA (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

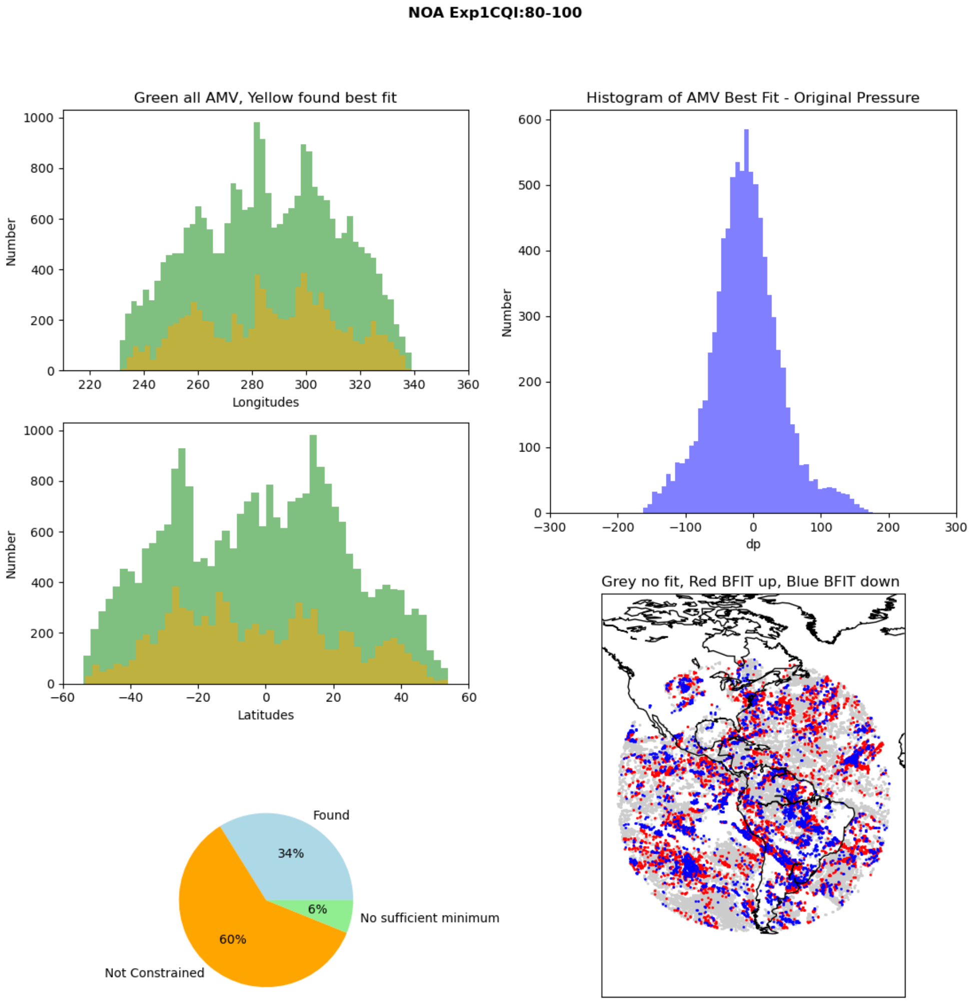

Figure 7-26: Experiment 1 NOA (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

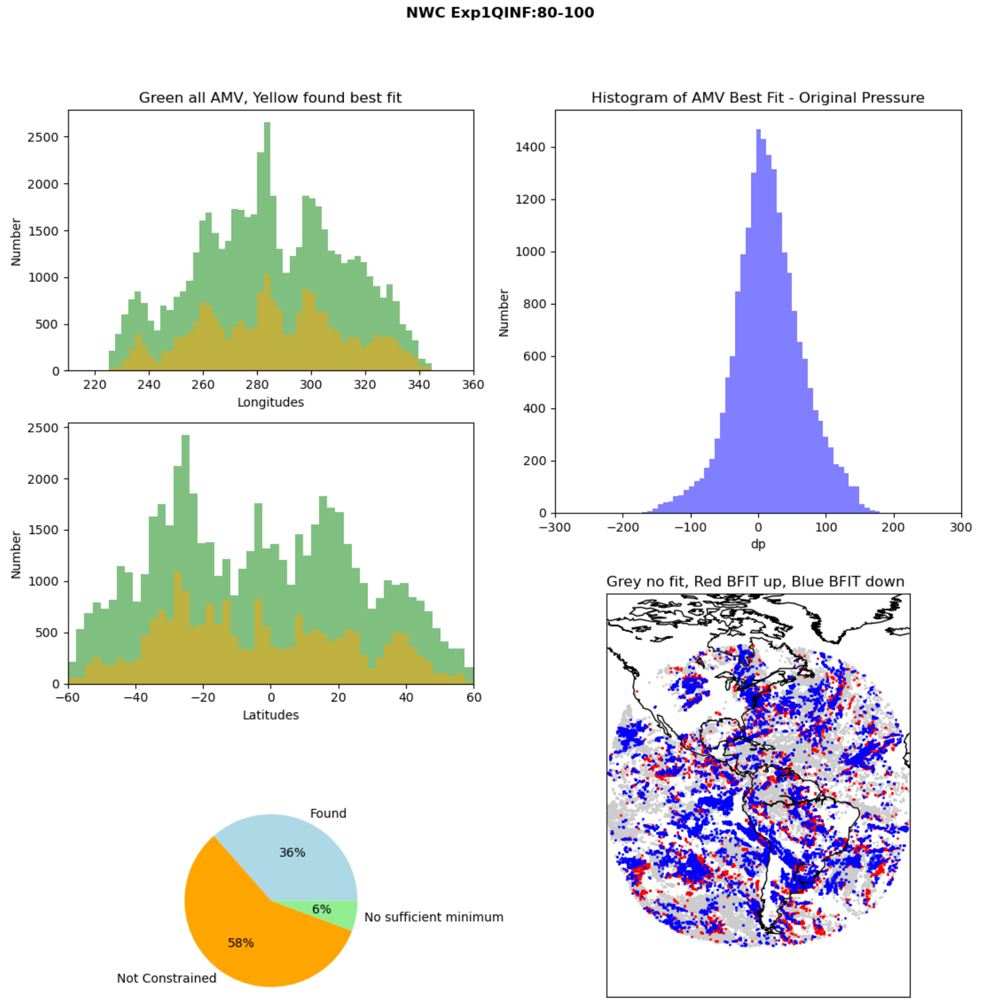

Figure 7-27: Experiment 1 NWC (QINF): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

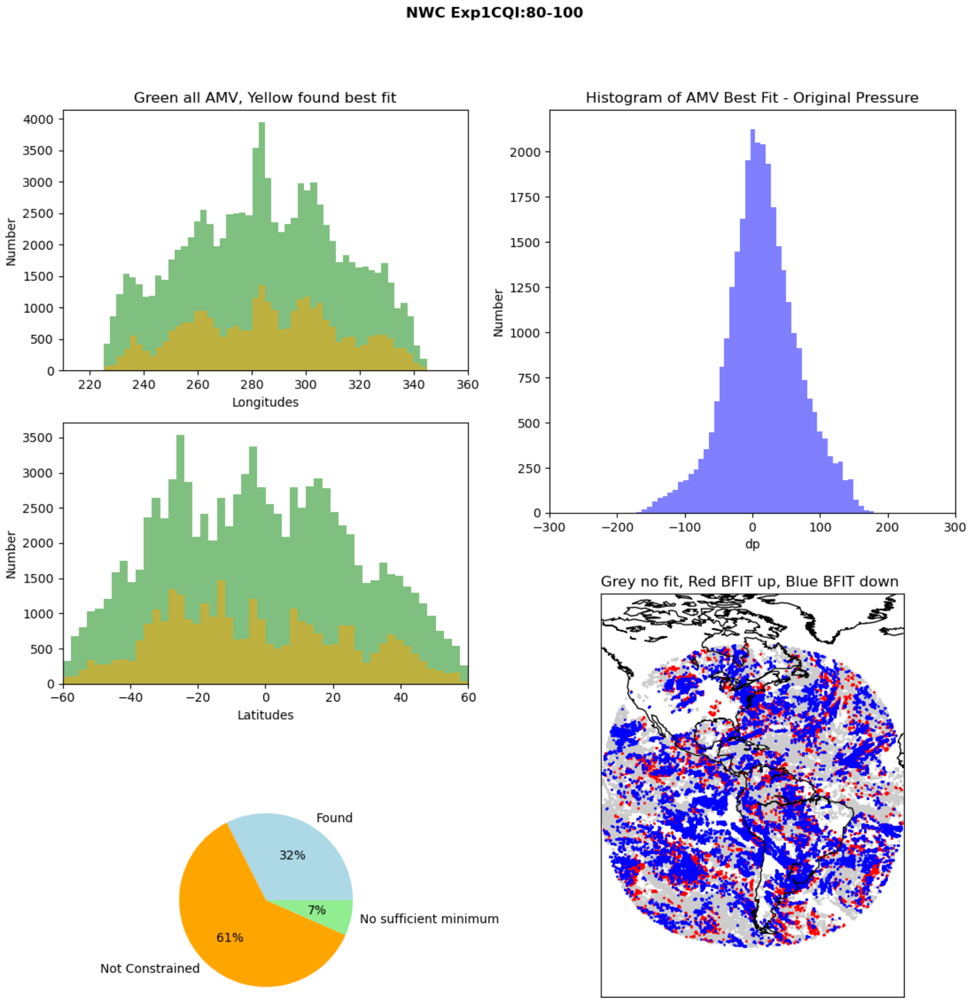

Figure 7-28: Experiment 1 NWC (CQI): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

g) Common QI (CQI) evaluation

Throughout this AMV intercomparison, it was detected that although all AMV producers were using the "Common Quality Index (CQI)" in their AMV datasets, it was a fact that it was not working exactly the same way in all centres, and so the quality of AMVs from different centres with a similar CQI threshold could be very different.

This could be caused by two different reasons:

- The possibility that different densities in the AMV datasets, and so different distances between neighbor AMVs could have an impact in the CQI (in the "spatial quality test", which specifically depends on the distance with the nearest AMV).
- The possibility that different AMV datasets can have very different qualities before applying the quality control, and so the possibilities of the quality control to homogenize qualities is limited by the fact of these preliminary differencies before the quality control.

Due to this, an additional check has been made through which AMVs are compared against NWP analysis winds considering all 10-unit bins between 0% and 100% in the CQI. This test is used for the first time in the AMV intercomparisons and is useful to detect differencies in the AMV datasets caused by the two mentioned reasons. Results are shown in Table 7-19 to Table 7-25, one for each AMV dataset. After an analysis of these tables, the following conclusions were extracted:

On one hand, it is a fact that the quality of the AMV datasets before applying the quality control is very different. The RMSE of the lowest quality AMVs is between 6-8 ms^{-1} for BRZ, JMA, NOA, and NWC, which is rather homogeneous, but it reaches values of 35 ms^{-1} in KMA and 55 ms^{-1} in EUM, being at least four times worse. Two outputs can be extracted from this:

1. It is a fact that all AMV centres can calculate wrong AMVs, but BRZ/JMA/NOA/NWC are able to remove AMVs with gross errors before the quality control, and so the preliminary quality of their AMVs before the quality control is rather good. The way they do this can be very variable and partially based on what AMV centres say in Chapter 6 (in the question checking if any filtering is defined in the AMV data provided for the AMV intercomparison).
2. A special remark is needed to be done here related to an "NWP consistency" filtering done for example by BRZ: although this filtering can improve in general the quality of the AMVs, it can reduce also importantly the applicability of them as "new observations." This is because the AMVs can replicate too much the NWP wind information, and so good AMVs defining a difference with the NWP forecast can be removed and not be

available, for example, for nowcasting applications and NWP assimilation. As AMVs should be as much as possible independent from NWP winds, as already said previously this kind of filtering should be removed or reduced as much as possible.

On the other hand, considering EUM and KMA datasets, the part of AMVs with errors bigger than 10 ms^{-1} is significant (11% for KMA, 19% for EUM), and especially when compared to the other AMV datasets, which have none. This could not only imply that their filtering of AMVs with gross errors is weak, but also that there is a real issue in the processing of (at least a part) their AMVs. Both centres should analyze as much as possible the information in the AMV intercomparison study, to try to extract useful conclusions about this.

Finally, evaluating the usefulness of the CQI in the definition of good AMVs, it is clear that it is very useful for all centres, reducing progressively errors in all of them up to RMSE values of around 4 ms^{-1} for AMVs with CQI > 90%. However, it can also be seen here that for EUM and KMA, for which errors start at much higher levels, the smallest RMSE errors for CQI > 90% only reach values around 6 ms^{-1}.

Table 7-19: Experiment 1: BRZ all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	160	22	6.18	2.79	6.78	5.82	6.56
10-19	396	51	6.41	3.16	7.14	6.04	6.95
20-29	691	86	6.05	2.92	6.72	5.60	6.41
30-39	974	125	5.55	2.77	6.20	5.19	5.96
40-49	2022	357	4.87	2.90	5.67	4.36	5.31
50-59	4140	690	4.46	2.74	5.24	4.01	4.88
60-69	5807	1107	3.99	2.66	4.79	3.51	4.41
70-79	5849	1081	3.65	2.55	4.45	3.24	4.11
80-89	8019	1485	3.46	2.60	4.32	3.05	3.96
90-100	17607	3614	3.10	2.54	4.01	2.72	3.65

Table 7-20: Experiment 1: EUM all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	2593	67	44.99	32.58	55.55	44.85	55.53
10-19	1135	76	26.50	28.02	38.57	26.19	38.53
20-29	1269	115	14.77	18.06	23.33	14.38	23.24
30-39	2219	392	10.21	14.30	17.57	9.52	17.34
40-49	2325	399	8.26	9.21	12.37	7.61	12.08
50-59	3613	545	7.95	8.70	11.78	7.38	11.51
60-69	3693	653	6.24	6.23	8.82	5.62	8.46
70-79	4673	987	5.81	5.58	8.06	5.12	7.63
80-89	6709	1449	5.17	5.06	7.23	4.53	6.81
90-100	39622	13073	4.02	4.53	6.06	3.29	5.51

Table 7-21: Experiment 1: JMA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	0	0	-	-	-	-	-
10-19	2	0	6.99	1.14	7.08	6.99	7.08
20-29	13	7	4.89	3.60	6.07	3.96	5.52
30-39	267	65	4.34	3.53	5.59	3.83	5.19
40-49	1676	645	3.99	3.95	5.61	3.40	5.21
50-59	1060	301	3.93	3.94	5.57	3.47	5.24
60-69	2028	535	3.76	3.93	5.44	3.38	5.21
70-79	3506	893	3.31	3.51	4.82	3.00	4.63
80-89	7577	1959	3.15	3.25	4.52	2.82	4.28
90-100	97485	31899	3.57	4.17	5.49	3.17	5.24

Table 7-22: Experiment 1: KMA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	1989	52	30.21	17.69	35.01	30.03	34.97
10-19	684	37	18.99	15.99	24.83	18.68	24.74
20-29	865	75	14.36	14.39	20.33	13.91	20.18
30-39	1248	147	15.24	15.02	21.40	14.74	21.25
40-49	1607	213	10.02	10.91	14.82	9.54	14.65
50-59	2930	418	8.36	8.29	11.78	7.79	11.52
60-69	2703	506	5.95	5.92	8.39	5.32	7.96
70-79	3468	702	5.37	5.09	7.40	4.79	7.02
80-89	5583	1308	4.85	4.70	6.75	4.17	6.23
90-100	35371	12508	4.00	4.19	5.79	3.17	5.16

Table 7-23: Experiment 1: NOA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	127	16	6.07	2.74	6.65	5.46	6.09
10-19	170	32	5.64	2.73	6.26	4.86	5.70
20-29	327	45	5.40	2.81	6.09	4.94	5.74
30-39	425	73	4.96	2.63	5.61	4.44	5.25
40-49	759	144	4.50	2.54	5.17	3.93	4.72
50-59	1316	274	4.36	2.66	5.11	3.80	4.68
60-69	1834	431	4.12	2.60	4.87	3.55	4.42
70-79	2023	489	4.05	2.66	4.84	3.42	4.32
80-89	3271	876	3.72	2.43	4.44	3.11	3.93
90-100	22673	7912	2.99	2.44	3.86	2.37	3.27

Table 7-24: Experiment 1: NWC all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	0	0	-	-	-	-	-
10-19	11	3	6.43	5.11	8.21	5.07	7.49
20-29	90	10	6.19	4.17	7.47	5.79	7.17
30-39	173	24	6.09	3.56	7.06	5.48	6.61
40-49	341	48	4.81	3.01	5.67	4.41	5.40
50-59	1171	219	5.12	3.44	6.17	4.61	5.80
60-69	2309	525	4.60	3.28	5.65	3.96	5.11
70-79	4069	948	4.39	3.25	5.46	3.82	4.98
80-89	9100	2231	3.95	3.02	4.98	3.36	4.45
90-100	86361	28789	3.30	2.76	4.30	2.63	3.67

8. Experiment 2

a) Approach

AMV producers extract cloudy AMVs with GOES-16/ABI 11.2µm infrared channel, using the specific operational configuration for each AMV centre, with their typical settings for target box size, search box size and target locations. This tries to compare the performance of the AMV datasets generated by each AMV processing centre using their best practices.

There was also an option to use outputs from NOAA/NESDIS Cloud product in the height assignment, for a better comparison of results. However, only EUM, NOA and NWC used this Cloud product in the height assignment, so limiting partially the comparison in the results.

This experiment was run for three different image triplet times (denoted as Experiments 2a, 2b 2c), to match the times of the corresponding comparison datasets:

- 2a: 11:20/11:30/11:40 UTC for comparison with Aircraft wind data and ADM-Aeolus satellite Doppler wind lidar (DWL) wind profiles (using Mie scattering).
- 2b: 11:50/12:00/12:10 UTC for comparison with rawinsondes and NWP analysis winds.
- 2c: 18:50/19:00/19:10 UTC for comparison with CALIPSO satellite cloud height data.

Experiment 2b is used to test differences in the AMV calculation process for the different centres, between their specific operational configurations and the prescribed configuration defined in Experiment 1. Additionally, there was a similar Experiment 2 in the previous AMV Intercomparison, interesting to see if anything has changed since then using the operational configuration in the AMV algorithms.

Experiment 2c is similar to Experiment 3 in the previous AMV Intercomparison, for which the comparisons with CALIPSO satellite provided limited results. A better case with more collocation pairs between AMV heights and CALIPSO heights is defined here for a more complete output.

Experiment 2a is a new experiment that did not occur in any previous Intercomparisons. In fact, the Aeolus satellite is only available since 2018.

For the three Experiments 2a), 2b) and 2c), in this chapter, an initial comparison of AMV quantities, AMV distribution in layers, and distribution of AMV speed and pressure values for the different centres are evaluated in Subchapter 8b).

Later, only for Experiment 2b and for contrast with Experiment 1, an evaluation of differences in the AMV speed, direction, pressure, and Quality Index values for collocated AMVs is evaluated in Subchapter 8c). Then, comparisons against rawinsondes and NWP analysis winds are evaluated in Subchapters 8d) and 8e). A verification of the height assignment for the different centres is also done using NWP model best-fit pressure in Subchapter 8f). And an evaluation of the quality of the AMVs with respect to the CQI is done in Subchapter 8g).

Additional evaluation of Experiment 2a is done in Chapters 11 and 12, where the comparisons against aircraft wind data and ADM-Aeolus DWL wind profiles are respectively presented.

Additional evaluation of Experiment 2c is done in Chapter 13, where the comparisons with CALIPSO satellite cloud height data are presented.

b) Parameter distributions

For each one of the three experiments and AMV datasets, a summary of the different AMV parameters (number of AMVs, distribution in high/medium/low layer, speed, and pressure distributions in the whole troposphere and in the three layers) is shown here.

Four different tables are shown for each experiment related to four different Quality Index thresholds: Quality Index without forecast (QINF) >= 50% and >= 80%, and CQI >= 50% and >= 80%. This results in a total of 12 tables for the three experiments.

Considering Experiment 2b) in Table 8-5 to Table 8-8:

- The total number of AMVs ranges between 34,000 for NOA and 105,000 for JMA considering all AMVs, and between 25,000 for BRZ and 95,000 for JMA considering CQI >= 80%, with differences of around 4 times in the number of AMVs in the different centres. This means small differences with the number of AMVs obtained in Experiment 1. And this also means much smaller differences between the prescribed and operational configuration, than those seen in the previous AMV intercomparison.
- Considering CQI >= 80%, the maximum speed has a very small range between 65 and 68 ms^{-1} for all centres except BRZ (with a value of 45 ms^{-1}). The mean speed has also a very small range between 12 and 14 ms^{-1} for all centres except BRZ (with a value of 9 ms^{-1}).
- Considering CQI >= 80%, the minimum pressure has a wider range than in Experiment 1, between 71 hPa for EUM and 179 hPa for EUM, so showing the differences caused by using the operational configuration and height assignment processes. The maximum pressure has instead a very similar range between 965 hPa for KMA and 1050 hPa for EUM. The mean pressure has also a very similar range between 509 hPa for KMA and 610 hPa for JMA (with the exception of BRZ, which is again an outlier with 708 hPa).
- Related to this, the distribution of AMVs in the different layers shows slightly larger differences than in Experiment 1, with 28-52% of AMVs in the high layer, 8-18% of AMVs in the medium layer, and 37-54% of AMVs in the low layer for all centres except again BRZ (which has different AMV percentages of 18%/21%/61% respectively in the high/medium/low layer).
- With all this, the AMV parameter distributions using the specific operational configuration show somewhat larger differences between the different centres, excepting again BRZ, which shows again a significantly different behaviour.

Comparing with results for the Experiment with prescribed configuration in the previous AMV intercomparison (Experiment 2):

- Increases in the amount of AMVs are seen again in part of the centres (EUM, JMA) and decreases are seen in other centres (BRZ, NOA, NWC), so reflecting the differences implemented in all AMV algorithms between both AMV intercomparisons.
- Speed and pressure ranges are respectively smaller than and similar to those presented in the previous intercomparison, so showing some additional homogenization between the AMVs from different centres. BRZ has also been in both comparisons the most different dataset.
- Comparing values in this prescribed experiment, four years ago with AHI radiometer and now with ABI radiometer, the main difference is the mean pressure, which has significantly fallen to lower levels from around 450 hPa to 600 hPa, so showing a larger proportion of low level AMVs, such as also occurred comparing both Experiments 1. The distribution of AMVs in the different layers four years ago in the AHI experiment also showed a larger proportion of AMVs in the high layer (48-63%) and a smaller proportion of AMVs in the low layer (25-35%), although this can depend as already said in Experiment 1 both on the characteristics of the scanning region but also on the specific cases used.

Considering now the results for Experiment 2a) in Table 8-1 to Table 8-5 and for Experiment 2c) in Table 8-10 to Table 8-14, and remembering that the only difference with Experiment 2b) is the image times used for the AMV calculation (with triplets centered here at 11:30 UTC and 19:00 UTC, respectively):

- The total number of AMVs, the maximum speed and the mean speed show very similar values than those for Experiment 2b). The main difference is EUM, which shows some maximum speed outliers of up to 150 ms^{-1} in Experiment 2a).
- The minimum pressure, the maximum pressure, the mean pressure, and the distribution of AMVs in the three layers show also very similar ranges to those for Experiment 2b).
- With all this, the behaviour of the AMV datasets is as expected, very similar in the three similar Experiments 2a), 2b), and 2c).

The “AMV parameter distribution histograms” in Chapter 17 (shown for Experiment 2a) in Figure 17-13 to Figure 17-24; for Experiment 2b) Figure 17-25 to Figure 17-36; and for Experiment 2c) in Figure 17-37 to Figure 17-48) complement this information, with histograms showing the distribution of AMV speed, direction, pressure and Quality Index values using both Quality Index thresholds.

In all cases, a map is also included showing the geographical coverage of each AMV dataset, using three color codes: green for AMVs with Quality index >= 80%, blue for AMVs with Quality index >= 50% and red for AMVs with Quality index < 50%.

Major observations in the variable histograms for the three experiments and AMV datasets show:

- Considering the speed, the histogram maxima are at slowest speeds, and the proportion of data reduces progressively for higher speeds in all centres. The main difference is related to the maximum speeds in the histogram, showing again the fact indicated previously: the maximum speed is between 65 and 70 ms^{-1} for all centres except for BRZ, with a value of 45 ms^{-1}.
- Considering the direction histogram, in Experiments 2a) and 2b) all centres show two maximums for easterly and westerly winds, being the main difference a pair of smaller submaximums around the westerly direction, which are more pronounced for BRZ, JMA and NOA. In Experiment 2c) the easterly maximum includes two submaximums in general for all centres, and the westerly maximum includes three submaximums in general for all centres.
- Considering the pressure histogram, all centres show two maximums at high levels (250-300 hPa) and low levels (900-950 hPa) except BRZ, which shows a less pronounced maximum at high levels.
- Considering the Common Quality Control histogram, all centres show a maximum near 100% with smaller frequencies for progressively smaller CQI values. The maximum is however less noticeable for BRZ.
- Considering the specific Quality Index without forecast histogram, a similar distribution is shown with another maximum near 100%. The maximum is here less noticeable for BRZ, KMA and NWC.

Table 8-1: Experiment 2a statistical summary of AMV datasets for QINF >= 50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63703	46135	105082	34532	53197	93443
QI>=50	47096	38361	102641	33005	42106	82360
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	96.65	50.81	94.97	64.03	86.51	66.17
SPD_mean	12.76	9.13	12.18	12.08	13.72	12.80
P_min	49.70	102.67	125.00	105.62	104.03	182.00
P_max	1050.00	1000.00	1001.30	999.80	970.47	974.00
P_mean	586.42	697.52	617.74	559.66	509.79	644.05
Low_winds	44.60	58.53	49.74	42.46	36.85	54.11
Mid_winds	16.54	23.16	14.73	9.48	11.38	17.11
High_winds	38.87	18.32	35.52	48.05	51.76	28.78
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	46.07	31.93	90.80	32.92	81.94	29.22
Low_SPD_mean	8.32	8.37	8.53	8.37	8.81	8.86
Low_P_min	700.04	700.00	700.00	700.06	700.00	700.00
Low_P_max	1050.00	1000.00	1001.30	999.80	970.47	974.00
Low_P_mean	884.32	882.71	909.35	896.09	850.28	878.24
Mid_SPD_min	2.50	3.75	2.51	3.00	2.50	2.50
Mid_SPD_max	66.13	35.84	90.27	56.22	60.74	47.93
Mid_SPD_mean	12.71	9.44	10.65	11.74	13.51	16.66
Mid_P_min	400.00	400.02	400.10	400.02	400.04	401.00
Mid_P_max	699.94	699.98	699.90	699.90	699.94	699.00
Mid_P_mean	514.23	552.22	514.56	539.49	517.68	495.69
High_SPD_min	2.50	3.76	2.50	3.01	2.50	2.50
High_SPD_max	96.65	50.81	94.97	64.03	86.51	66.17
High_SPD_mean	17.88	11.16	17.92	15.42	17.26	17.89
High_P_min	49.70	102.67	125.00	105.62	104.03	182.00
High_P_max	399.98	400.00	400.00	400.00	399.98	400.00
High_P_mean	275.31	289.4	252.20	266.36	265.62	291.95

Table 8-2: Experiment 2a statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63703	46135	105082	34532	53197	93443
QI>=50	54419	41734	103529	33005	47656	93186
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	148.98	50.81	94.97	64.03	95.93	66.17
SPD_mean	12.61	9.60	12.16	12.08	13.26	12.55
P_min	49.70	50.00	125.00	105.62	104.03	182.00
P_max	1050.00	1000.00	1001.30	999.80	970.47	974.00
P_mean	593.39	693.07	617.22	559.66	507.52	639.67
Low_winds	44.41	57.52	49.64	42.46	36.21	52.89
Mid_winds	19.59	23.96	14.82	9.48	12.14	18.36
High_winds	35.99	18.52	35.55	48.05	51.65	28.75
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	148.98	31.93	90.80	32.92	95.93	35.71
Low_SPD_mean	8.62	8.66	8.53	8.37	8.73	8.72
Low_P_min	700.04	700.00	700.00	700.06	700.00	700.00
Low_P_max	1050.00	1000.00	1001.30	999.80	970.47	974.00
Low_P_mean	879.93	881.80	909.27	896.09	848.81	876.57
Mid_SPD_min	2.50	3.75	2.51	3.00	2.50	2.50
Mid_SPD_max	126.47	46.05	90.27	56.22	60.74	62.37
Mid_SPD_mean	12.74	10.16	10.62	11.74	13.11	16.33
Mid_P_min	400.00	400.03	400.10	400.02	400.04	401.00
Mid_P_max	699.96	699.98	699.90	699.90	699.96	699.00
Mid_P_mean	528.39	550.31	514.39	539.49	520.95	502.66
High_SPD_min	2.50	3.76	2.50	3.01	2.50	2.50
High_SPD_max	148.08	50.81	94.97	64.03	94.65	66.17
High_SPD_mean	17.46	11.78	17.87	15.42	16.47	17.17
High_P_min	49.70	50.00	125.00	105.62	104.03	182.00
High_P_max	399.98	400.00	400.00	400.00	399.98	400.00
High_P_mean	275.18	291.61	252.25	266.36	265.10	291.41

Table 8-3: Experiment 2a statistical summary of AMV datasets for QINF >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63703	46135	105082	34532	53197	93443
QI>=80	36574	22916	88548	28347	26027	58545
SPD_min	2.50	3.75	67.37	3.00	2.50	2.50
SPD_max	68.86	46.23	12.72	64.03	68.86	66.17
SPD_mean	13.72	8.63	125.00	12.69	16.01	13.94
P_min	87.84	102.67	1001.30	105.62	125.75	182.00
P_max	1050.00	1000.00	621.29	999.80	958.44	974.00
P_mean	591.20	709.25	50.67	565.10	525.74	651.99
Low_winds	46.00	60.99	13.63	43.60	39.85	55.53
Mid_winds	14.31	20.76	35.71	8.27	9.17	16.54
High_winds	39.69	18.25	2.50	48.13	50.97	27.93
Low_SPD_min	2.50	3.75	27.53	3.00	2.51	2.50
Low_SPD_max	46.07	31.93	8.75	26.92	26.24	26.60
Low_SPD_mean	8.61	8.07	700.00	8.61	9.21	9.48
Low_P_min	700.11	700.04	1001.30	700.06	700.00	700.00
Low_P_max	1050.00	1000.00	910.16	999.80	958.44	974.00
Low_P_mean	889.69	889.85	2.52	900.35	856.60	880.88
Mid_SPD_min	2.51	3.75	46.67	3.00	2.59	2.51
Mid_SPD_max	66.13	33.94	11.19	56.22	60.74	47.93
Mid_SPD_mean	14.01	8.71	400.10	12.56	16.28	18.37
Mid_P_min	400.00	400.03	699.90	400.02	400.04	401.00
Mid_P_max	699.94	699.94	516.16	699.90	699.59	699.00
Mid_P_mean	507.57	551.02	2.50	540.61	511.34	490.38
High_SPD_min	2.50	3.76	67.37	3.01	2.50	2.50
High_SPD_max	68.86	46.23	18.92	64.03	68.86	66.17
High_SPD_mean	19.54	10.41	125.00	16.42	21.28	20.16
High_P_min	87.84	102.67	400.00	105.62	125.75	182.00
High_P_max	399.98	399.97	251.50	400.00	399.98	400.00
High_P_mean	275.42	285.67	105082	265.60	269.65	292.63

Table 8-4: Experiment 2a statistical summary of AMV datasets for CQI >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63703	46135	105082	34532	53197	93443
QI>=80	44999	25761	94175	28347	40159	88890
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	148.98	50.81	67.37	64.03	68.86	66.17
SPD_mean	13.12	9.03	12.50	12.69	13.88	12.69
P_min	87.84	102.67	125.00	105.62	104.03	182.00
P_max	1050.00	1000.00	1001.30	999.80	961.39	974.00
P_mean	598.14	709.23	620.11	565.10	509.47	642.75
Low_winds	45.90	61.10	50.33	43.60	37.27	53.55
Mid_winds	17.40	20.37	14.05	8.27	10.58	17.97
High_winds	36.70	18.53	35.61	48.13	52.16	28.48
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	148.98	28.81	29.65	26.92	45.55	29.41
Low_SPD_mean	8.74	8.23	8.66	8.61	8.88	8.77
Low_P_min	700.05	700.00	700.00	700.06	700.00	700.00
Low_P_max	1050.00	1000.00	1001.30	999.80	961.39	974.00
Low_P_mean	884.64	890.38	909.79	900.35	851.42	877.13
Mid_SPD_min	2.50	3.76	2.51	3.00	2.50	2.50
Mid_SPD_max	66.13	46.05	46.67	56.22	60.74	47.93
Mid_SPD_mean	13.43	9.33	10.99	12.56	13.84	16.73
Mid_P_min	400.00	400.03	400.10	400.02	400.04	401.00
Mid_P_max	699.96	699.94	699.90	699.90	699.59	699.00
Mid_P_mean	524.80	550.41	515.66	540.61	514.79	501.78
High_SPD_min	2.50	3.76	2.50	3.01	2.50	2.50
High_SPD_max	68.86	50.81	67.37	64.03	68.86	66.17
High_SPD_mean	18.46	11.35	18.53	16.42	17.46	17.52
High_P_min	87.84	102.67	125.00	105.62	104.03	182.00
High_P_max	399.98	400.00	400.00	400.00	399.98	400.00
High_P_mean	274.57	286.44	251.92	265.60	264.08	291.01

Table 8-5: Experiment 2b statistical summary of AMV datasets for QINF >= 50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63436	45995	105387	34244	52605	92872
QI>=50	46739	38299	102923	32751	41602	81422
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	122.22	44.30	91.57	66.14	78.61	67.43
SPD_mean	12.80	9.12	12.25	12.17	13.73	12.88
P_min	71.21	103.77	125.00	104.64	102.74	179.00
P_max	1050.00	1000.00	999.50	998.63	971.79	974.00
P_mean	587.74	696.09	608.58	557.72	509.71	645.30
Low_winds	44.75	58.25	48.50	42.16	36.67	54.59
Mid_winds	16.78	23.32	15.38	9.83	11.63	16.59
High_winds	38.48	18.43	36.13	48.01	51.69	28.82
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	47.78	26.70	91.57	29.67	78.61	27.55
Low_SPD_mean	8.39	8.36	8.60	8.43	8.84	9.02
Low_P_min	700.03	700.06	700.00	700.09	700.00	700.00
Low_P_max	1050.00	1000.00	999.50	998.63	971.79	974.00
Low_P_mean	885.79	883.02	902.30	894.13	850.63	879.11
Mid_SPD_min	2.50	3.75	2.50	3.01	2.51	2.50
Mid_SPD_max	122.22	35.30	74.95	55.89	58.86	61.96
Mid_SPD_mean	12.77	9.53	10.74	11.57	13.43	16.95
Mid_P_min	400.00	400.11	400.10	400.04	400.01	401.00
Mid_P_max	700.00	699.99	699.90	699.98	699.91	699.00
Mid_P_mean	512.36	551.47	517.97	539.48	520.01	494.84
High_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
High_SPD_max	101.45	44.30	69.31	66.14	75.12	67.43
High_SPD_mean	17.94	11.02	17.81	15.58	17.26	17.83
High_P_min	71.21	103.77	125.00	104.64	102.74	179.00
High_P_max	399.99	399.94	400.00	399.95	399.95	400.00
High_P_mean	274.01	288.37	252.83	266.04	265.53	288.95

Table 8-6: Experiment 2b statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63436	45995	105387	34244	52605	92872
QI>=50	54204	41722	103916	32751	47112	92645
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	169.35	44.92	91.57	66.14	82.85	67.43
SPD_mean	12.63	9.59	12.23	12.17	13.24	12.67
P_min	71.21	102.09	125.00	104.64	102.44	179.00
P_max	1050.00	1000.00	999.50	998.63	971.79	974.00
P_mean	593.88	692.26	608.00	557.72	507.62	640.79
Low_winds	44.17	57.37	48.38	42.16	36.17	53.16
Mid_winds	20.21	24.10	15.47	9.83	12.24	18.17
High_winds	35.61	18.53	36.15	48.01	51.59	28.67
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	119.06	26.70	91.57	29.67	49.81	35.59
Low_SPD_mean	8.64	8.66	8.59	8.43	8.74	8.89
Low_P_min	700.03	700.06	700.00	700.09	700.00	700.00
Low_P_max	1050.00	1000.00	999.50	998.63	971.79	974.00
Low_P_mean	882.01	881.61	902.24	894.13	848.93	877.33
Mid_SPD_min	2.50	3.75	2.50	3.01	2.51	2.50
Mid_SPD_max	162.19	38.65	74.95	55.89	64.34	61.96
Mid_SPD_mean	12.77	10.20	10.71	11.57	13.07	16.71
Mid_P_min	400.00	400.11	400.10	400.04	400.01	401.00
Mid_P_max	700.00	699.99	699.90	699.98	699.91	699.00
Mid_P_mean	527.22	550.27	517.82	539.48	522.08	504.00
High_SPD_min	2.50	3.76	2.50	3.00	2.50	2.50
High_SPD_max	169.35	44.92	79.19	66.14	82.85	67.43
High_SPD_mean	17.50	11.70	17.75	15.58	16.45	17.11
High_P_min	71.21	102.09	125.00	104.64	102.44	179.00
High_P_max	399.99	399.95	400.00	399.95	399.95	400.00
High_P_mean	274.35	290.78	252.86	266.04	264.89	288.87

Table 8-7: Experiment 2b statistical summary of AMV datasets for QINF >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63436	45995	105387	34244	52605	92872
QI>=80	36218	23014	88920	28056	25369	58126
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	67.59	40.03	66.67	66.14	65.30	62.52
SPD_mean	13.74	8.62	12.80	12.78	16.12	14.01
P_min	90.07	105.07	125.00	104.64	102.74	179.00
P_max	1050.00	1000.00	999.50	998.27	971.79	974.00
P_mean	592.69	707.92	611.62	562.51	524.70	655.70
Low_winds	46.14	60.77	49.35	43.20	39.56	56.38
Mid_winds	14.66	21.00	14.30	8.61	9.33	16.01
High_winds	39.21	18.23	36.34	48.19	51.11	27.62
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	47.78	23.71	49.33	28.92	28.17	27.55
Low_SPD_mean	8.67	8.08	8.83	8.69	9.36	9.61
Low_P_min	700.03	700.06	700.00	700.20	700.00	700.00
Low_P_max	1050.00	1000.00	999.50	998.27	971.79	974.00
Low_P_mean	891.00	889.11	902.74	898.43	856.99	881.88
Mid_SPD_min	2.50	3.75	2.50	3.02	2.53	2.50
Mid_SPD_max	58.24	35.30	54.80	55.89	48.99	58.83
Mid_SPD_mean	14.13	8.75	11.23	12.10	16.03	18.73
Mid_P_min	400.00	400.11	400.10	400.04	400.07	401.00
Mid_P_max	700.00	699.99	699.90	699.98	699.85	699.00
Mid_P_mean	506.61	551.78	520.32	540.96	513.37	489.88
High_SPD_min	2.51	3.76	2.50	3.00	2.50	2.50
High_SPD_max	67.59	40.03	66.67	66.14	65.30	62.52
High_SPD_mean	19.56	10.26	18.82	16.56	21.36	20.27
High_P_min	90.07	105.07	125.00	104.64	102.74	179.00
High_P_max	399.99	399.94	400.00	399.92	399.95	400.00
High_P_mean	273.82	283.88	252.23	265.26	269.58	290.05

Table 8-8: Experiment 2b statistical summary of AMV datasets for CQI >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63436	45995	105387	34244	52605	92872
QI>=80	44637	25843	94535	28056	39551	88548
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	67.59	44.92	66.97	66.14	65.30	67.43
SPD_mean	13.16	9.02	12.58	12.78	13.91	12.81
P_min	71.21	105.07	125.00	104.64	102.74	179.00
P_max	1050.00	1000.00	999.50	998.27	965.96	974.00
P_mean	599.75	708.09	610.41	562.51	509.09	643.56
Low_winds	45.78	60.77	49.00	43.20	37.08	53.76
Mid_winds	18.22	20.85	14.75	8.61	10.72	17.80
High_winds	36.00	18.38	36.26	48.19	52.21	28.44
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	47.78	26.70	49.33	28.92	49.75	28.25
Low_SPD_mean	8.81	8.24	8.74	8.69	8.94	8.94
Low_P_min	700.03	700.06	700.00	700.20	700.00	700.00
Low_P_max	1050.00	1000.00	999.50	998.27	965.96	974.00
Low_P_mean	886.76	890.20	902.65	898.43	851.86	877.85
Mid_SPD_min	2.50	3.75	2.50	3.02	2.52	2.50
Mid_SPD_max	58.24	36.51	54.80	55.89	48.99	61.96
Mid_SPD_mean	13.44	9.39	11.04	12.10	13.72	17.07
Mid_P_min	400.00	400.11	400.10	400.04	400.06	401.00
Mid_P_max	700.00	699.99	699.90	699.98	699.91	699.00
Mid_P_mean	524.45	550.71	519.36	540.96	517.10	503.26
High_SPD_min	2.50	3.76	2.50	3.00	2.50	2.50
High_SPD_max	67.59	44.92	66.97	66.14	65.30	67.43
High_SPD_mean	18.55	11.21	18.39	16.56	17.47	17.45
High_P_min	71.21	105.07	125.00	104.64	102.74	179.00
High_P_max	399.99	399.94	400.00	399.92	399.95	400.00
High_P_mean	272.87	284.35	252.53	265.26	264.00	288.51

Table 8-9: Experiment 2c statistical summary of AMV datasets for QINF >= 50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63546	48807	108585	38772	52281	87823
QI>=50	48635	41266	106320	37409	42649	78112
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	113.76	46.00	127.21	64.85	85.63	78.10
SPD_mean	13.12	9.41	12.58	12.36	14.10	12.71
P_min	77.08	51.56	125.00	103.26	104.29	175.00
P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
P_mean	554.66	669.15	592.02	538.85	491.43	623.03
Low_winds	40.56	56.40	46.69	39.84	35.01	52.90
Mid_winds	13.25	16.68	11.85	8.23	9.17	11.40
High_winds	46.19	26.92	41.46	51.94	55.82	35.70
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	44.48	25.21	127.21	33.52	53.08	32.53
Low_SPD_mean	8.51	8.57	8.68	8.83	9.11	9.11
Low_P_min	700.03	700.07	700.00	700.04	700.00	700.00
Low_P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
Low_P_mean	901.34	897.02	917.20	906.56	864.69	879.69
Mid_SPD_min	2.51	3.75	2.50	3.01	2.50	2.50
Mid_SPD_max	51.67	37.27	87.20	48.08	55.52	65.33
Mid_SPD_mean	13.19	10.04	11.07	12.04	14.53	14.19
Mid_P_min	400.01	400.05	400.10	400.02	400.01	401.00
Mid_P_max	699.98	699.97	699.90	699.94	699.84	699.00
Mid_P_mean	529.08	551.22	511.34	535.90	520.17	516.94
High_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
High_SPD_max	113.76	46.00	72.95	64.85	85.63	78.10
High_SPD_mean	17.15	10.76	17.39	15.12	17.15	17.58
High_P_min	77.08	51.56	125.00	103.26	104.29	175.00
High_P_max	399.98	400.00	400.00	399.89	399.95	400.00
High_P_mean	257.59	264.72	248.94	257.29	252.62	276.63

Table 8-10: Experiment 2c statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63546	48807	108585	38772	52281	87823
QI>=50	55455	44616	107204	37409	47554	87595
SPD_min	2.50	-54.63	2.50	3.00	2.50	2.50
SPD_max	150.82	3.75	127.21	64.85	89.03	78.10
SPD_mean	12.91	46.00	12.55	12.36	13.62	12.40
P_min	77.08	9.80	125.00	103.26	102.07	172.00
P_max	1050.00	51.56	999.90	998.85	987.99	974.00
P_mean	562.52	1000.00	591.66	538.85	488.20	620.71
Low_winds	40.95	665.37	46.62	39.84	34.33	52.22
Mid_winds	15.47	55.44	11.91	8.23	9.87	12.37
High_winds	43.58	17.63	41.47	51.94	55.80	35.40
Low_SPD_min	2.50	26.93	2.50	3.00	2.50	2.50
Low_SPD_max	114.05	3.75	127.21	33.52	53.08	32.53
Low_SPD_mean	8.82	27.34	8.67	8.83	9.00	9.00
Low_P_min	700.03	8.78	700.00	700.04	700.00	700.00
Low_P_max	1050.00	700.07	999.90	998.85	987.99	974.00
Low_P_mean	897.69	1000.00	917.06	906.56	862.88	877.91
Mid_SPD_min	2.50	895.68	2.50	3.01	2.50	2.50
Mid_SPD_max	139.93	3.75	87.20	48.08	50.57	65.33
Mid_SPD_mean	12.99	38.52	11.05	12.04	13.84	13.94
Mid_P_min	400.01	10.69	400.10	400.02	400.01	401.00
Mid_P_max	699.98	400.05	699.90	699.94	699.96	699.00
Mid_P_mean	536.69	699.97	511.32	535.90	523.40	521.97
High_SPD_min	2.50	550.05	2.50	3.00	2.50	2.50
High_SPD_max	150.82	3.75	108.96	64.85	89.03	78.10
High_SPD_mean	16.72	46.00	17.35	15.12	16.43	16.88
High_P_min	77.08	11.33	125.00	103.26	102.07	172.00
High_P_max	399.98	51.56	400.00	399.89	399.95	400.00
High_P_mean	256.71	400.00	248.90	257.29	251.42	275.84

Table 8-11: Experiment 2c statistical summary of AMV datasets for QINF >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63546	48807	108585	38772	52281	87823
QI>=80	38243	26408	92847	32879	28585	57220
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	76.38	40.45	67.77	64.85	74.77	78.10
SPD_mean	14.11	8.97	13.11	12.89	16.22	13.71
P_min	88.87	60.97	125.00	105.42	108.15	175.00
P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
P_mean	561.49	679.40	592.67	540.38	509.98	631.50
Low_winds	41.91	58.39	47.00	40.27	37.70	54.37
Mid_winds	11.23	14.59	10.98	7.15	7.70	10.39
High_winds	46.86	27.03	42.02	52.58	54.60	35.24
Low_SPD_min	2.51	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	40.29	21.11	30.96	31.81	37.08	32.53
Low_SPD_mean	8.78	8.28	8.88	9.07	9.69	9.59
Low_P_min	700.05	700.10	700.00	700.04	700.00	700.00
Low_P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
Low_P_mean	908.34	903.43	918.78	911.03	873.42	883.40
Mid_SPD_min	2.51	3.75	2.50	3.03	2.50	2.50
Mid_SPD_max	51.67	34.18	46.81	48.08	49.90	65.33
Mid_SPD_mean	14.79	9.26	11.68	12.65	17.62	15.34
Mid_P_min	400.01	400.05	400.10	400.05	400.01	401.00
Mid_P_max	699.98	699.97	699.90	699.94	699.13	699.00
Mid_P_mean	522.59	551.03	511.80	535.23	506.46	512.31
High_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
High_SPD_max	76.38	40.45	67.77	64.85	74.77	78.10
High_SPD_mean	18.70	10.31	18.21	15.84	20.54	19.60
High_P_min	88.87	60.97	125.00	105.42	108.15	175.00
High_P_max	399.98	400.00	400.00	399.89	399.91	400.00
High_P_mean	260.58	264.69	249.07	257.26	259.55	277.97

Table 8-12: Experiment 2c statistical summary of AMV datasets for CQI >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	63546	48807	108585	38772	52281	87823
QI>=80	46020	28997	98222	32879	40762	83613
SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
SPD_max	76.38	43.57	67.77	64.85	74.77	78.10
SPD_mean	13.47	9.29	12.90	12.89	14.27	12.53
P_min	88.87	51.56	125.00	105.42	104.63	172.00
P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
P_mean	568.78	680.84	592.17	540.38	488.91	623.56
Low_winds	42.57	58.74	46.84	40.27	35.03	52.85
Mid_winds	13.10	14.26	11.32	7.15	8.25	11.93
High_winds	44.33	27.00	41.84	52.58	56.72	35.22
Low_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
Low_SPD_max	45.45	25.21	30.96	31.81	53.08	32.53
Low_SPD_mean	8.98	8.41	8.80	9.07	9.22	9.05
Low_P_min	700.03	700.10	700.00	700.04	700.00	700.00
Low_P_max	1050.00	1000.00	999.90	998.85	987.99	974.00
Low_P_mean	903.79	903.84	918.17	911.03	866.39	878.62
Mid_SPD_min	2.50	3.75	2.50	3.03	2.50	2.50
Mid_SPD_max	51.67	37.27	49.78	48.08	49.90	65.33
Mid_SPD_mean	13.91	9.93	11.45	12.65	15.16	14.19
Mid_P_min	400.01	400.05	400.10	400.05	400.01	401.00
Mid_P_max	699.98	699.97	699.90	699.94	699.84	699.00
Mid_P_mean	534.15	549.96	511.63	535.23	516.03	520.90
High_SPD_min	2.50	3.75	2.50	3.00	2.50	2.50
High_SPD_max	76.38	43.57	67.77	64.85	74.77	78.10
High_SPD_mean	17.65	10.87	17.88	15.84	17.25	17.20
High_P_min	88.87	51.56	125.00	105.42	104.63	172.00
High_P_max	399.98	400.00	400.00	399.89	399.95	400.00
High_P_mean	23 257.34	264.76	249.05	257.26	251.82	275.61

c) Collocation plots

Plots of collocated AMV parameters from the different AMV algorithms for Experiment 2b) are shown in Figure 8-1 and Figure 8-3, to measure the respective differences (from top to bottom: speed, direction, pressure and quality control).
AMV pressure scatter plots comparing the EUM AMV pressure with the pressure of all other collocated AMVs are also shown in Figure 8-2 and Figure 8-4, to detect better the differences in the different AMV height assignment processes.
In both cases, a distance threshold of 55 km between AMVs and two quality control thresholds are used for this: QINF >= 50% and CQI >= 50%. The thresholds are kept low to still detect the variability of the parameters in the different AMV datasets.

There are around 25,000 collocated AMVs considering the QINF threshold, and around 31,000 collocated AMVs considering the CQI threshold. The plots of collocated parameters (Figure 8-1 and Figure 8-3) show:

- The large number of collocations acts again as an obstacle, as for Experiment 1), and especially considering the direction and quality control plots, in which the large amount of data avoids again to find any significant information. This can be compared again to what happens in chapters 9) and 10), in which the smaller number of collocations permits there to extract more conclusions.
- Considering the speed plot, a smaller number of higher-speed outliers is found, compared to those in Experiment 1). They are most frequently related to JMA (yellow dots), but also occur in the other AMV centres. The fact of using the specific operational configuration in all AMV centres seems to improve the result with respect to the one found in Experiment 1).
- Considering the pressure dots, the only informations that can be extracted is that BRZ and EUM can reach lower and higher levels (blue dots and green dots), that the frequency of BRZ AMVs is higher at mid-levels, and that NOA has also some higher-level outliers.

Considering the AMV pressure scatter plots for Experiment 2b) (Figure 8-2 and Figure 8-4), AMV pressures related to EUM and NWC relate again well to each other (pink dots), due to the fact of both using “CCC method height assignment”. The low-level correction that EUM applies but NWC does not apply, can also be seen below 900 hPa (where EUM pressure values are lower than those of NWC). However, compared to Experiment 1), there are more cases in which NWC defines a high level AMV where EUM defines a lower level AMV.
Pressure values for KMA and NOA have a smaller correspondence with the previous ones, although still not too different. KMA (red dots) also applies “CCC method height assignment” with its own Cloud product, but its results are noisier, with more values outside the diagonal. NOA (black dots) uses a different

method, whose main difference is to define higher levels for high-level AMVs above 500 hPa.
The most different height assignments are related to BRZ, which in general shows lower levels than EUM (although some low level AMVs are higher), and to JMA, which shows a much more random distribution of AMVs, especially with many AMVs which are located in high levels while the rest of centres locate them at low levels. As in Experiment 1), a good exercise here would be to check visually these JMA AMVs and the clouds they are related to and see in the corresponding satellite image if there are really high clouds or low clouds (such as defined by the other AMV centres) in these locations.

Finally, considering all elements together and as in Experiment 1), the height assignment procedure and the AMV pressure it defines keep on being the main driver in variability, over any other option defined in the AMV algorithms. In spite of this, a homogenization process has occurred in the different AMV algorithm since the AMV intercomparisons started, and now for example layer distribution, speed and pressure ranges are smaller than in the previous AMV intercomparison, and the comparisons against rawinsonde winds and NWP analysis winds also show that differences in errors between the different AMV datasets are also smaller.

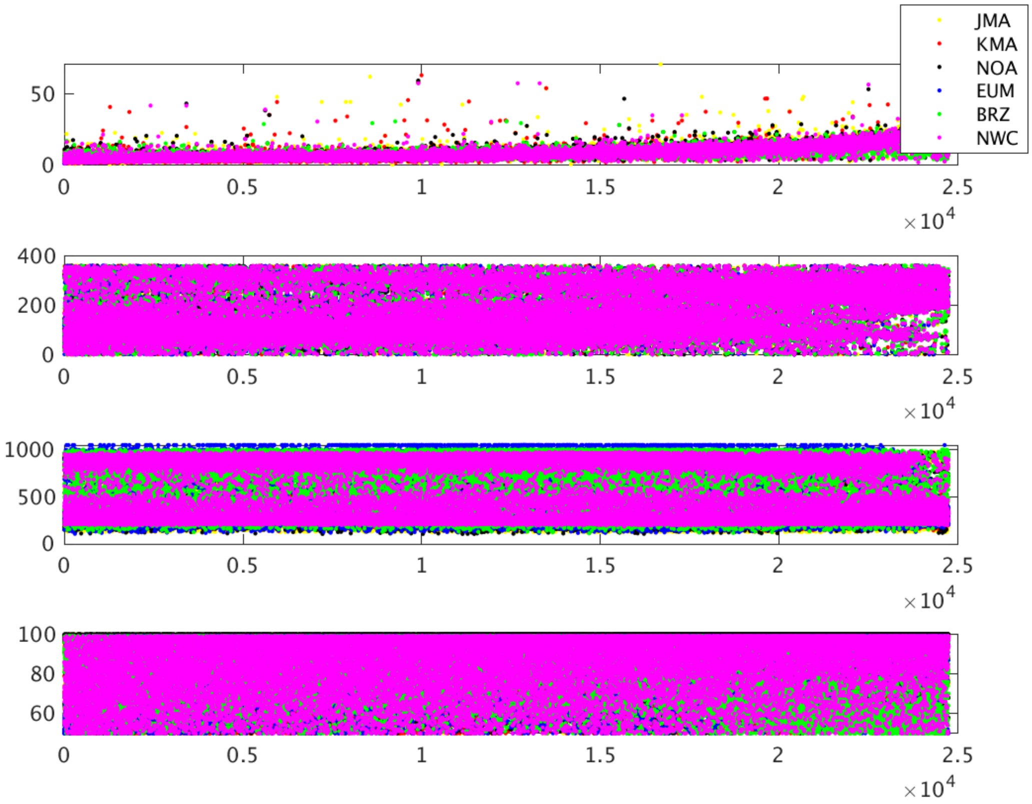

Figure 8-1: Experiment 2b (QINF >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

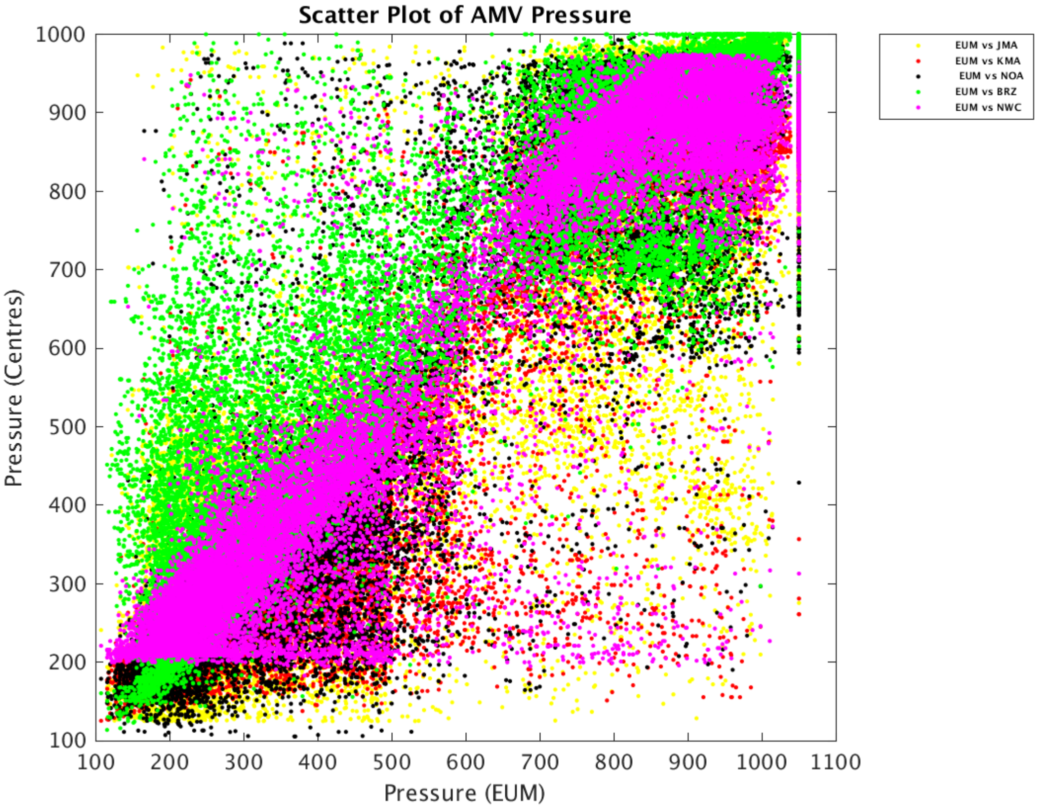

Figure 8-2: Experiment 2b (QINF >= 50). Scatter plot of AMV pressure for each center vs. EUM pressure.

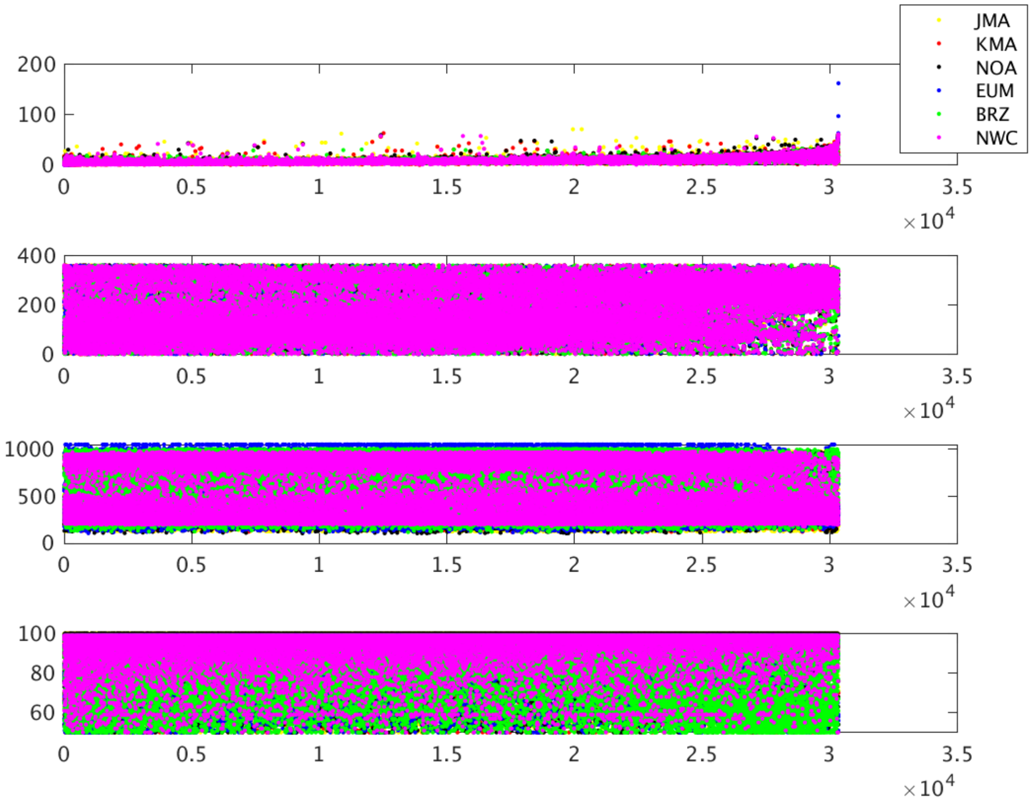

Figure 8-3: Experiment 2b (CQI >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

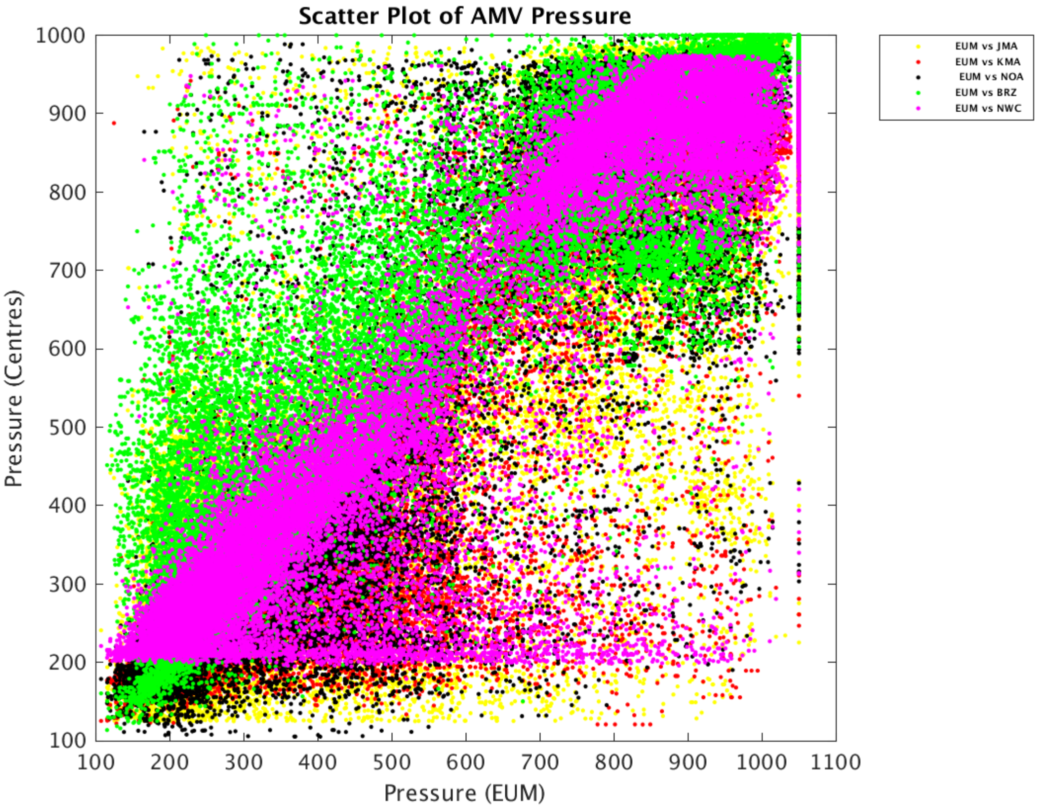

Figure 8-4: Experiment 2b (CQI >= 50). Scatter plot of AMV pressure for each center vs. EUM pressure.

d) Rawinsonde comparison

The comparison of all AMVs to nearby rawinsondes is summarized in the following tables for QINF, CQI >= 50% and QINF, CQI >= 80% (the same thresholds as used in the previous Intercomparison study). Collocated AMVs for all levels have also been compared for QINF, CQI >= 50%.

The QINF >=50% (Table 8-13) vector RMS ranges from 5.5 ms^{-1} (JMA, BRZ) to 6.1–6.6 ms^{-1} (NOA, NWC) to 7.3-8.5 ms^{-1} (EUM, KMA). In Table 8-14 (QINF threshold increased to 80%) the change in RMS statistics is neutral or slightly improved. Table 8-16 summarizes the statistics for the CQI >=50%, where vector RMS ranges from 5.6 ms^{-1} (JMA) to 6.1–6.9 ms^{-1} (NOA, NWC, BRZ) to 8.8 ms^{-1} (EUM, KMA). For the CQI > = 80% (Table 8-17) the statistics are about the same for all centres, excepting more than 1 ms^{-1} improvement in the RMS for EUM.
Considering only collocated AMVs compared to rawinsondes, the number of matched observations for QINF >=50% is reduced to approximately 1500 for each centre, which is 50% greater than the previous intercomparison study with only 1000 matches. The vector RMS is improved with less variability between centres (Table 8-15): Vector RMS ranges from 4.5 ms^{-1} (JMA) to 6.1 ms^{-1} (KMA). Results are slightly degraded for CQI >= 50% (Table 8-16) for most centres, excepting the RMS for EUM increased by 1.5 $ms^{-1.}$

Table 8-13: Experiment 2b: All AMVs (QINF >= 50) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS= speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	2225	1.20	16.01	0.22	3.45	-1.23	5.62
EUM	3040	0.52	14.54	-0.28	5.48	0.27	7.34
JMA	5562	0.24	13.90	-0.05	3.93	0.59	5.50
KMA	2716	0.33	12.67	-2.00	6.64	-1.61	8.58
NOA	2328	0.77	13.52	-0.09	4.49	-1.62	6.13
NWC	3942	0.36	14.59	0.67	4.98	2.90	6.63

Table 8-14: Experiment 2b: All AMVs (QINF >= 80) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS= speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1244	1.40	15.98	0.22	3.06	-2.96	5.33
EUM	2215	0.59	14.47	0.01	5.31	-0.28	7.13
JMA	4727	0.27	13.84	0.01	3.83	0.39	5.41
KMA	1580	0.44	12.18	-1.85	5.77	-1.87	7.24
NOA	1971	0.77	13.45	0.01	4.48	-1.96	6.08
NWC	2633	0.10	14.76	0.97	4.89	2.53	6.61

Table 8-15: Experiment 2b: Collocated AMVs (QINF >= 50) comparison to rawinsondes within 150 km. N = number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS = speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1459	1.17	16.41	0.47	3.71	1.47	6.01
EUM	1495	0.78	14.47	-0.27	3.85	-1.31	5.53
JMA	1513	0.06	14.54	-0.33	3.21	1.43	4.55
KMA	1516	-0.22	12.84	-0.90	4.70	-3.28	6.11
NOA	1514	-0.07	13.83	-0.22	3.95	-3.45	5.49
NWC	1498	1.25	14.64	0.14	3.34	1.05	4.88

Table 8-16: Experiment 2b: All AMVs (CQI >= 50) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS= speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	3996	0.09	13.99	0.08	4.82	-0.35	6.95
EUM	4033	0.54	14.64	-0.73	6.74	3.09	8.73
JMA	5647	0.25	13.91	-0.03	3.96	0.73	5.59
KMA	3370	0.33	12.80	-2.12	7.23	0.11	8.85
NOA	2328	0.77	13.52	-0.09	4.49	-1.62	6.13
NWC	5041	0.55	14.40	0.40	5.37	3.70	6.89

Table 8-17: Experiment 2b: All AMVs (CQI >= 80) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS= speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	3033	0.13	14.21	0.22	4.61	-0.81	6.80
EUM	3047	0.49	14.38	-0.37	5.84	2.75	7.85
JMA	5057	0.24	13.93	-0.01	3.83	0.45	5.39
KMA	2653	0.23	12.41	-1.82	6.53	-0.73	8.11
NOA	1971	0.77	13.45	0.01	4.48	-1.96	6.08
NWC	4679	0.61	14.35	0.55	5.35	3.62	6.87

Table 8-18: Experiment 2b: Collocated AMVs (CQI >= 50) comparison to rawinsondes within 150 km. N= number of matches; P bias = pressure bias; P RMS = pressure RMS; SpdBias = speed bias; SpdRMS= speed RMS; DirBias = wind direction bias; VecRMS = vector RMS.

Site	N	P bias	P RMS	Spd bias	Spd RMS	Dir bias	Vec RMS
BRZ	1881	0.72	15.92	0.38	3.76	0.81	6.12
EUM	1926	0.77	14.68	-0.31	5.46	-2.21	7.08
JMA	1949	-0.12	14.25	-0.31	3.54	2.34	4.96
KMA	1935	-0.42	13.18	-1.39	5.50	-2.81	7.04
NOA	1962	-0.14	13.87	-0.23	4.09	-2.86	5.64
NWC	1942	1.16	14.55	-0.14	3.68	0.20	5.21

e) Model Grid comparison

The Python scripts used to determine the Best fit height analysis also define the comparison of all AMVs to the NWP background model grid winds. This comparison was based on ECMWF ERA5 analysis using QINF, CQI >= 80%. The tables below are for all AMV and AMVs by pressure range (high, medium, and low).

The results are consistent and show similar variability as seen in the rawinsonde comparisons above, which is analogous to what was found in Experiment 2 of the 2018 Study, with the following notable exceptions:

- In the 2018 Study, BRZ had the largest deviation from the NWP background grid, except for the low-level AMVs where KMA and EUM had the largest deviations. In this current Study, BRZ shows a significant improvement in RMSE that is comparable to the sites with the best statistics (NOA, NWC). As already said for Experiment 1, this is due to improvements in the height assignment including the addition of a CO_2 technique, updates to the tracking algorithm, and the new "NWP consistency" filtering, whose impact should be however reduced (or removed completely) to reduce also the dependency on the NWP model.

In the 2018 Study, the RMSE for individual centres is approximately the same when considering all AMVs for QINF >= 80% and CQI >= 80%. However, that is not the case in the current study for EUM and KMA. For QINF >= 80 (Table 8-19), the RMSE for EUM is 5.30 ms-1, while for CQI >= 80 (Table 8-23) it is 6.31 ms-1. Similarly, the RMSE for KMA is 4.01 ms-1 (QINF >= 80) and 5.93 ms-1 (CQI >= 80). The other centres do not exhibit this variability. We can not offer an explanation, as this is also observed in Experiment 1.

The AMV/ERA5 RMS values for all levels for QINF >= 50% range from 3 to 4 ms^{-1}, with an outlier by EUM at 5.3 ms^{-1} (Table 8-19), which is substantially better than the AMV/rawinsonde comparison with an RMS range of 5.6 to 8.5 ms^{-1} (Table 8-13). This improvement in the statistics is again related to the fact that AMV winds relate better in general to the NWP winds than to the Rawinsonde winds, as other AMV comparisons also show.

When the AMVs are binned into three levels (High: 100-400 hPa, Middle: 400-700 hPa, Low: 700-1000 hPa), the middle level AMVs have the poorest RMS ranging from 3.6 to 7.2 ms^{-1}. The best winds are in the low levels with an RMS ranging from 1.9 to 3.4 ms^{-1}, due to generally slower winds in the low levels.

Table 8-19: Experiment 2b: All AMVs (QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	23014	4684	3.21	4.08	2.79	3.70
EUM	35325	11854	3.71	5.30	2.95	4.62
JMA	89041	33432	2.32	2.98	1.91	2.57
KMA	25440	9692	3.04	4.01	2.32	3.33
NOA	28056	9281	3.13	3.98	2.48	3.37
NWC	58271	18081	2.68	3.61	2.09	2.93

Table 8-20: Experiment 2b: High level AMVs (100-400 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	4196	1536	4.23	4.93	3.17	3.96
EUM	14264	6760	4.64	6.11	3.39	4.97
JMA	32375	18178	3.14	3.81	2.37	3.12
KMA	13002	6641	3.72	4.73	2.74	3.84
NOA	13520	6667	3.77	4.50	2.73	3.56
NWC	16101	8457	3.98	4.93	2.68	3.66

Table 8-21: Experiment 2b: Mid level AMVs (400-700 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	4792	498	4.58	5.35	4.26	5.10
EUM	5273	867	5.24	7.25	4.78	6.95
JMA	12666	1993	2.93	3.58	2.74	3.40
KMA	2342	383	3.97	5.17	3.49	4.77
NOA	2385	387	4.89	5.73	4.41	5.40
NWC	9323	2213	3.86	4.77	3.20	4.17

Table 8-22: Experiment 2b: Low level AMVs (700-1000 hPa, QINF >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	13985	2644	2.42	3.19	2.17	2.96
EUM	15733	4220	2.36	3.41	1.94	3.05
JMA	43930	13248	1.53	1.89	1.33	1.70
KMA	10069	2663	1.94	2.32	1.50	1.91
NOA	12119	2221	2.06	2.76	1.81	2.51
NWC	32847	7411	1.72	2.17	1.49	1.93

Table 8-23: Experiment 2b: All AMVs (CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	25843	5357	3.22	4.11	2.79	3.71
EUM	45173	13432	4.26	6.31	3.57	5.81
JMA	94720	35004	2.34	3.00	1.94	2.60
KMA	40954	13816	4.11	5.93	3.30	5.32
NOA	28056	9281	3.13	3.98	2.48	3.37
NWC	91483	26317	2.96	3.91	2.39	3.31

Table 8-24: Experiment 2b: High level AMVs (100-400 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	4749	1798	4.28	5.03	3.21	4.05
EUM	16614	7355	4.72	6.32	3.55	5.31
JMA	34362	18959	3.16	3.83	2.40	3.15
KMA	21408	9156	4.61	6.11	3.57	5.22
NOA	13520	6667	3.77	4.50	2.73	3.56
NWC	25989	11842	4.08	5.05	2.92	3.96

Table 8-25: Experiment 2b: Mid level AMVs (400-700 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	5345	611	4.62	5.40	4.26	5.13
EUM	8424	1106	6.32	8.67	5.94	8.48
JMA	13892	2177	2.95	3.58	2.74	3.40
KMA	4319	626	5.73	8.12	5.21	7.79
NOA	2385	387	4.89	5.73	4.41	5.40
NWC	16179	3348	4.10	5.06	3.53	4.56

Table 8-26: Experiment 2b: low level AMVs (700-1000 hPa, CQI >= 80) compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

EXP	N	BFN	VO	RMSE	VOAF	RMSEAF
BRZ	15706	2942	2.42	3.18	2.16	2.95
EUM	20062	4959	3.01	4.99	2.59	4.73
JMA	46388	13852	1.56	1.92	1.35	1.73
KMA	15180	4027	2.94	4.83	2.38	4.50
NOA	12119	2221	2.06	2.76	1.81	2.51
NWC	49315	11127	2.00	2.56	1.73	2.28

f) Best fit height

The Best Fit height analysis was completed for each wind producer according to the method described by Salonen et al. (2012), using exactly the same procedure than for Experiment 1 in Subchapter 7f). This technique finds the background model best-fit pressure associated with the AMV, which is where the vector difference between the observed AMV and model background is at a minimum.

The following figures show again the:

- Distribution of "Best Fit minus AMV pressure" differences, color-coded by low, medium, and high clouds (upper-left),
- Spatial distribution with same color coding (upper-right),
- Relationship between AMV pressure and latitude, color-coded to indicate if the Best fit moved the AMV higher (red) or lower (blue) (lower-left),
- Relationship between AMV pressure and speed, color-coded to indicate if the Best fit moved the AMV higher (red) or lower (blue) (lower-right).

Most of the plots are in agreement again in the following: throughout the middle portion of the image high-level clouds are adjusted, and in the eastern Pacific low-level clouds are adjusted due to the best fit.
The distribution of high, mid, and low-level clouds (upper left plots) is similar between the different centers with a spread of +/- 200 hPa for the high clouds, except JMA (Figure 8-13) with has again a much tighter and smoother distribution (+/- 100 hPa). This means that the JMA AMVs vary little from the ECMWF ERA5 analysis compared to the other AMV producers.
Also, the histograms for the low-level clouds (blue) are centered to the right of zero (for EUM, KMA, NWC)[4] which implies that low-level clouds are primarily adjusted downward (increasing pressure). An exception to this downward trend is NOAA AMVs (Figure 8-13), where low-level clouds are usually adjusted upward.

An additional set of figures for all AMV centres, for QINF >= 80% and CQI >= 80% (beginning with Figure 8-17) depicts the distribution of Best Fit statistics. Depending on the site, 29% to 38% of the AMVs are adjusted to a Best Fit pressure (lower-left in each figure). However, the BRZ AMVs with QINF >= 80% (Figure 8-17) is an exception with only 20% of the AMVs adjusted.

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[4] See Figure 8-7, Figure 8-11, Figure 8-15, respectively.

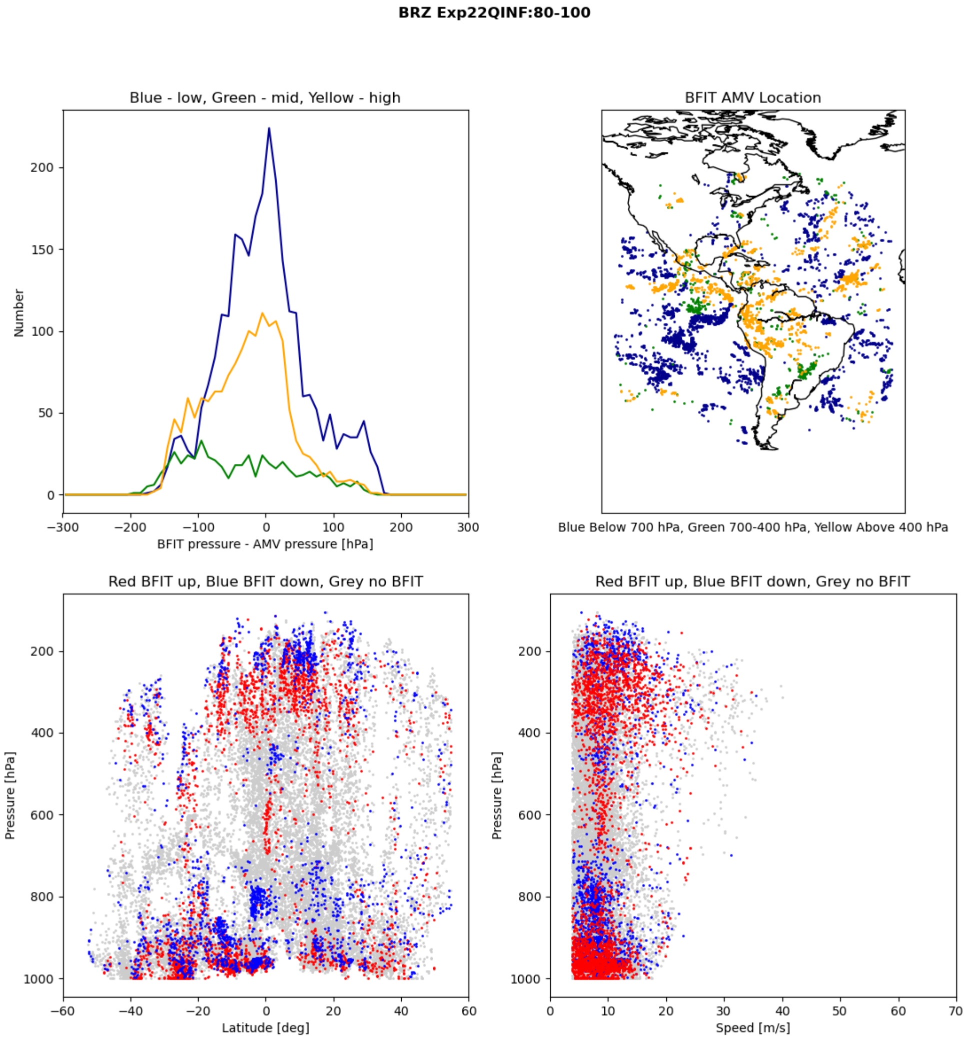

Figure 8-5: Experiment 2b. BRZ (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

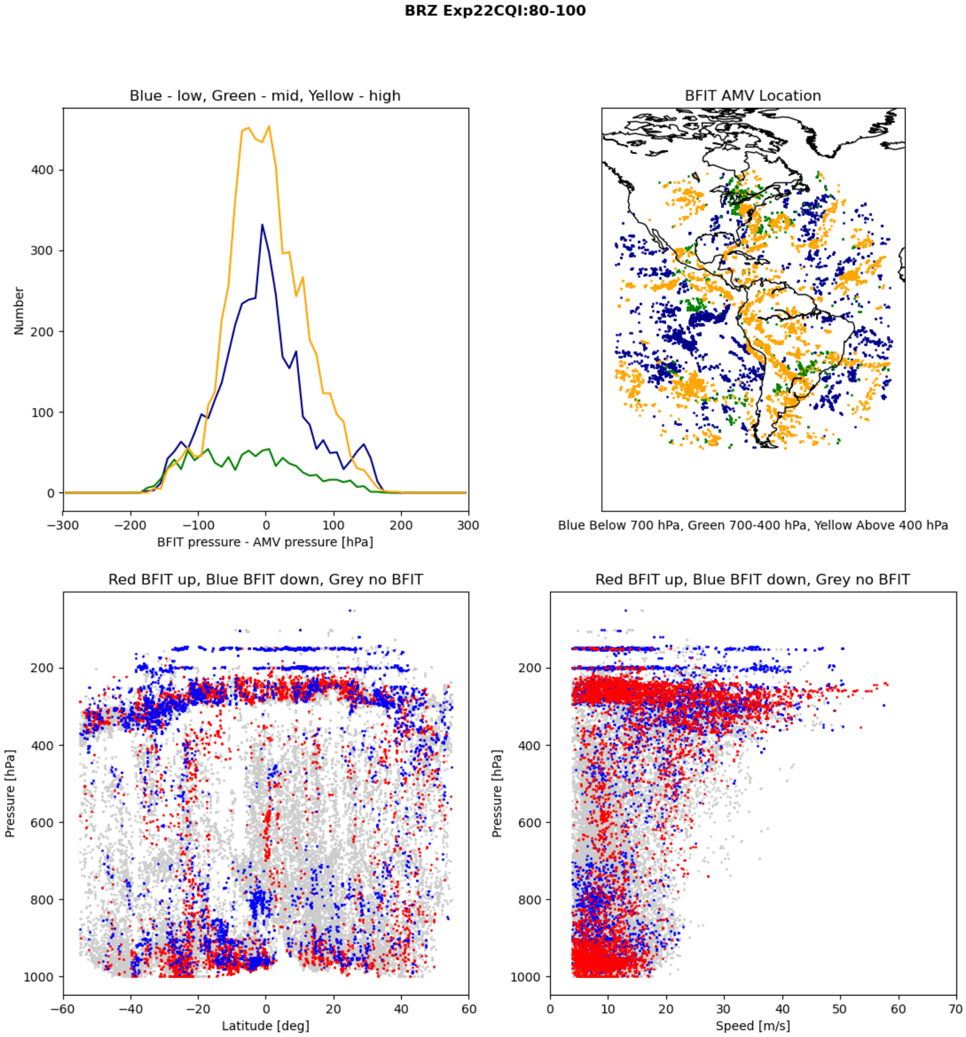

Figure 8-6: Experiment 2b. BRZ (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

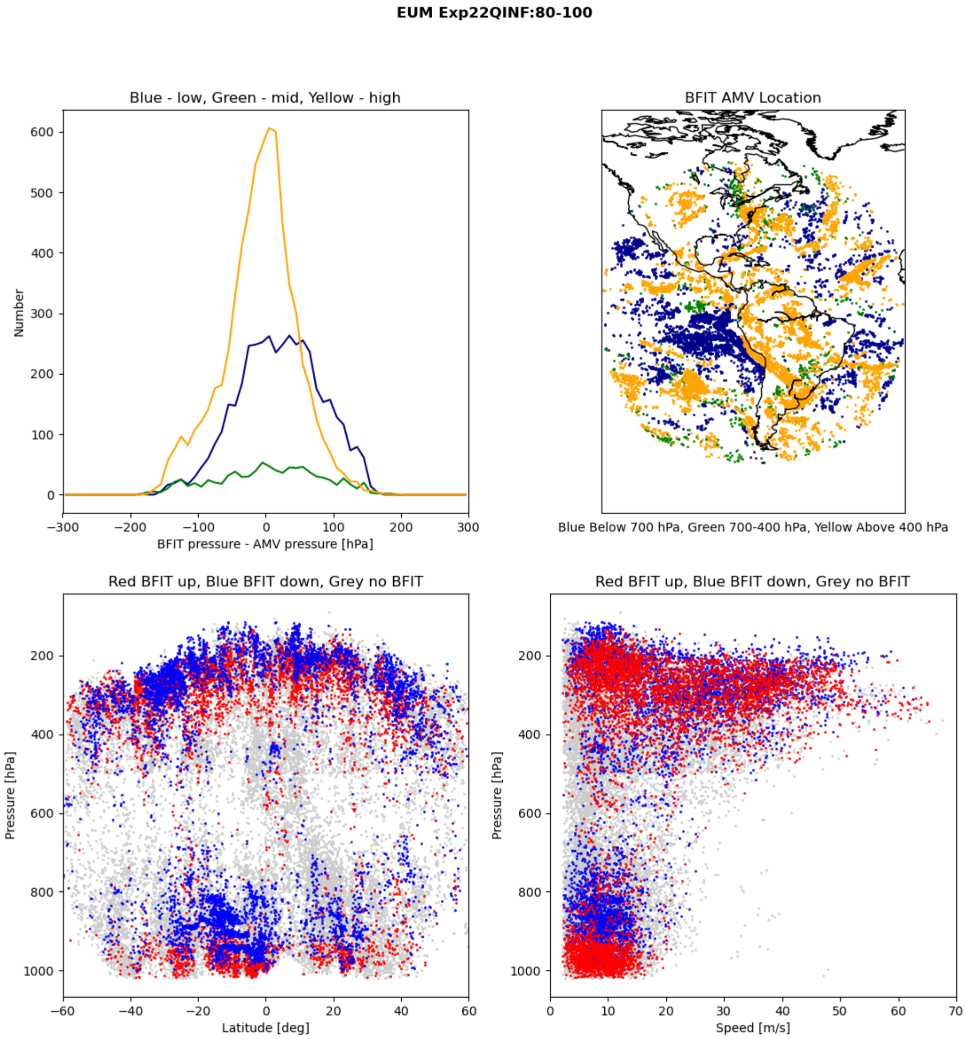

Figure 8-7: Experiment 2b. EUM (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

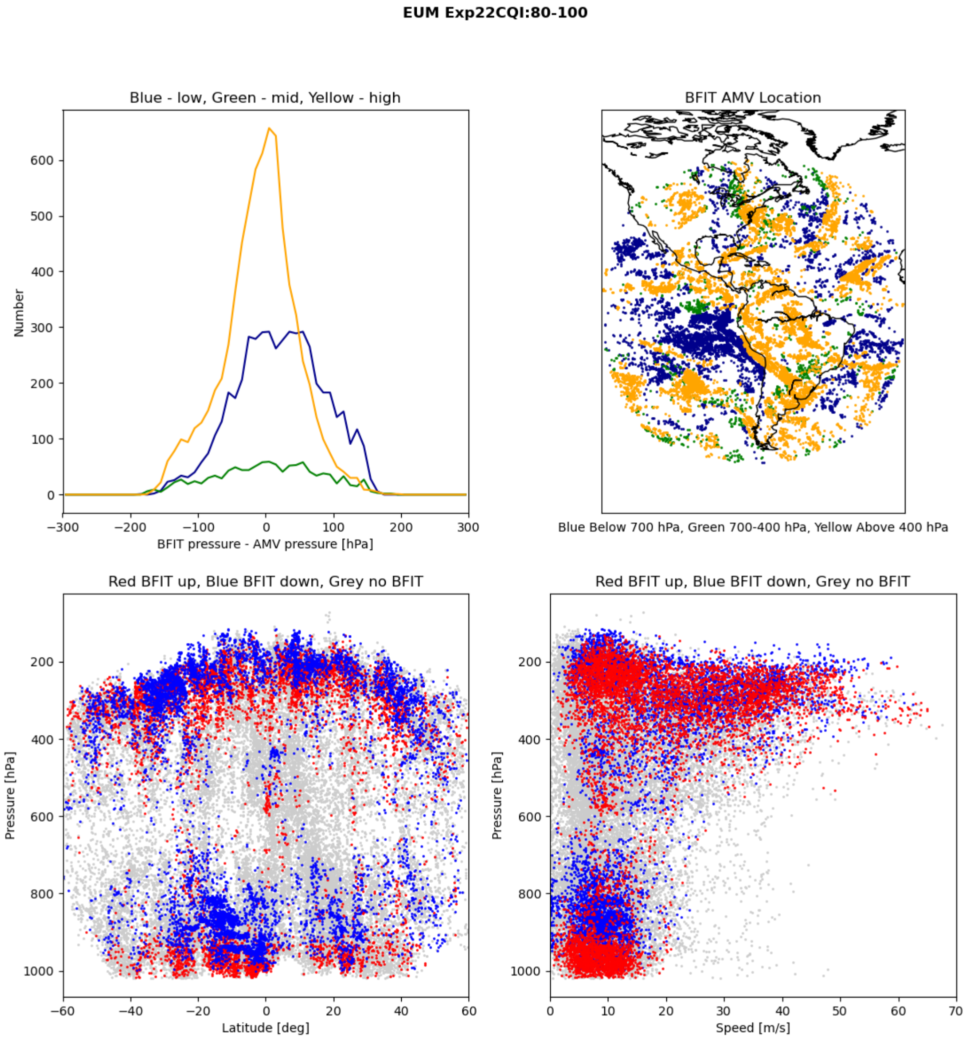

Figure 8-8: Experiment 2b. EUM (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

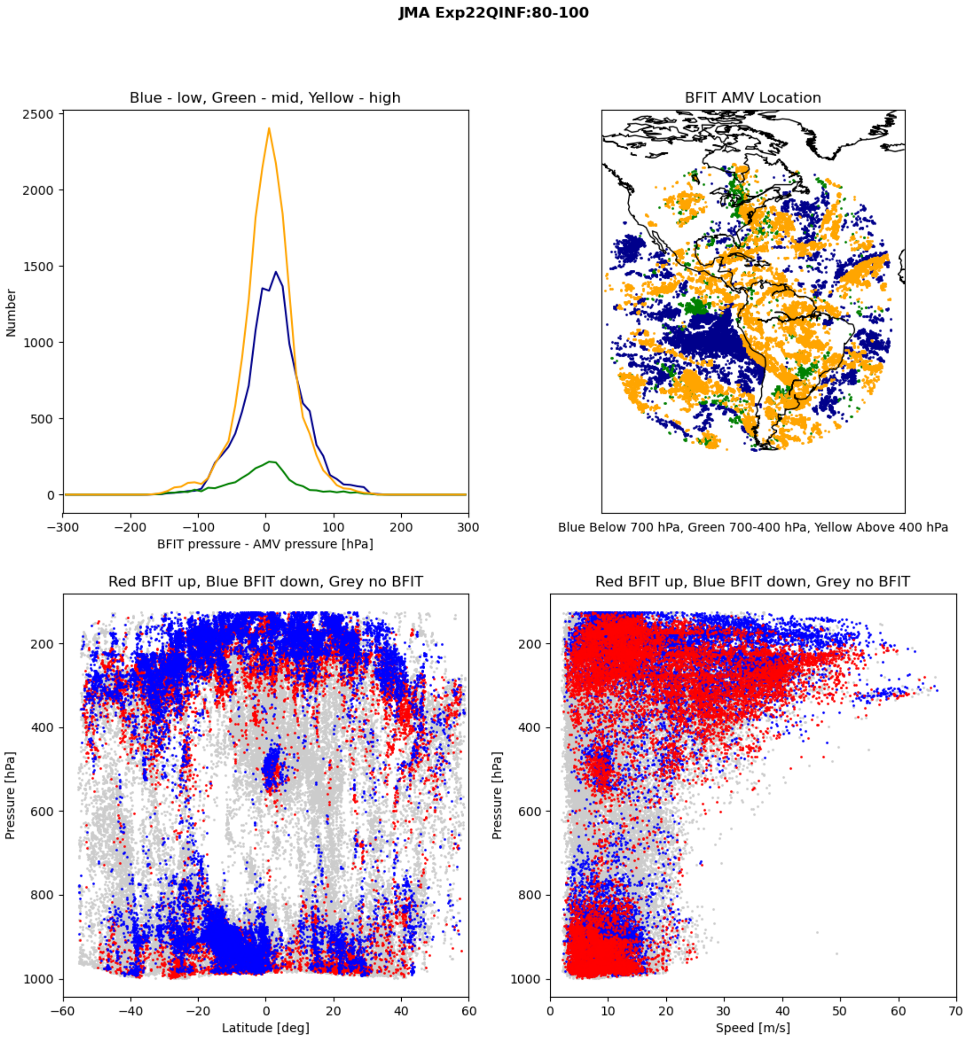

Figure 8-9: Experiment 2b. JMA (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

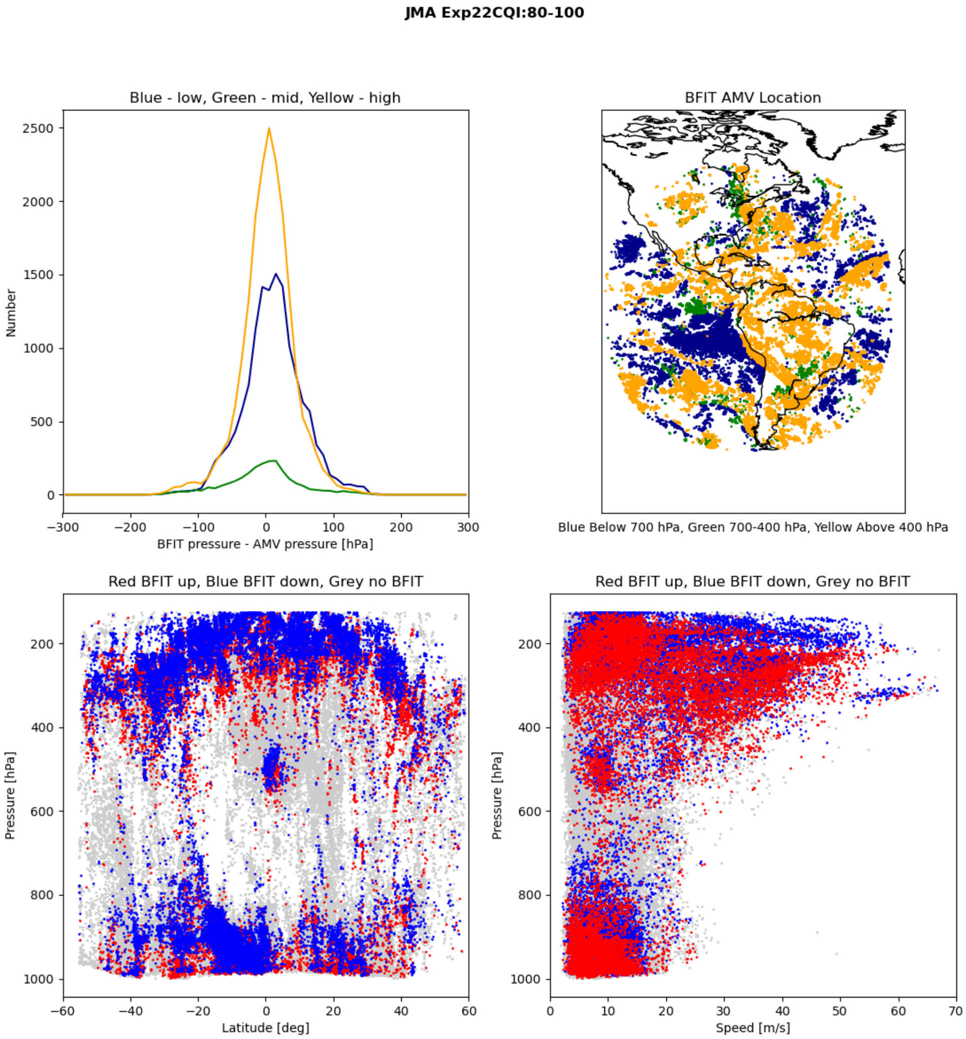

Figure 8-10: Experiment 2b. JMA (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

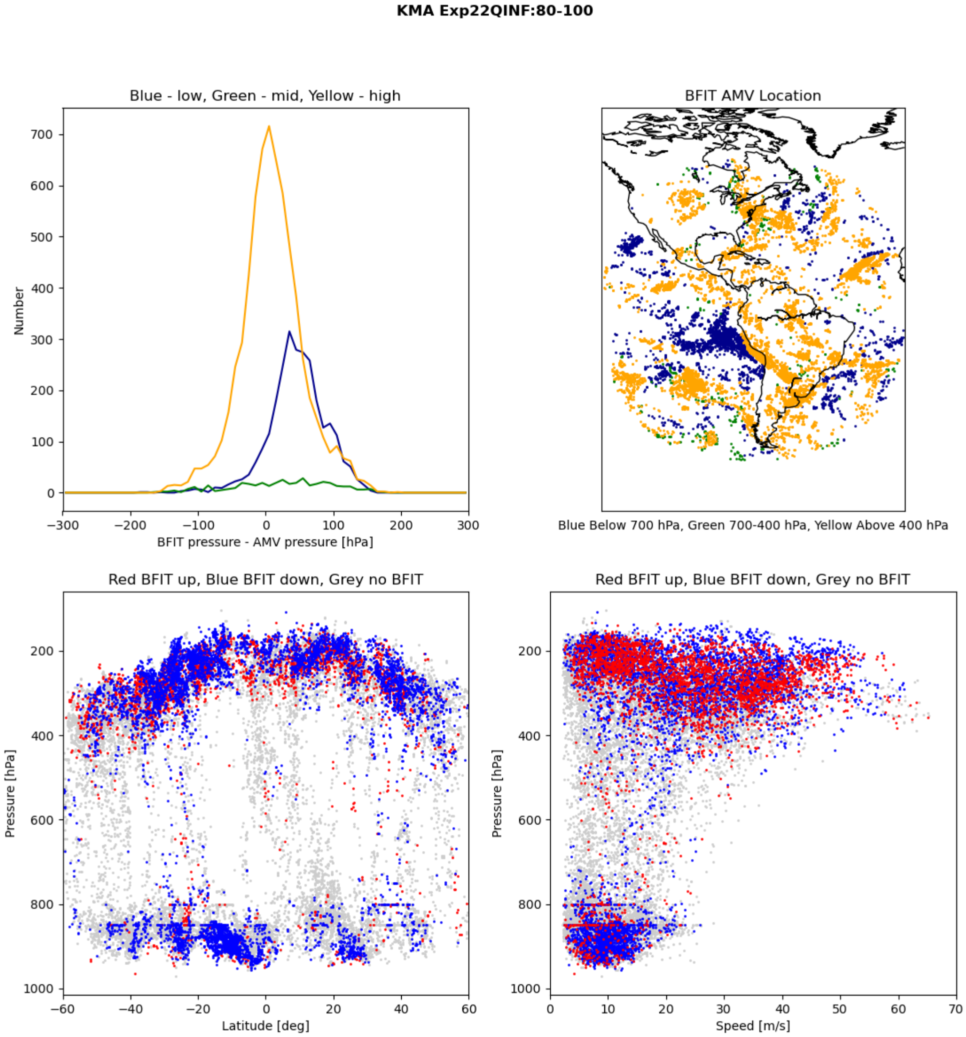

Figure 8-11: Experiment 2b. KMA (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

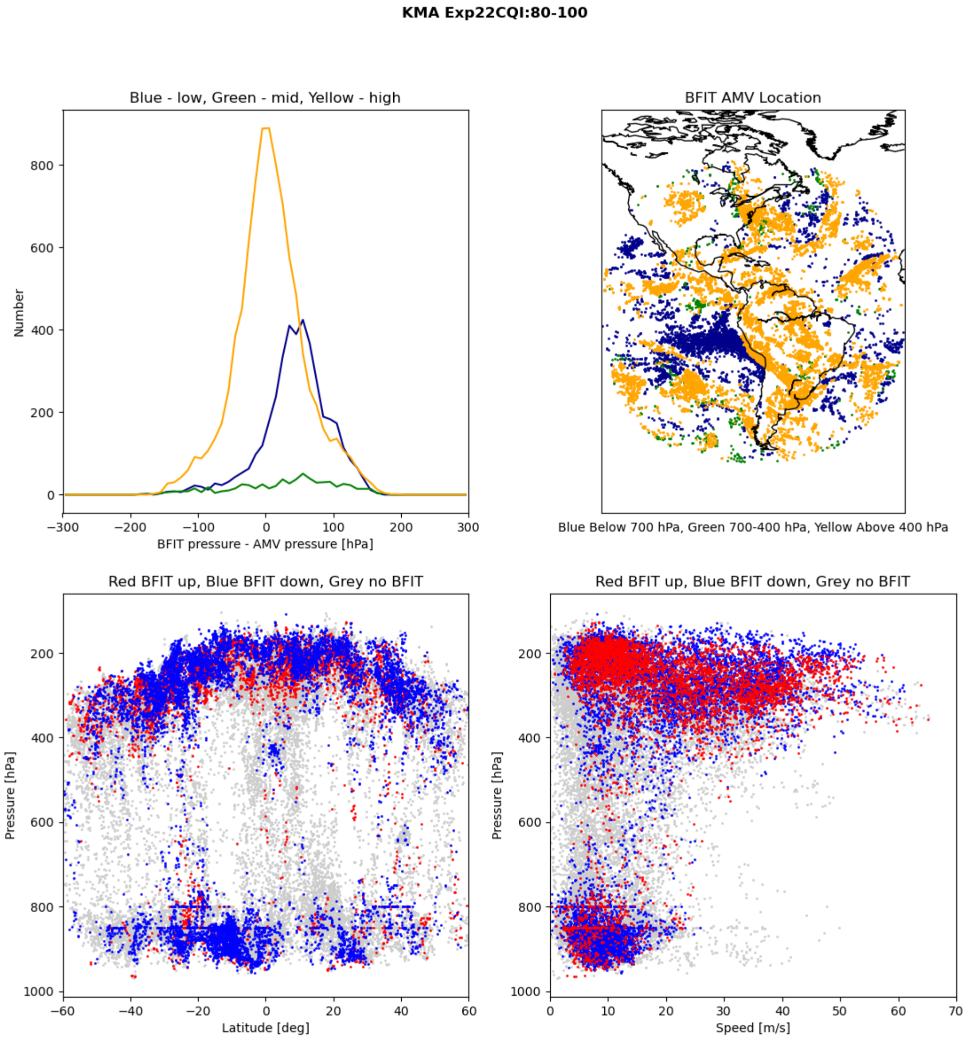

Figure 8-12: Experiment 2b. KMA (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

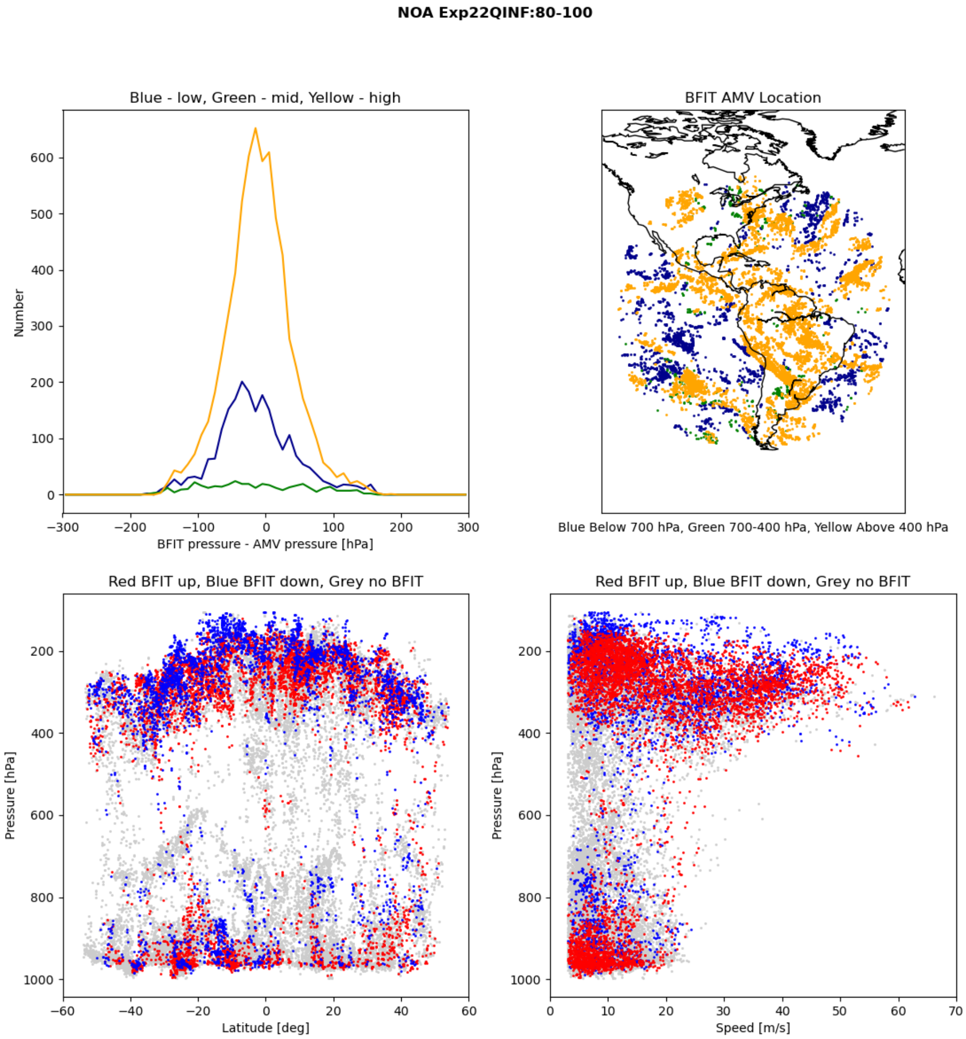

Figure 8-13: Experiment 2b. NOA (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

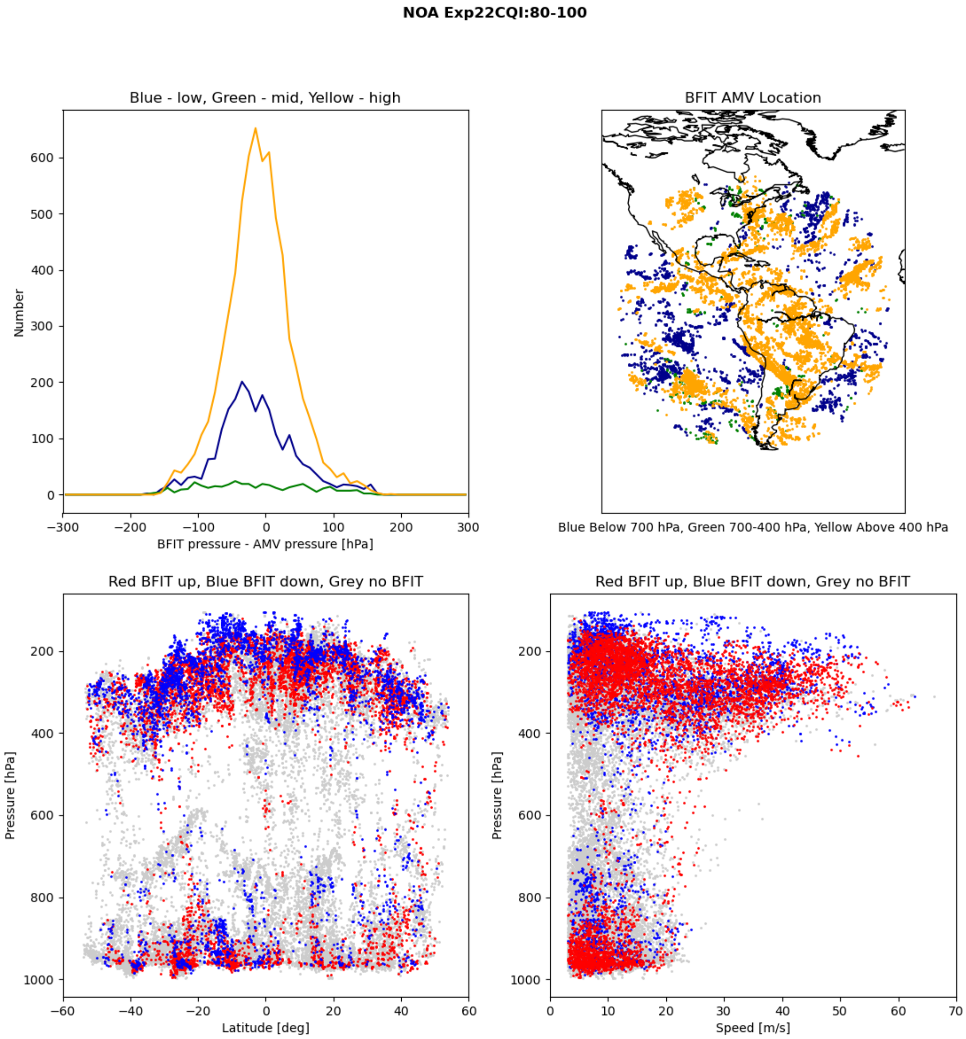

Figure 8-14: Experiment 2b. NOA (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

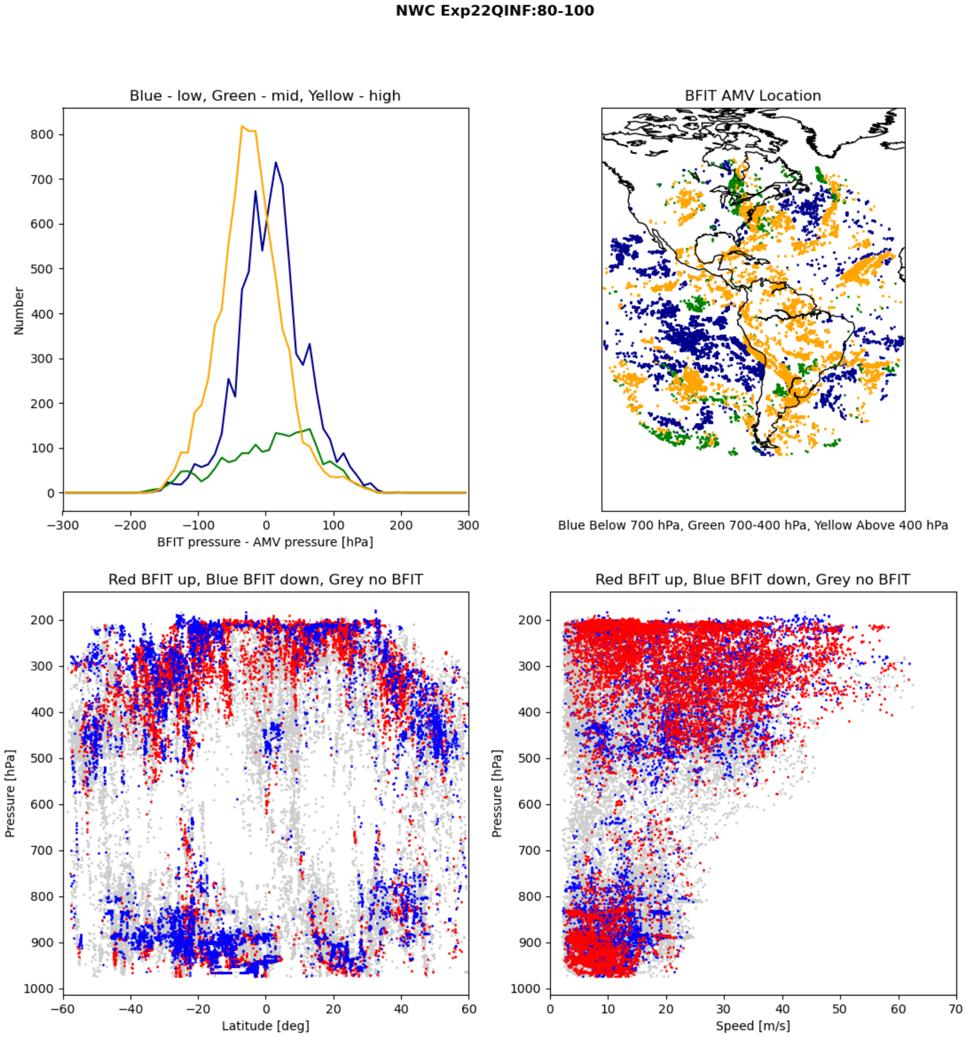

Figure 8-15: Experiment 2b. NWC (QINF >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

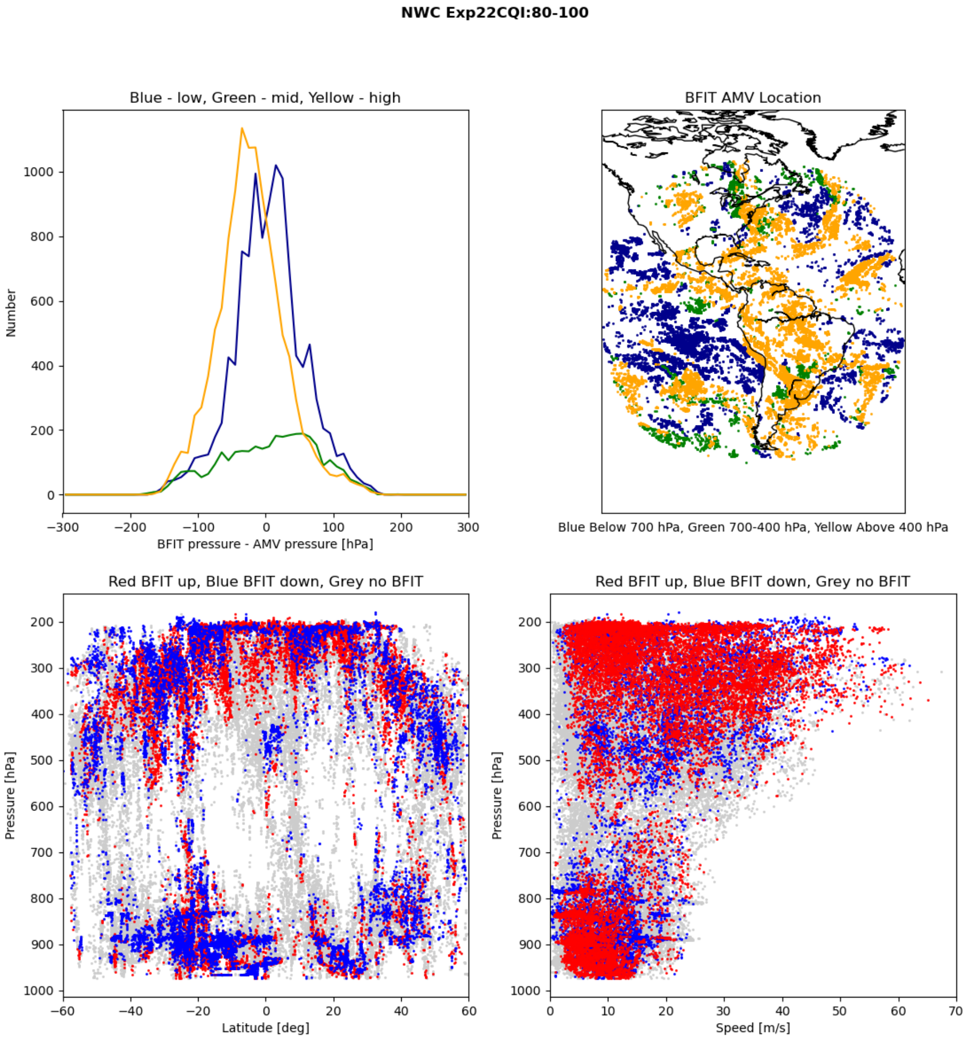

Figure 8-16: Experiment 2b. NWC (CQI >= 80): Distribution of Best Fit – AMV pressure by height (upper-left); Best Fit AMV location (color-coded by height); AMV pressure vs. Latitude (color-coded by Best Fit height adjustment); AMV pressure vs. Speed (color-coded by Best Fit height adjustment).

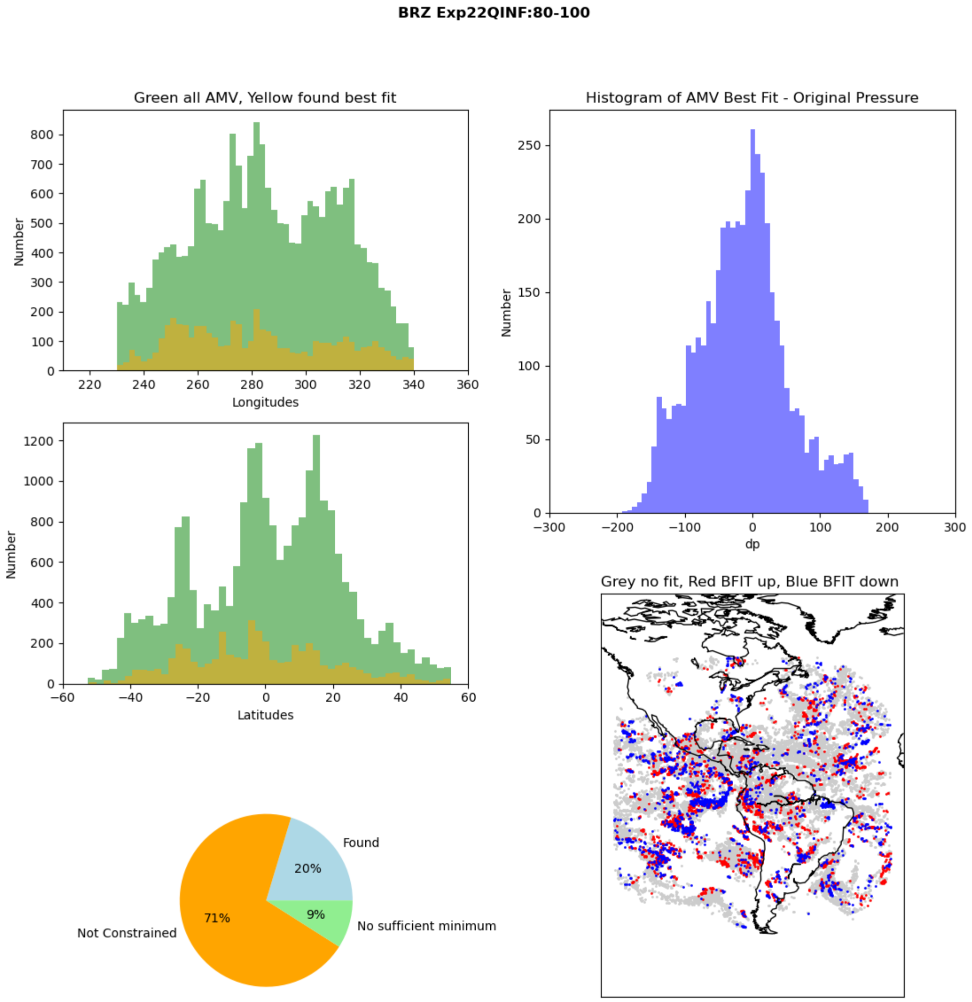

Figure 8-17: Experiment 2b. BRZ (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

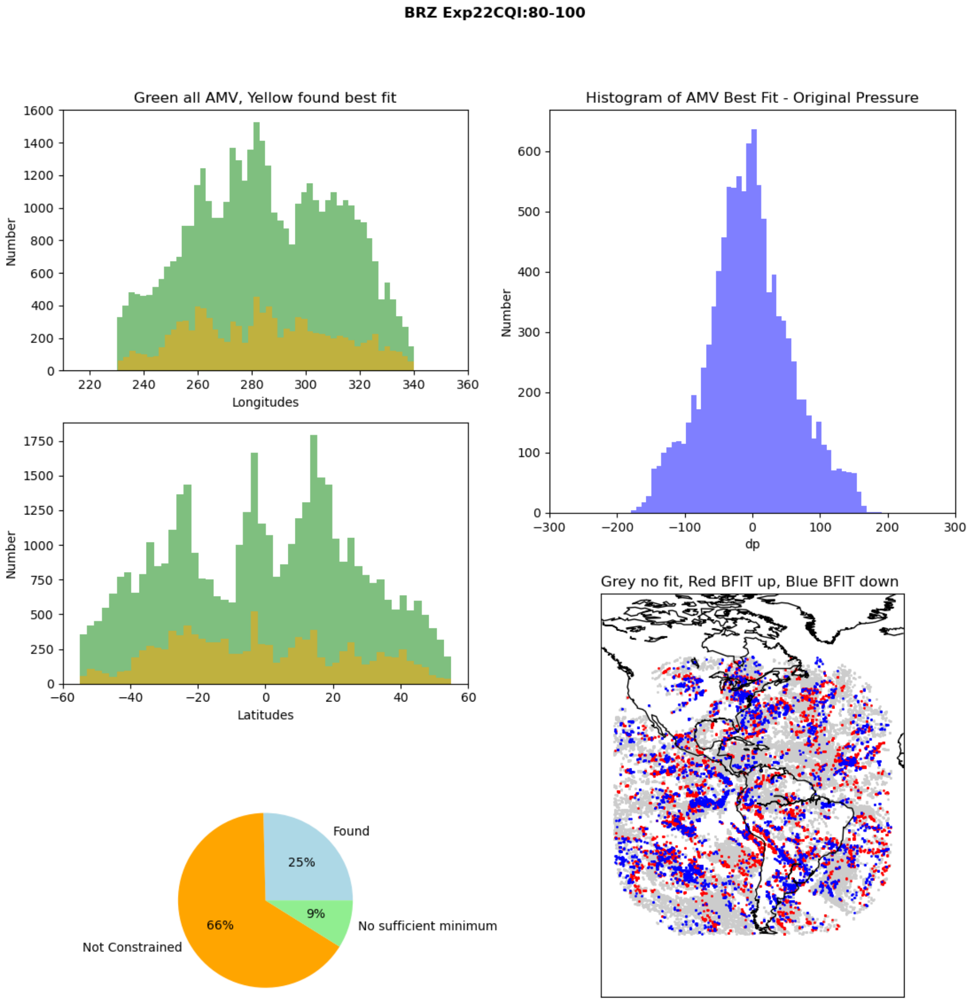

Figure 8-18: Experiment 2b. BRZ (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

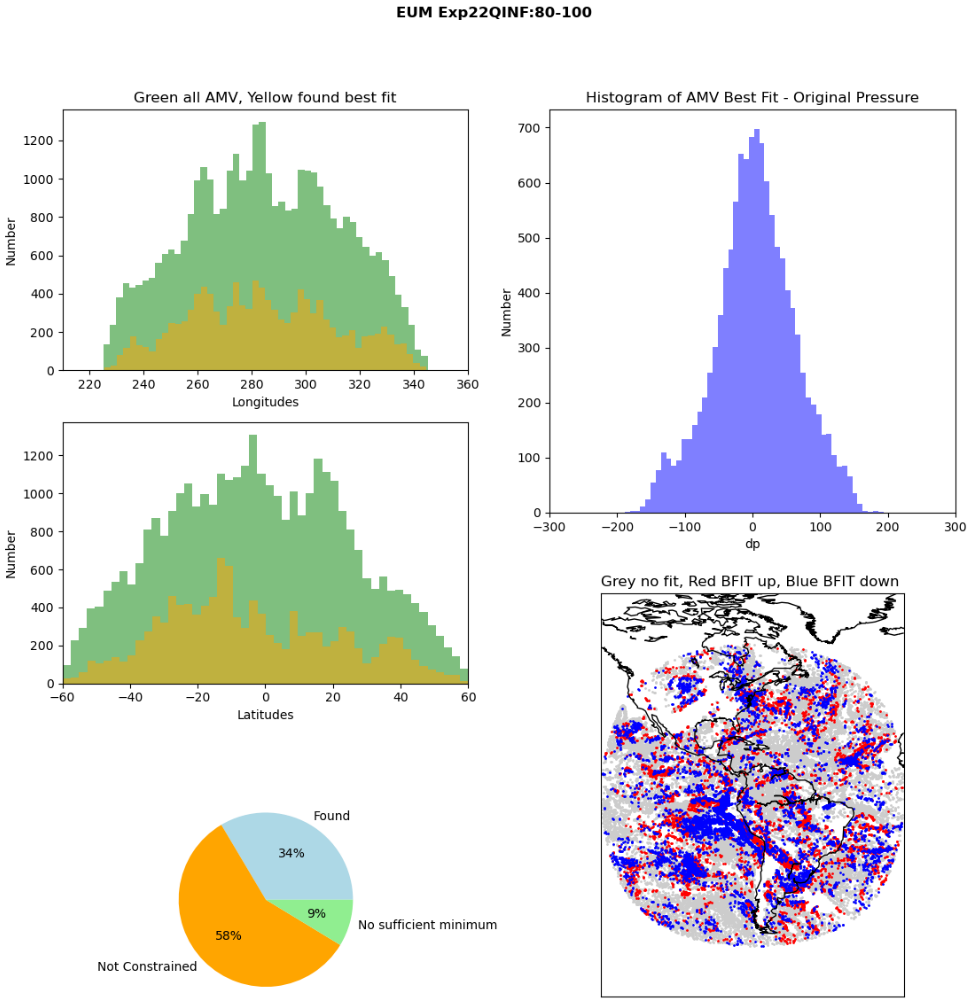

Figure 8-19: Experiment 2b. EUM (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

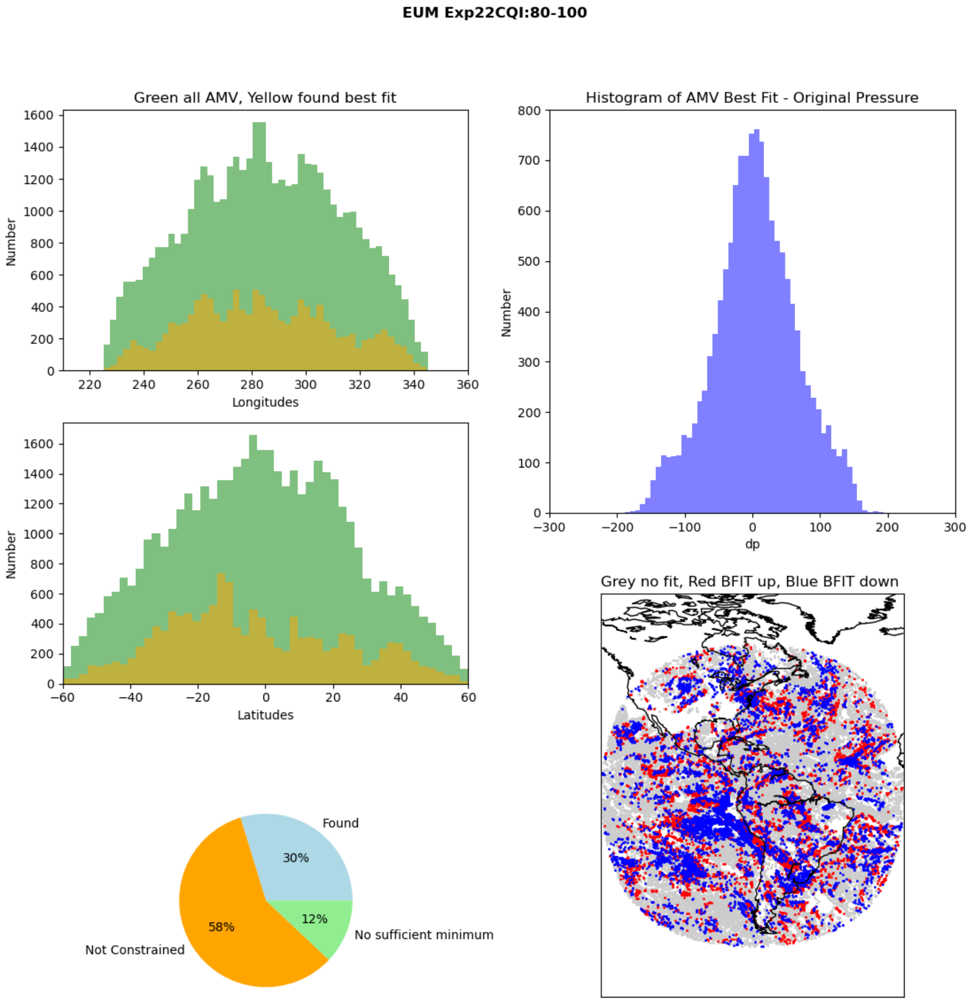

Figure 8-20: Experiment 2b. EUM (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

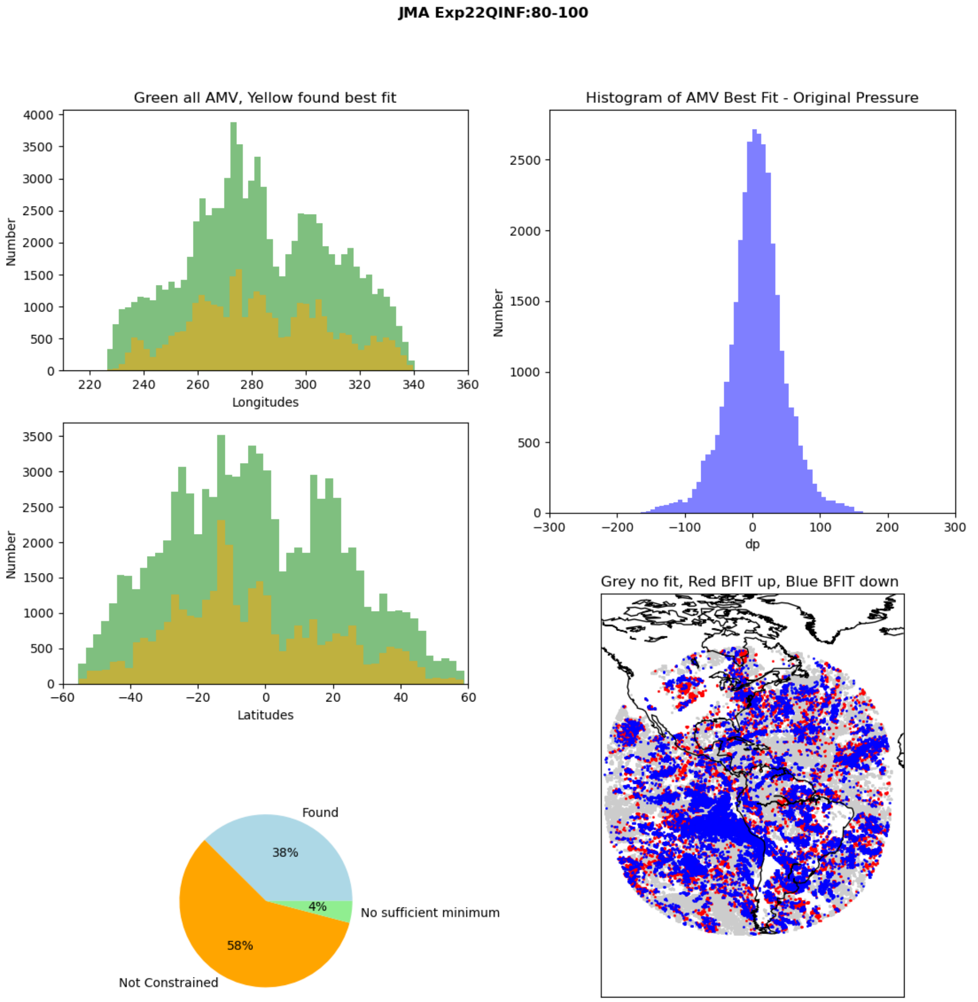

Figure 8-21: Experiment 2b. JMA (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

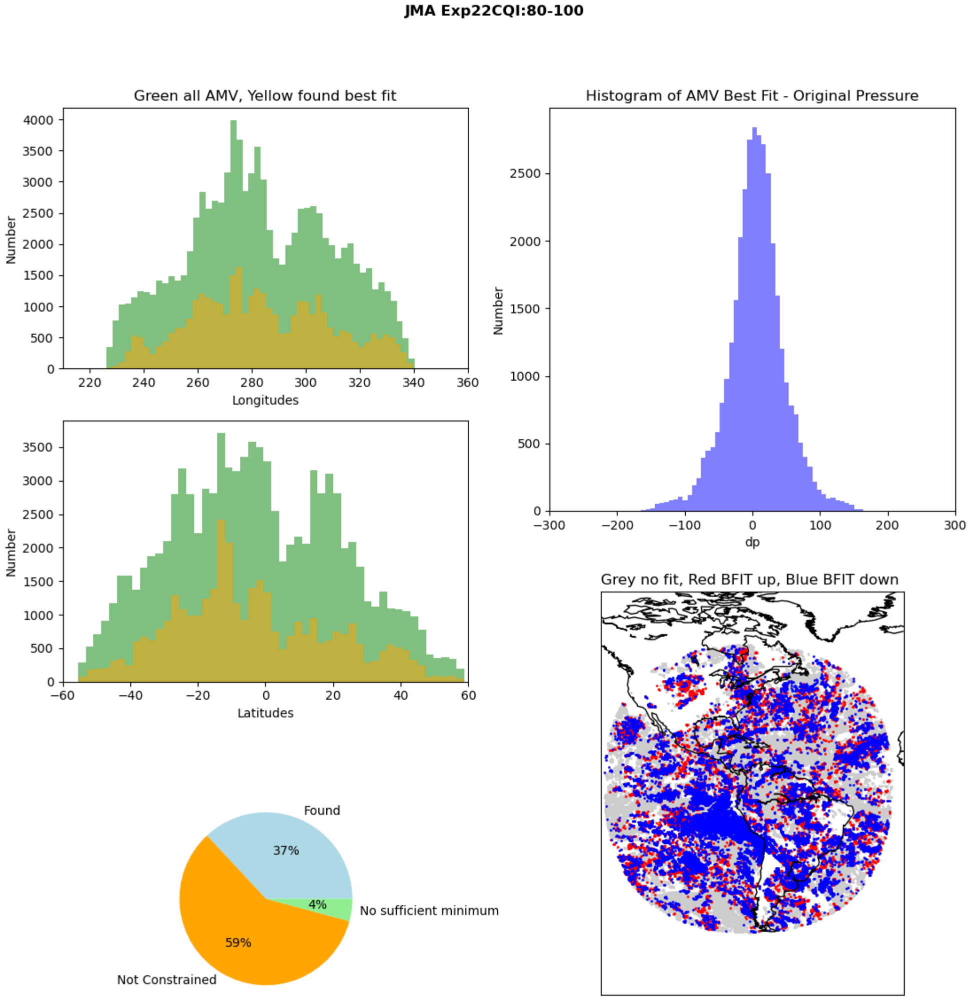

Figure 8-22: Experiment 2b. JMA (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

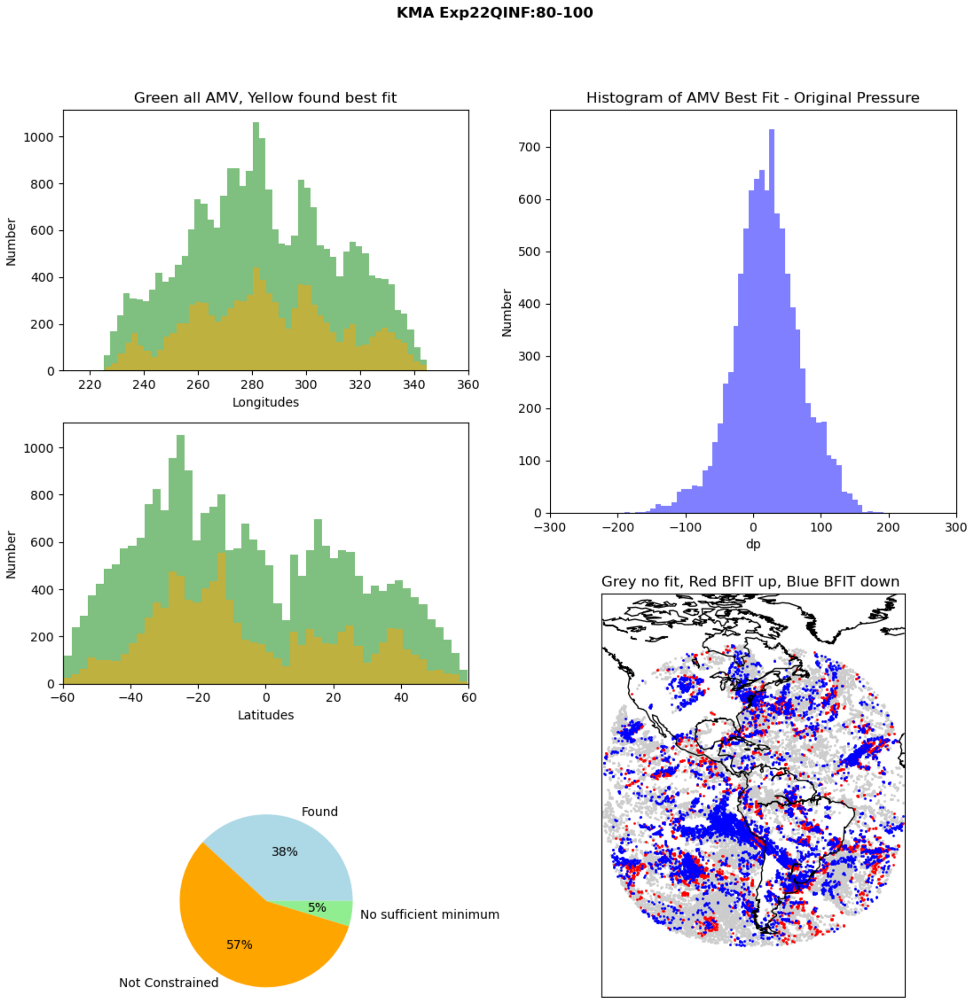

Figure 8-23: Experiment 2b. KMA (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

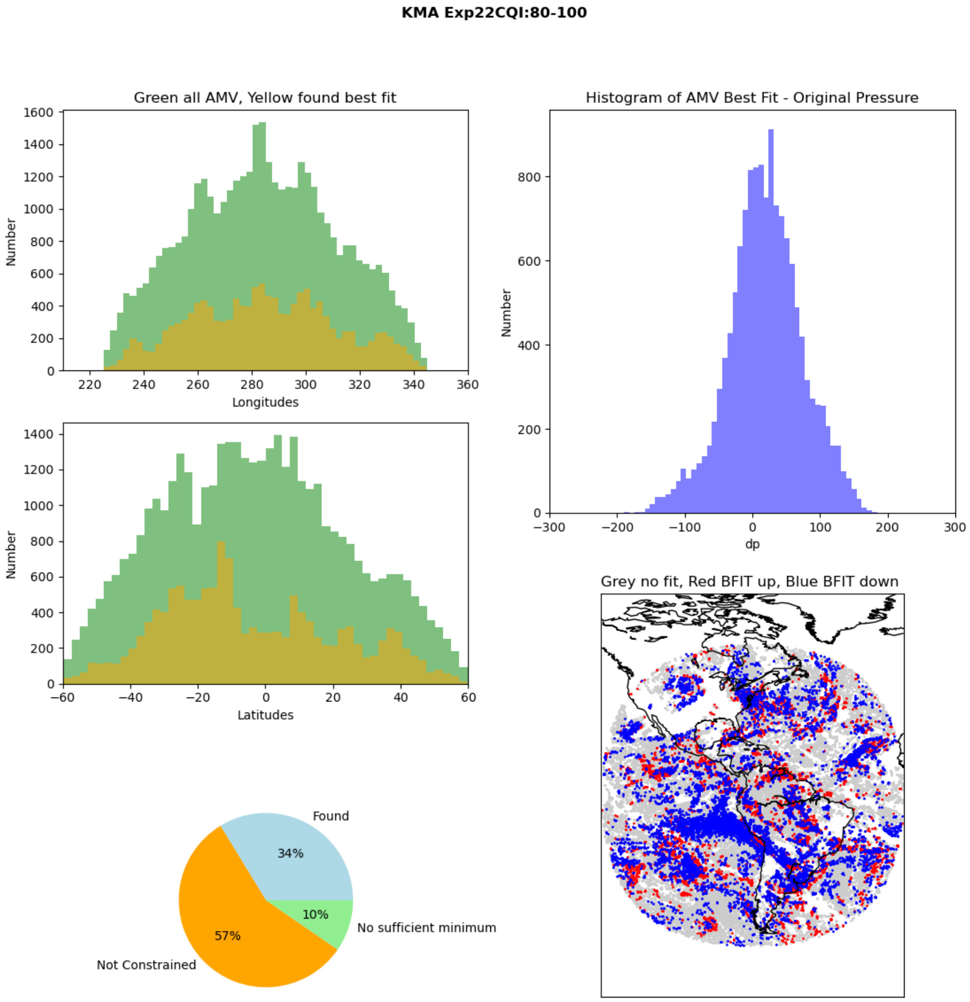

Figure 8-24: Experiment 2b. KMA (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

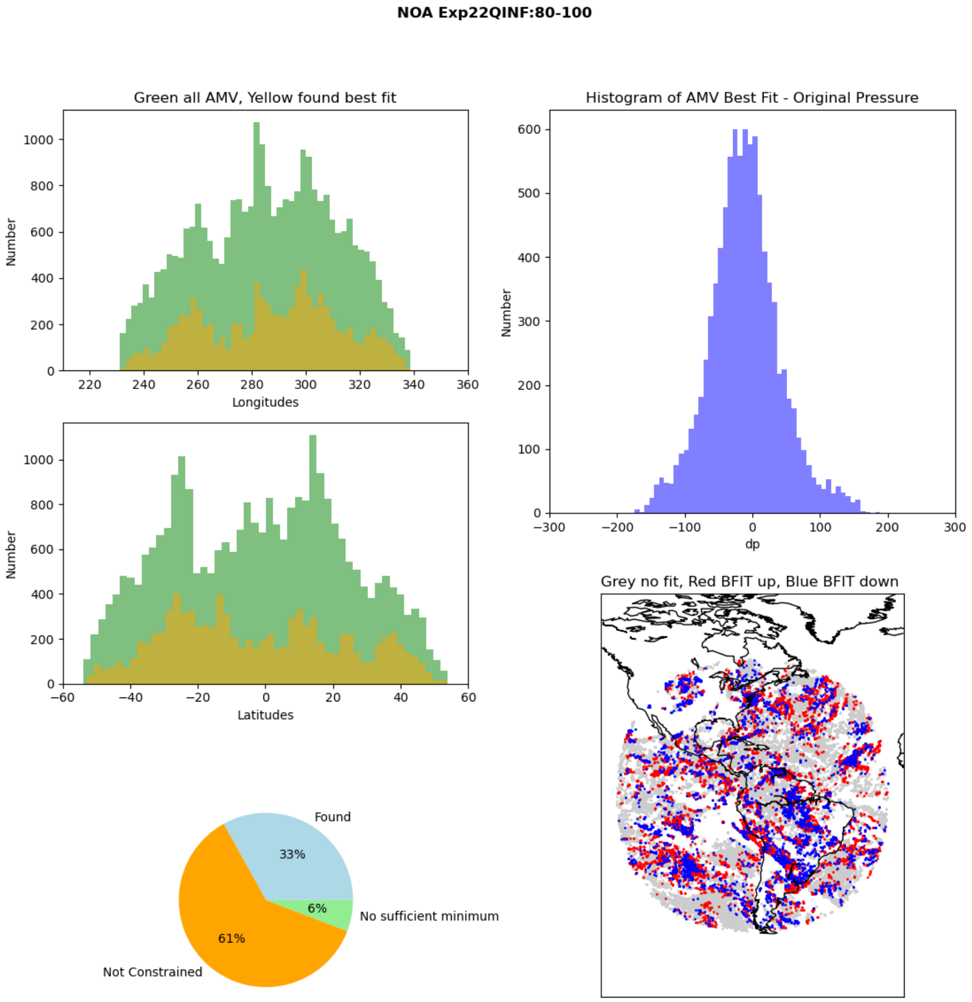

Figure 8-25: Experiment 2b. NOA (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

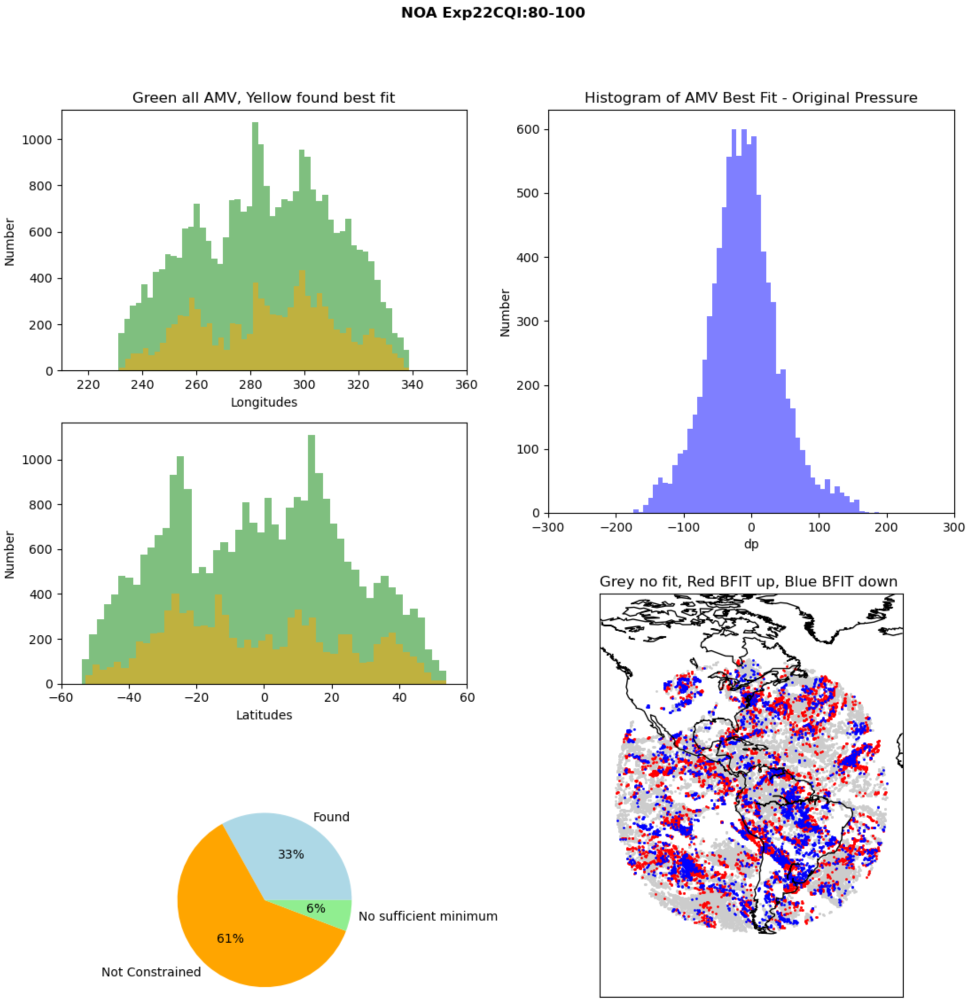

Figure 8-26: Experiment 2b. NOA (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

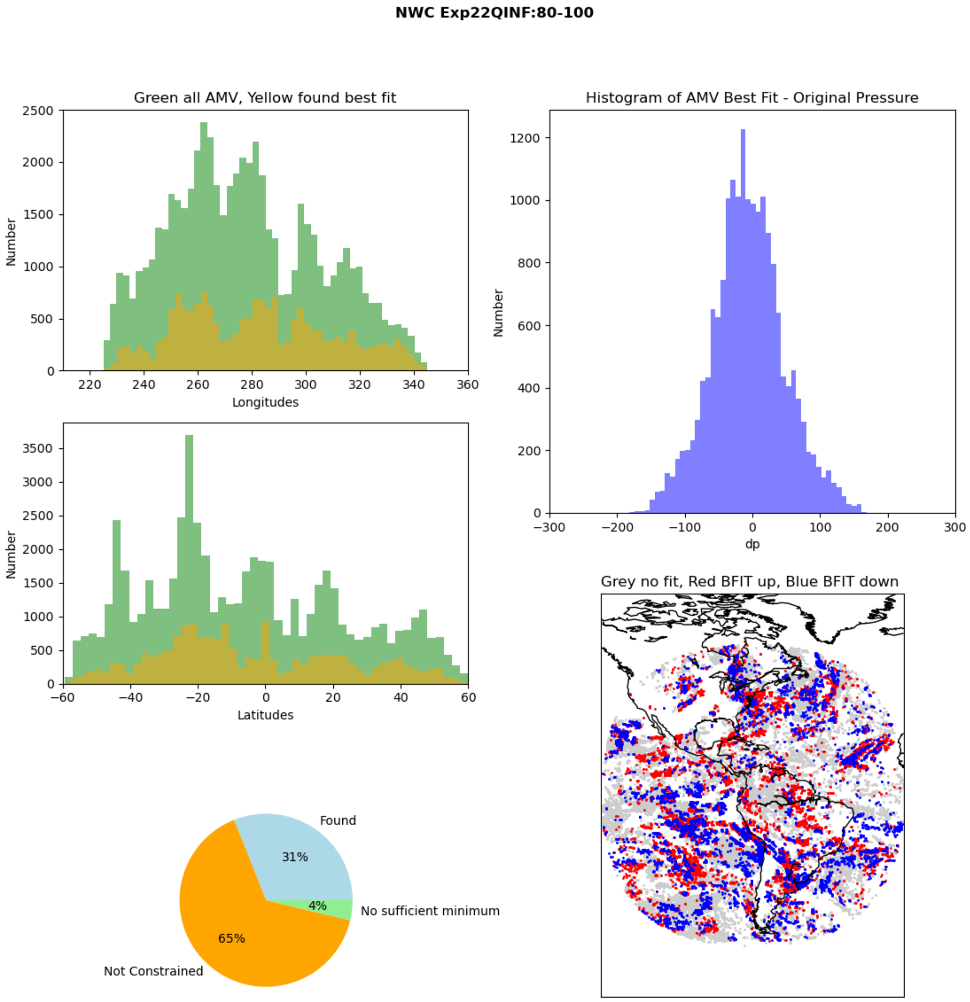

Figure 8-27: Experiment 2b. NWC (QINF >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

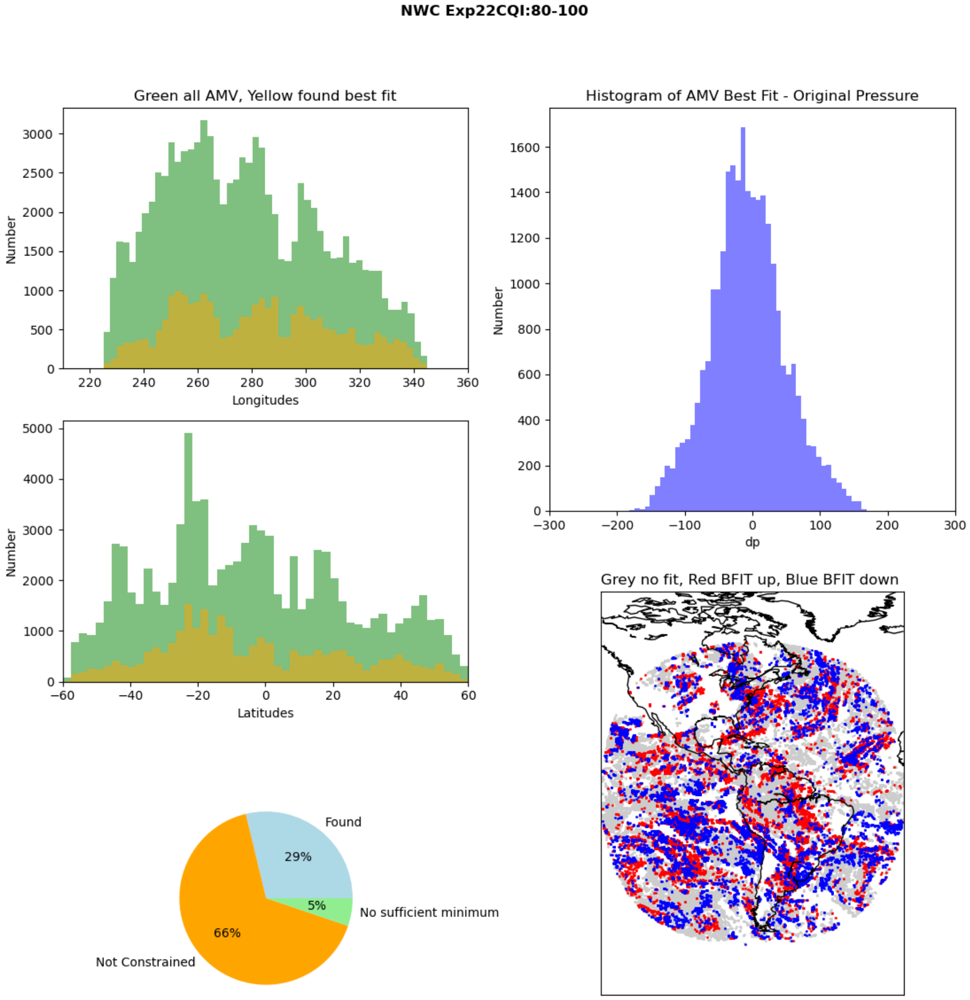

Figure 8-28: Experiment 2b. NWC (CQI >= 80): Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Latitude (upper-left); Distribution of all AMVs (green) and Best Fit AMVs (gold) vs. Longitude (middle left); Percent of AMVs used in Best Fit (Found) and those that didn't meet criteria (Not Constrained, No sufficient minimum) (lower-left). Frequency of pressure difference "Best Fit – original AMV pressure" (upper-right); spatial distribution of Best Fit modified AMVs (color code by Best Fit height adjustment) (lower-right).

g) CQI evaluation: Experiment 2b

The evaluation shown in Chapter 7g) for the AMV extraction with common configuration for all AMV centres, is repeated here for Experiment 2b) with the specific operational configuration for each AMV centre, to check if the behaviour of the CQI with the AMV specific configuration is similar or somehow different.

Through this, AMVs in Experiment 2b) are also compared against NWP analysis winds considering all 10-unit bins between 0% and 100% in the CQI. Results are shown in Table 8-27 to Table 8-33, one for each AMV dataset. The conclusions of this analysis are the following:

- The behaviour with the specific operational configuration in Experiment 2b) is very similar to the one seen in Chapter 7g) for the common configuration for all AMV datasets. The JMA AMVs are the only ones showing some differences, with AMVs having visibly better statistics for CQI > 50%, but visibly worse statistics for CQI < 50% (with even 1% of AMVs with RMSE larger than 10 m/s). No reason is found for this, taking even into account that the difference in AMV densities between Experiments 1 and 2b are not significant.
- In the rest of AMV centres, the quality for the worst AMVs with lowest CQI values, and for the best AMVs with highest CQI values are very similar to those shown for Experiment 1). EUM dataset shows again RMSE values larger than 10 ms^{-1} for the 20% of its AMVs, and KMA dataset again for 11% of its AMVs.
- With all this, the fact of using the common or the specific operational configuration in all AMV centres has a very small impact in the behaviour of the "Common quality control", and so all conclusions defined in Chapter 7g) for Experiment 1) are valid also in this case.

Finally, evaluating the usefulness of the "Common Quality control (CQI)" in the definition of good AMVs, it is clear that is is very useful for all centres, reducing progressively errors in all of them up to RMSE values of around 3-4 ms^{-1} for AMVs with CQI > 90%. However, it can also be seen here that for EUM and KMA, for which errors start at much higher levels, the smallest RMSE errors for CQI > 90% only reach values around 6 ms^{-1}.

Table 8-27: Experiment 2b: BRZ all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	170	21	5.98	2.86	6.62	5.73	6.49
10-19	395	53	6.48	3.17	7.21	6.03	6.94
20-29	715	89	6.05	2.94	6.73	5.59	6.41
30-39	965	154	5.56	2.84	6.24	5.05	5.87
40-49	2025	363	4.77	2.79	5.53	4.27	5.15
50-59	4127	740	4.45	2.71	5.21	3.97	4.83
60-69	5863	1149	3.96	2.67	4.78	3.49	4.40
70-79	5889	1088	3.66	2.56	4.46	3.23	4.09
80-89	8087	1531	3.44	2.57	4.30	3.02	3.92
90-100	17756	3826	3.12	2.53	4.02	2.69	3.62

Table 8-28: Experiment 2b: EUM all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	3014	53	58.94	43.03	72.98	58.84	72.97
10-19	1210	103	35.87	40.06	53.77	35.50	53.73
20-29	1351	133	16.55	24.99	29.98	16.08	29.88
30-39	2441	411	11.19	19.23	22.25	10.56	22.10
40-49	2282	355	8.85	14.26	16.78	8.26	16.61
50-59	3425	534	7.72	9.00	11.86	7.08	11.57
60-69	3608	623	6.00	5.88	8.41	5.39	8.05
70-79	4671	947	5.64	5.36	7.78	4.98	7.36
80-89	6775	1363	4.99	4.86	6.97	4.41	6.58
90-100	38863	12069	4.14	4.61	6.19	3.42	5.66

Table 8-29: Experiment 2b: JMA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	2	0	8.85	4.08	9.74	8.85	9.74
10-19	5	0	8.86	8.20	12.07	8.86	12.07
20-29	9	0	20.18	22.68	30.36	20.18	30.36
30-39	136	23	19.49	27.95	34.08	19.09	34.02
40-49	1430	303	15.25	22.97	27.57	14.79	27.48
50-59	1515	318	5.30	6.49	8.38	4.84	8.11
60-69	3160	724	3.79	3.78	5.35	3.38	5.05
70-79	5016	1255	2.97	2.09	3.63	2.58	3.30
80-89	9842	2656	2.63	1.86	3.22	2.29	2.90
90-100	84878	32348	2.31	1.88	2.98	1.90	2.57

Table 8-30: Experiment 2b: KMA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	1989	52	30.21	17.69	35.01	30.03	34.97
10-19	684	37	18.99	15.99	24.83	18.68	24.74
20-29	865	75	14.36	14.39	20.33	13.91	20.18
30-39	1248	147	15.24	15.02	21.40	14.74	21.25
40-49	1607	213	10.02	10.91	14.82	9.54	14.65
50-59	2930	418	8.36	8.29	11.78	7.79	11.52
60-69	2703	506	5.95	5.92	8.39	5.32	7.96
70-79	3468	702	5.37	5.09	7.40	4.79	7.02
80-89	5583	1308	4.85	4.70	6.75	4.17	6.23
90-100	35371	12508	4.00	4.19	5.79	3.17	5.16

Table 8-31: Experiment 2b: NOA all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	96	11	6.21	2.43	6.67	5.70	6.29
10-19	119	14	5.56	2.53	6.11	5.16	5.85
20-29	250	38	5.53	2.65	6.14	5.01	5.78
30-39	353	64	5.21	2.79	5.91	4.66	5.56
40-49	675	125	4.73	2.63	5.41	4.20	5.03
50-59	1223	236	4.66	2.73	5.40	4.06	4.91
60-69	1593	333	4.40	2.71	5.17	3.82	4.71
70-79	1879	454	3.98	2.58	4.74	3.34	4.18
80-89	3173	813	3.78	2.49	4.52	3.15	3.99
90-100	24883	8468	3.05	2.45	3.91	2.39	3.28

Table 8-32: Experiment 2b: NWC all AMVs compared to background grid: NWP analysis wind. N = total number of AMVs; BFN = number of AMVs with best fit level; VO = mean vector difference; RMSE = root mean square error; VOAF = mean vector difference after best fit; RMSEAF = root mean square error after best fit.

CQI	N	BFN	VO	StdDev	RMSE	VOAF	RMSEAF
0-9	0	0	-	-	-	-	-
10-19	3	1	8.87	3.00	9.37	6.83	8.35
20-29	47	12	6.69	3.91	7.75	5.45	6.96
30-39	77	6	5.47	3.70	6.61	5.12	6.37
40-49	169	31	5.30	3.84	6.54	4.65	6.06
50-59	697	158	4.64	3.53	5.83	3.96	5.22
60-69	1395	283	4.49	3.28	5.56	3.93	5.13
70-79	2555	618	4.08	3.08	5.11	3.43	4.51
80-89	6097	1449	3.68	2.79	4.62	3.12	4.09
90-100	85386	24868	2.91	2.53	3.86	2.33	3.25

9. Experiment 3

a) Approach

AMV producers extract clear air AMVs with GOES-16/ABI 6.2 µm water vapour channel using their operational configuration for clear air AMV calculation; three images 10 minutes apart (11:20, 11:30 and 11:40 UTC) are used for this procedure.

Results are compared with those in Experiment 4, doing the same but with images 20 minutes apart (11:10, 11:30 and 11:50 UTC). As already said, the use of two different time steps in Experiments 3 and 4, not considered in the previous AMV Intercomparison studies, is good to detect in the different AMV datasets if a different time step has different implications.

AMVs are provided by all AMV processing centres except JMA, which is not calculating operationally clear air AMVs. AMVs in both experiments are compared with aircraft wind data and ADM-Aeolus lidar wind profiles obtained with Rayleigh scattering (optimal option for clear air features).

To keep the structure similar to the one shown in Chapters 7 and 8 for Experiments 1 and 2, in this chapter 9 for Experiment 3 (and also in chapter 10 for Experiment 4) the following equivalent contents will be shown:

a) Approach
b) Parameter distributions
c) Collocation plots

This way, an equivalent analysis can be done for the clear air AMVs obtained in these two experiments, which have very different characteristics to the cloudy AMVs obtained in previous experiments.

The specific results obtained in the comparison of the AMV datasets in both experiments with Aeolus Doppler Wind Lidar (DWL) wind profiles and Aircraft wind data are shown respectively in chapters 11 and 12.

b) Parameter distributions

As in previous chapters, for each one of the AMV datasets a summary of the different AMV parameters (number of AMVs, distribution in high/medium/low layer, speed, and pressure distributions in the whole troposphere and the three layers) is shown. Four different tables are shown for each AMV dataset, related to four different Quality index thresholds: Quality index without forecast (QINF) >= 50% and >= 80%, and Common Quality Index (CQI) >= 50% and >= 80%.

Comparing the values of the different parameters in Tables 9-1 to 9-4:

- The total number of AMVs generally ranges from 700 in NOA to 39,000 for KMA (considering all AMVs) and from 300 in NOA to 5,000 in KMA (considering CQI >= 80%). This reflects the greater variability in the calculation process of clear air AMVs in the different centres, which is less homogenized than the calculation process of cloudy AMVs (actually this is the first time that clear air AMVs are included in the AMV intercomparisons).
  In any case, the fact that KMA calculates a number of clear air AMVs which is 50 times larger than the one for NOA seems a excessive difference, and some coordination in the way clear air AMVs are calculated by the different centres seems necessary.
- Considering CQI >= 80%, the maximum speed ranges from 34 ms^{-1} to 78 ms^{-1}, with an outlier of 115 ms^{-1} in EUM. The mean speed ranges between 11 ms^{-1} for BRZ and 16 ms^{-1} for KMA.
- Considering CQI >= 80%, the minimum pressure ranges between 50 and 270 hPa. The maximum pressure ranges between 400 hPa and 545 hPa, although here two centres have a limit in clear air AMVs not to be lower than 400 hPa (KMA and NWC).
- Related to this, all centres concentrate at least a 99% of all clear air AMVs in the high layer, except for EUM which shows a 27% of AMVs in the medium layer.

The “AMV parameter distribution histograms” in Chapter 17 (shown for Experiment 3 in Figure 17-49 to Figure 17-58) complement this information, with histograms showing the distribution of AMV speed, direction, pressure and Quality index values using both Quality index thresholds.
In all cases, a map is also included showing the geographical coverage of each AMV dataset, using three colour codes: green dots for AMVs with Quality Index >= 80%, blue dots for AMVs with Quality index >= 50% and red dots for AMVs with Quality index < 50%.

Major observations in the variable histograms for the different centres show:

- Considering the speed, there are small differences. Histogram maxima are around 10 ms^{-1} for all centres except EUM, which shows a maximum for slower speeds. The concentration of AMVs around the speed maximum is generally small, but higher for KMA and EUM. The concentration of AMVs falls quickly for higher speeds in all centres except NWC, for which it is still important up to 20 ms^{-1}. The maximum in the speed histogram is around 35 ms^{-1} for all centres except KMA and NWC, for which it is around 50 ms^{-1}.

- Considering the direction histogram EUM, KMA and NWC show two clear maximums for easterly and westerly winds. For BRZ and NOA the westerly wind maximum is less clear, showing more than one maximum around the westerly direction.
- Considering the pressure histogram, all centres show a maximum around 300 hPa. The EUM maximum is however lower, and the histogram reaches also lower pressure values.
- Considering the Common Quality Control histogram, all centres show a maximum near 100% with similar frequencies for lower values. NWC is the exception here, with frequencies reducing progressively for lower QI values.
- Considering the specific Quality Control without forecast histogram, a similar distribution is shown in general, being the exceptions KMA (for which the maximum frequency is around 65%), and NWC (for which the frequency reduction below 100% is less significant).

Table 9-1: Experiment 3 statistical summary of AMV datasets for QINF >= 50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13233	7105	-	736	39575	10395
QI>=50	5844	5761	-	588	15150	7397
SPD_min	2.50	3.76	-	3.07	2.50	2.51
SPD_max	72.39	37.16	-	36.99	74.27	54.71
SPD_mean	12.49	11.04	-	11.57	16.85	15.14
P_min	265.36	131.81	-	260.02	180.00	245.00
P_max	449.92	459.65	-	448.98	400.00	399.00
P_mean	366.88	276.69	-	309.50	263.85	309.91
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	25.80	0.28	-	0.68	0.00	0.00
High_winds	74.20	99.72	-	99.32	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.51	4.05	-	3.39	-	-
Mid_SPD_max	43.26	11.44	-	24.47	-	-
Mid_SPD_mean	12.73	8.01	-	12.13	-	-
Mid_P_min	400.00	400.49	-	400.11	-	-
Mid_P_max	449.92	459.65	-	448.98	-	-
Mid_P_mean	422.07	427.87	-	436.57	-	-
High_SPD_min	2.50	3.76	-	3.07	2.50	2.51
High_SPD_max	72.39	37.16	-	36.99	74.27	54.71
High_SPD_mean	12.40	11.05	-	11.57	16.85	15.14
High_P_min	265.36	131.81	-	260.02	180.00	245.00
High_P_max	399.98	399.07	-	398.83	400.00	399.00
High_P_mean	347.69	276.27	-	308.62	263.85	309.91

Table 9-2: Experiment 3 statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13233	7105	-	736	39575	10395
QI>=50	9796	6595	-	588	23665	10134
SPD_min	2.50	3.76	-	3.07	2.50	2.51
SPD_max	114.86	37.56	-	36.99	95.04	62.22
SPD_mean	12.01	11.71	-	11.57	14.72	14.58
P_min	262.65	50.00	-	260.02	180.00	239.00
P_max	544.77	459.65	-	448.98	400.00	399.00
P_mean	367.24	279.50	-	309.50	267.48	309.98
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	27.11	0.44	-	0.68	0.00	0.00
High_winds	72.89	99.56	-	99.32	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.51	4.05	-	3.39	-	-
Mid_SPD_max	57.91	15.07	-	24.47	-	-
Mid_SPD_mean	11.98	9.66	-	12.13	-	-
Mid_P_min	400.00	400.49	-	400.11	-	-
Mid_P_max	544.77	459.65	-	448.98	-	-
Mid_P_mean	429.52	422.23	-	436.57	-	-
High_SPD_min	2.50	3.76	-	3.07	2.50	2.51
High_SPD_max	114.86	37.56	-	36.99	95.04	62.22
High_SPD_mean	12.02	11.72	-	11.57	14.72	14.58
High_P_min	262.65	50.00	-	260.02	180.00	239.00
High_P_max	399.98	399.07	-	398.83	400.00	399.00
High_P_mean	344.08	278.87	-	308.62	267.48	309.98

Table 9-3: Experiment 3 statistical summary of AMV datasets for QINF >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13233	7105	-	736	39575	10395
QI>=80	2867	3509	-	334	5458	3387
SPD_min	2.51	3.76	-	3.09	2.54	2.54
SPD_max	51.90	30.71	-	34.24	74.27	54.71
SPD_mean	13.70	10.44	-	12.31	22.00	16.73
P_min	273.37	188.59	-	261.47	180.00	248.00
P_max	449.92	459.65	-	400.11	400.00	399.00
P_mean	369.62	273.52	-	310.62	255.15	308.46
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	27.07	0.14	-	0.30	0.00	0.00
High_winds	72.93	99.86	-	99.70	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.53	4.05	-	17.13	-	-
Mid_SPD_max	41.61	8.05	-	17.13	-	-
Mid_SPD_mean	14.44	6.34	-	17.13	-	-
Mid_P_min	400.00	405.28	-	400.11	-	-
Mid_P_max	449.92	459.65	-	400.11	-	-
Mid_P_mean	421.13	436.09	-	400.11	-	-
High_SPD_min	2.51	3.76	-	3.09	2.54	2.54
High_SPD_max	51.90	30.71	-	34.24	74.27	54.71
High_SPD_mean	13.42	10.45	-	12.30	22.00	16.73
High_P_min	273.37	188.59	-	261.47	180.00	248.00
High_P_max	399.97	399.07	-	398.83	400.00	399.00
High_P_mean	350.50	273.28	-	310.35	255.15	308.46

Table 9-4: Experiment 3 statistical summary of AMV datasets for CQI >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13233	7105	-	736	39575	10395
QI>=80	5923	4147	-	334	14516	7838
SPD_min	2.50	3.76	-	3.09	2.50	2.51
SPD_max	114.86	33.74	-	34.24	78.48	62.22
SPD_mean	12.85	10.98	-	12.31	16.43	14.95
P_min	271.47	50.00	-	261.47	180.00	245.00
P_max	544.77	459.65	-	400.11	400.00	399.00
P_mean	368.79	274.62	-	310.62	264.98	309.95
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	27.45	0.12	-	0.30	0.00	0.00
High_winds	72.55	99.88	-	99.70	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.51	4.05	-	17.13	-	-
Mid_SPD_max	51.04	8.73	-	17.13	-	-
Mid_SPD_mean	12.94	6.56	-	17.13	-	-
Mid_P_min	400.00	402.51	-	400.11	-	-
Mid_P_max	544.77	459.65	-	400.11	-	-
Mid_P_mean	429.09	435.54	-	400.11	-	-
High_SPD_min	2.50	3.76	-	3.09	2.50	2.51
High_SPD_max	114.86	33.74	-	34.24	78.48	62.22
High_SPD_mean	12.81	10.98	-	12.30	16.43	14.95
High_P_min	271.47	50.00	-	261.47	180.00	245.00
High_P_max	399.98	399.07	-	398.83	400.00	399.00
High_P_mean	345.97	274.42	-	310.35	264.98	309.95

c) Collocation plots

Plots of collocated AMV parameters from the different algorithms are shown in Figure 9-1 and Figure 9-3 to measure the respective differences (from top to bottom: speed, direction, pressure, and Quality Index).
AMV pressure scatter plots comparing the NWC AMV pressure with the pressure of all other collocated AMVs are also shown in Figure 9-2 and Figure 9-4 to detect better the differences in the different AMV height assignment processes.
In both cases, a distance threshold of 55 km between AMVs and two quality control thresholds are used for this: “Quality index without forecast (QINF)” >= 50% and “Common Quality Index (CQI)” >= 50%. The thresholds are kept low to still detect the variability of the parameters in the different AMV datasets.

There are around 470 collocated AMVs considering the QINF threshold, and around 760 collocated AMVs considering the CQI threshold. The plots of collocated parameters (Figure 9-1 and Figure 9-3) show:

- There is a relatively good agreement in AMV speed between the different centres, with a few fast outliers for each centre, and a few slow outliers for BRZ (green dots) and NOA (black dots).
- There is a general agreement in AMV direction between the different centres, with some outliers by KMA (red dots) and BRZ (green dots).
- There are more differences in the AMV pressure for the different centres, with lowest-level AMVs generally related to EUM (blue dots) and highest-level AMVs generally related to KMA (red dots). The AMV pressure of the three other centres coordinates better.
- The differences in the Quality control values for the AMVs in the different centres are much more significant, for both QINF and CQI. Visually there seems to be no relationship between each other. This can be explained by the fact that the Quality control of each AMV does not only depend on itself, but also on the AMVs it is compared to in the Quality control, and they can be very different for each collocated AMV.

Considering the AMV pressure scatter plots (Figure 9-2 and Figure 9-4), AMV pressures from BRZ, NOA and NWC relate in the diagonal (showing a correspondence in their values), with higher-level outliers related to KMA (red dots), and lower-level outliers related to EUM (pink dots).

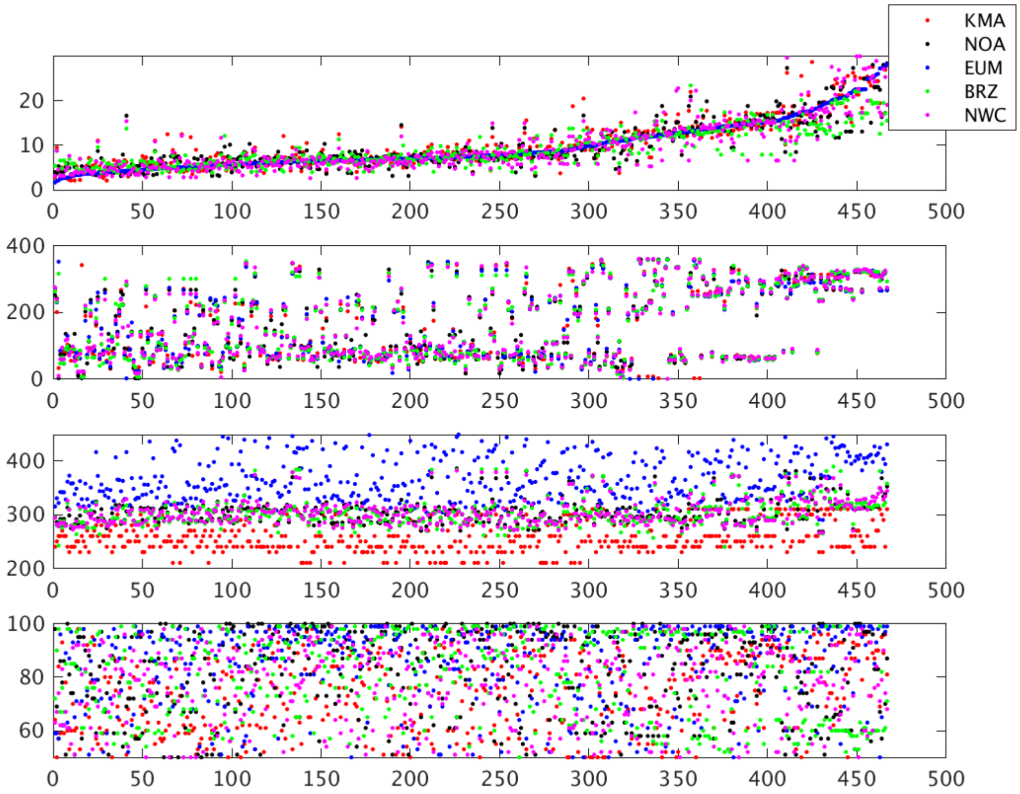

Figure 9-1: Experiment 3 (QINF >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

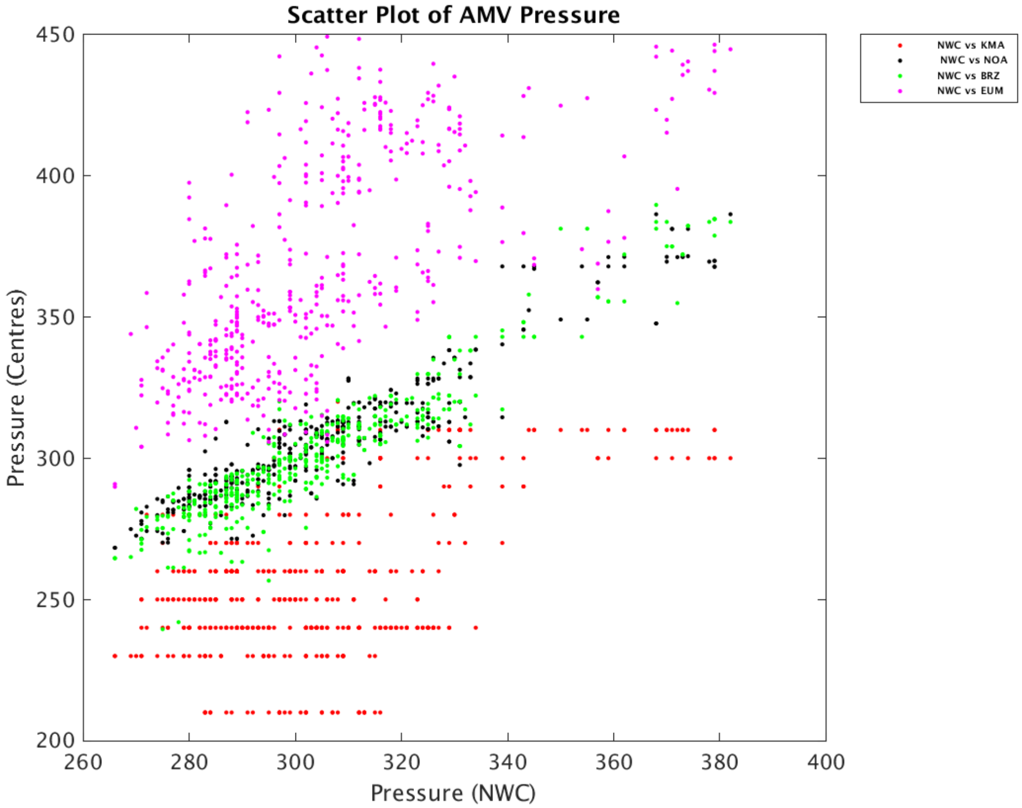

Figure 9-2: Experiment 3 (QINF >= 50). Scatter plot of AMV pressure for each center vs. NWC pressure.

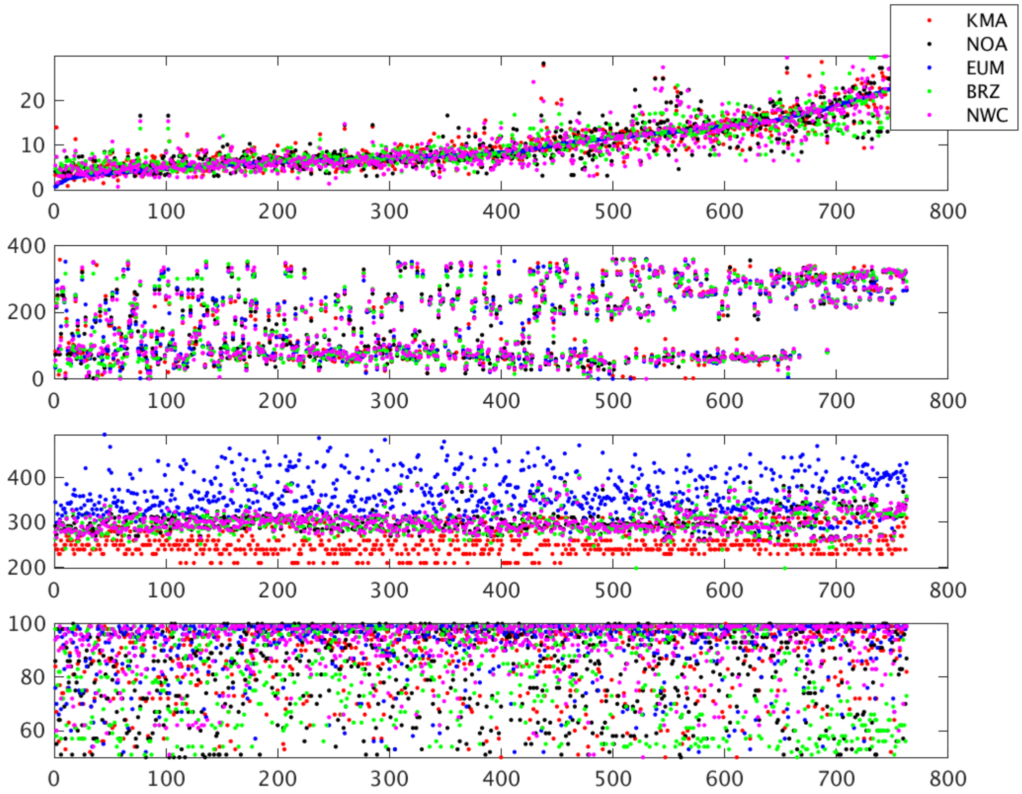

Figure 9-3: Experiment 3 (CQI >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

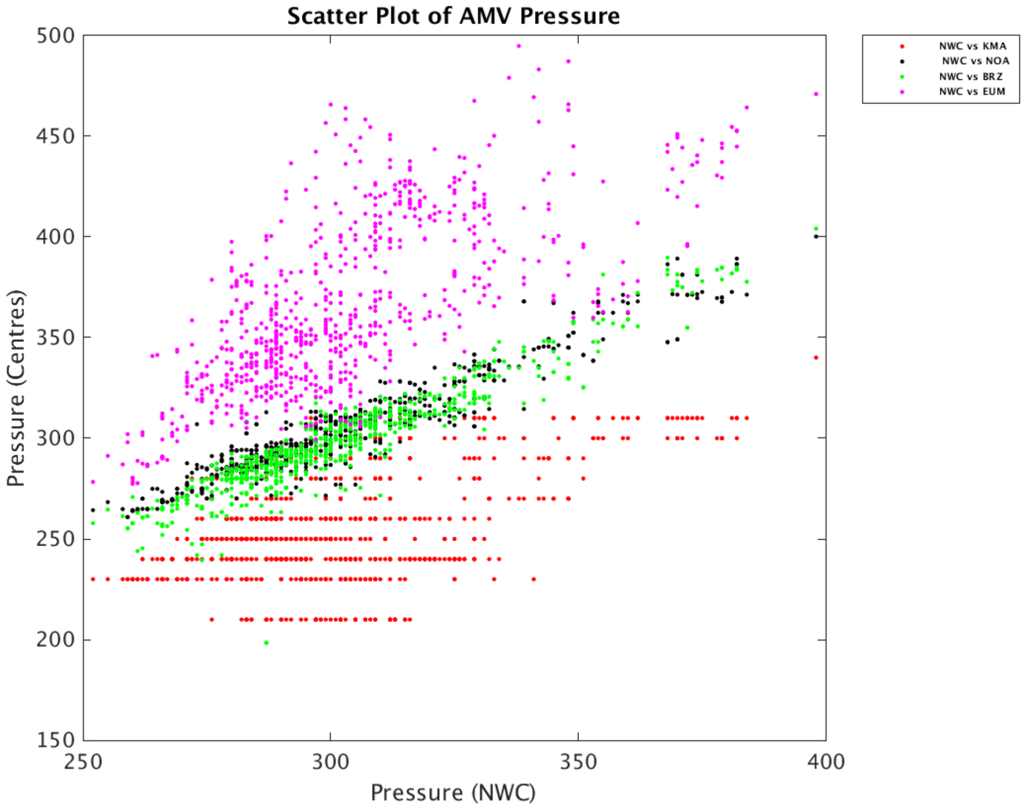

Figure 9-4: Experiment 3 (CQI >= 50). Scatter plot of AMV pressure for each center vs. NWC pressure.

10. Experiment 4

a) Approach

AMV producers extract clear air AMVs with GOES-16/ABI 6.2 µm water vapor channel using their operational configuration for clear air AMV calculation; three images 20 minutes apart (11:10, 11:30 and 11:50 UTC) are used for this procedure.

As already said, results are compared with those in Experiment 3, doing the same but with images 10 minutes apart (11:20, 11:30 and 11:40 UTC). The use of two different time steps in Experiments 3 and 4, not considered in the previous AMV Intercomparison studies, is good to detect in the different AMV datasets if a different time step has different implications.

Again, AMVs are provided by all AMV processing centres except JMA, which is not calculating operationally clear air AMVs. And AMVs are compared with aircraft wind data and ADM-Aeolus lidar wind profiles obtained with Rayleigh scattering (optimal option for clear air features).

Similar contents to those in chapter 9 will be shown in this chapter:

a) Approach
b) Parameter distributions
c) Collocation plots

The specific results obtained in the comparison of the AMV datasets in both experiments with Aeolus Doppler Wind Lidar (DWL) wind profiles and Aircraft wind data are shown respectively in chapters 11 and 12.

b) Parameter distributions

As in previous chapters, for each one of the AMV datasets a summary of the different AMV parameters (number of AMVs, distribution in high/medium/low layer, speed and pressure distributions in the whole troposphere and the three layers) is shown. Four different tables are shown for each AMV dataset, related to four different Quality Index thresholds: QINF >= 50% and >= 80%, and CQI >= 50% and >= 80%.

Comparing the values of the different parameters in Table 10-1 to Table 10-4 with those in Experiment 3 for clear air AMVs calculated with images 10 minutes apart:

- The total number of AMVs compared to those calculated in Experiment 3 is very similar, ranging from 500 in NOA to 40,000 for KMA (considering all AMVs). There are slight increments of 1% in the number of AMVs in EUM, BRZ and KMA, but reductions around 25% in NOA and around 50% in NWC, which are not logical and should be investigated.
- Considering CQI >= 80% the range in the number of AMVs goes from 200 in NOA to 10,000 in KMA, and the maximum speed ranges from 34 ms^{-1} to 75 ms^{-1}, without the outliers seen in than case for EUM. The mean speed ranges between 12 ms^{-1} for BRZ and 16 ms^{-1} for KMA. Both speed ranges are very similar to those seen in Experiment 3.
- Considering CQI >= 80%, the minimum pressure ranges between 159 and 273 hPa, without the high-level outliers seen in Experiment 3 for BRZ. The maximum pressure ranges between 384 hPa and 542 hPa, although here again two centres have a limit in clear air AMVs not to be lower than 400 hPa (KMA and NWC). Both pressure ranges are also similar to those seen in Experiment 3.
- Again, all centres concentrate at least a 99% of all clear air AMVs in the high layer, with the exception of EUM which shows a 28% of AMVs in the medium layer.

The “AMV parameter distribution histograms” in Chapter 17 (shown for Experiment 4 in Figure 17-59 to Figure 17-68) complement this information, with histograms showing the distribution of AMV speed, direction, pressure and Quality index values using both Quality index thresholds. A map also shows the geographical coverage of each AMV dataset, with green dots for AMVs with Quality index >= 80%, blue dots for AMVs with Quality index >= 50% and red dots for AMVs with Quality index < 50%.

Comparing the speed/direction/pressure/quality control histograms in Experiment 4 with those in Experiment 3 very few differences are seen, and the AMV calculation process seems to work the same way for all centres.

The only noticeable difference is related to the number of calculated AMVs, which through the slight increase of 1% seen in BRZ, EUM and KMA with images 20 minutes apart, a slight optimization in the calculation of water vapour AMVs with the longer 20-minute separation between images is seen (as also suggested for example by García-Pereda & Borde, 2014). In any case, as this reference also says, the optimal separation between images is different (shorter) for infrared and visible images, and for higher resolution images.

Related to this, the reductions in the number of AMVs around 25% in NOA and around 50% in NWC, are not logical and should be investigated.

Table 10-1: Experiment 4 statistical summary of AMV datasets for QINF >= 50.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13417	7162	-	562	39945	5227
QI>=50	4202	5903	-	421	11177	3560
SPD_min	2.50	3.75	-	3.06	2.50	2.53
SPD_max	74.97	38.07	-	45.92	65.64	61.31
SPD_mean	13.59	11.88	-	11.64	16.74	14.12
P_min	271.04	159.05	-	261.47	180.00	240.00
P_max	449.97	429.86	-	390.08	400.00	399.00
P_mean	367.66	280.95	-	311.08	262.48	307.75
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	25.89	0.78	-	0.00	0.00	0.00
High_winds	74.11	99.22	-	100.00	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.52	3.93	-	-	-	-
Mid_SPD_max	62.51	26.78	-	-	-	-
Mid_SPD_mean	14.17	17.11	-	-	-	-
Mid_P_min	400.01	400.10	-	-	-	-
Mid_P_max	449.97	429.86	-	-	-	-
Mid_P_mean	421.37	410.55	-	-	-	-
High_SPD_min	2.50	3.75	-	3.06	2.50	2.53
High_SPD_max	74.97	38.07	-	45.92	65.64	61.31
High_SPD_mean	13.39	11.84	-	11.64	16.74	14.12
High_P_min	271.04	159.05	-	261.47	180.00	240.00
High_P_max	399.95	398.93	-	390.08	400.00	399.00
High_P_mean	348.90	279.94	-	311.08	262.48	307.75

Table 10-2: Experiment 4 statistical summary of AMV datasets for CQI >= 50

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13417	7162	-	562	39945	5227
QI>=50	7548	6565	-	421	17543	5025
SPD_min	2.50	3.75	-	3.06	2.50	2.53
SPD_max	74.97	45.80	-	45.92	99.62	61.31
SPD_mean	13.54	12.36	-	11.64	15.35	13.98
P_min	271.04	159.05	-	261.47	180.00	240.00
P_max	550.40	432.40	-	390.08	400.00	399.00
P_mean	368.67	283.34	-	311.08	265.83	308.57
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	27.46	0.99	-	0.00	0.00	0.00
High_winds	72.54	99.01	-	100.00	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.51	3.93	-	-	-	-
Mid_SPD_max	73.09	26.78	-	-	-	-
Mid_SPD_mean	13.60	16.68	-	-	-	-
Mid_P_min	400.01	400.10	-	-	-	-
Mid_P_max	550.40	432.40	-	-	-	-
Mid_P_mean	429.59	411.69	-	-	-	-
High_SPD_min	2.50	3.75	-	3.06	2.50	2.53
High_SPD_max	74.97	45.80	-	45.92	99.62	61.31
High_SPD_mean	13.51	12.31	-	11.64	15.35	13.98
High_P_min	271.04	159.05	-	261.47	180.00	240.00
High_P_max	399.95	398.93	-	390.08	400.00	399.00
High_P_mean	345.60	282.05	-	311.08	265.83	308.57

Table 10-3: Experiment 4 statistical summary of AMV datasets for QINF >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13417	7162	-	562	39945	5227
QI>=80	1957	3954	-	218	4005	1749
SPD_min	2.51	3.75	-	3.25	2.62	2.57
SPD_max	54.64	38.07	-	34.81	60.52	61.31
SPD_mean	14.47	11.70	-	12.06	20.26	14.86
P_min	274.85	159.05	-	268.18	180.00	248.00
P_max	449.97	427.83	-	384.24	400.00	399.00
P_mean	369.58	277.06	-	311.40	254.80	307.82
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	28.00	0.68	-	0.00	0.00	0.00
High_winds	72.00	99.32	-	100.00	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.59	7.89	-	-	-	-
Mid_SPD_max	51.11	26.78	-	-	-	-
Mid_SPD_mean	15.20	17.70	-	-	-	-
Mid_P_min	400.01	400.63	-	-	-	-
Mid_P_max	449.97	427.83	-	-	-	-
Mid_P_mean	421.09	410.00	-	-	-	-
High_SPD_min	2.51	3.75	-	3.25	2.62	2.57
High_SPD_max	54.64	38.07	-	34.81	60.52	61.31
High_SPD_mean	14.19	11.66	-	12.06	20.26	14.86
High_P_min	274.85	159.05	-	268.18	180.00	248.00
High_P_max	399.82	398.93	-	384.24	400.00	399.00
High_P_mean	349.54	276.15	-	311.40	254.80	307.82

Table 10-4: Experiment 4 statistical summary of AMV datasets for CQI >= 80.

	EUM	BRZ	JMA	NOA	KMA	NWC
Total AMVs	13417	7162	-	562	39945	5227
QI>=80	4023	4586	-	218	10393	3772
SPD_min	2.50	3.75	-	3.25	2.51	2.53
SPD_max	74.97	38.07	-	34.81	65.01	61.31
SPD_mean	13.57	12.16	-	12.06	16.21	14.12
P_min	272.85	159.05	-	268.18	180.00	242.00
P_max	542.45	427.83	-	384.24	400.00	399.00
P_mean	369.25	279.29	-	311.40	262.50	307.58
Low_winds	0.00	0.00	-	0.00	0.00	0.00
Mid_winds	28.16	0.78	-	0.00	0.00	0.00
High_winds	71.84	99.22	-	100.00	100.00	100.00
Low_SPD_min	-	-	-	-	-	-
Low_SPD_max	-	-	-	-	-	-
Low_SPD_mean	-	-	-	-	-	-
Low_P_min	-	-	-	-	-	-
Low_P_max	-	-	-	-	-	-
Low_P_mean	-	-	-	-	-	-
Mid_SPD_min	2.52	7.57	-	-	-	-
Mid_SPD_max	51.11	26.78	-	-	-	-
Mid_SPD_mean	14.03	17.54	-	-	-	-
Mid_P_min	400.01	400.10	-	-	-	-
Mid_P_max	542.45	427.83	-	-	-	-
Mid_P_mean	429.51	410.96	-	-	-	-
High_SPD_min	2.50	3.75	-	3.25	2.51	2.53
High_SPD_max	74.97	38.07	-	34.81	65.01	61.31
High_SPD_mean	13.40	12.11	-	12.06	16.21	14.12
High_P_min	272.85	159.05	-	268.18	180.00	242.00
High_P_max	399.95	398.93	-	384.24	400.00	399.00
High_P_mean	345.62	278.25	-	311.40	262.50	307.58

c) Collocation plots

Again, plots of collocated AMV parameters from the different algorithms are shown in Figure 10-1 and Figure 10-3 to measure the respective differences (from top to bottom: speed, direction, pressure, and Quality Index).
AMV pressure scatter plots comparing the NWC AMV pressure with the pressure of all other collocated AMVs are also shown in Figure 10-2 and Figure 10-4 to detect better the differences in the different AMV height assignment processes.
In both cases, a distance threshold of 55 km between AMVs and two quality control thresholds are used for this: QINF >= 50% and CQI >= 50%. The thresholds are kept low to still detect the variability of the parameters in the different AMV datasets.

Comparing the AMV collocation plots of Experiment 4 with those for Experiment 3 (Figure 9-1 and Figure 9-3), the only difference is a small reduction in the amount of collocated AMVs: around 410 collocated AMVs considering the QINF threshold, and around 670 collocated AMVs considering the CQI threshold. Considering the different variables (speed, direction, pressure, and Quality Index), the collocation plots look very similar.
With this it is confirmed again that the fact of using images 10 minutes apart or 20 minutes apart has only an impact in the number of AMVs and very little in corresponding speeds, directions, pressure, and quality control values.

Considering the AMV pressure scatter plots of Experiment 4 with those for Experiment 3 (Figure 9-2 and Figure 9-4), we see again no visible differences as AMV pressure values behave similarly in both experiments.
In both figures, AMV pressures from BRZ, NOA and NWC relate to themselves in the diagonal (showing a correspondence in their values), with higher-level outliers related to KMA (red dots), and lower-level outliers related to EUM (pink dots).

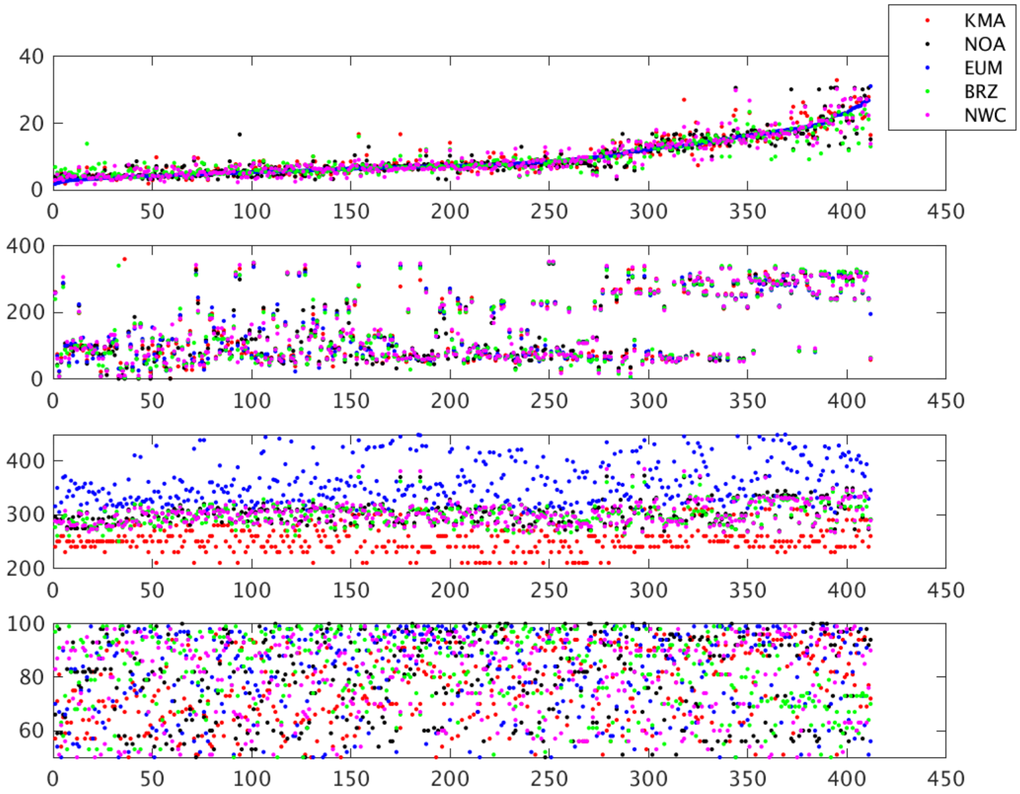

Figure 10-1: Experiment 4 (QINF >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

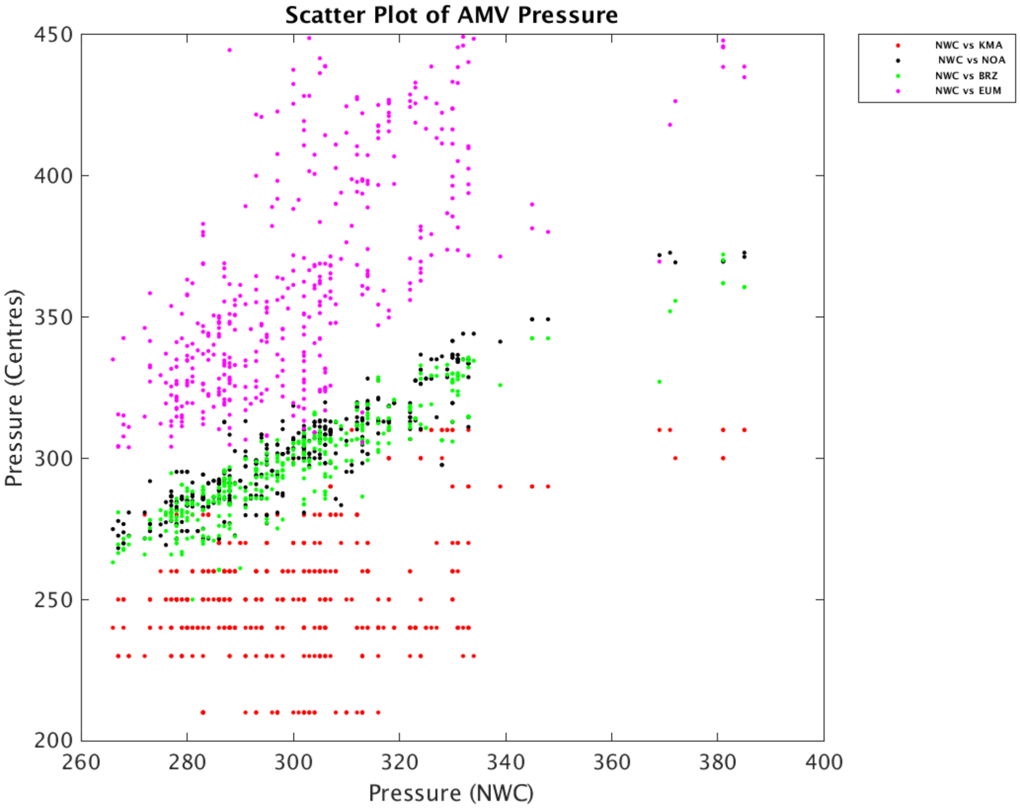

Figure 10-2: Experiment 4 (QINF >= 50). Scatter plot of AMV pressure for each center vs. NWC pressure.

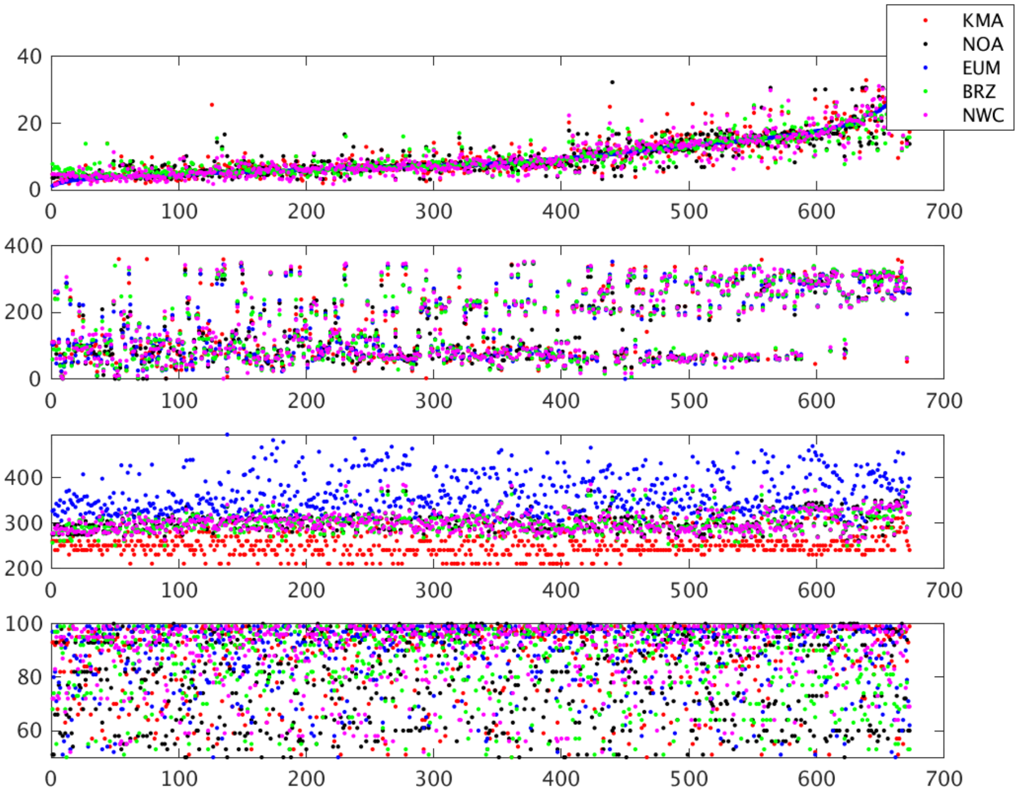

Figure 10-3: Experiment 4 (CQI >= 50). Plots of collocated AMVs of speed (top), direction (2nd), pressure (3rd), and QI (bottom) are color-coded based on legend in upper-right. The x-axis is AMV number.

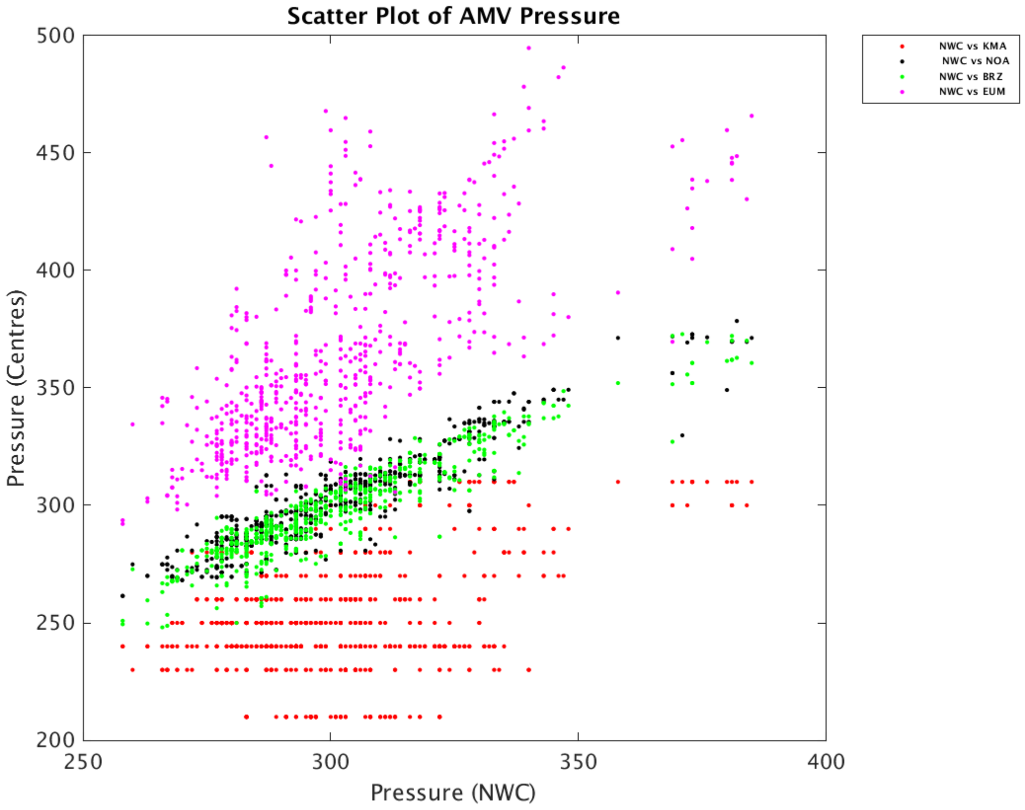

Figure 10-4: Experiment 4 (CQI >= 50). Scatter plot of AMV pressure for each center vs. NWC pressure.

11. Aeolus comparison

This comparison uses the standard AMV configuration defined by the individual producers, using their typical settings for target selection, target box size and search box size, and the height assignment of their choice. Image data with central image at 11:30 UTC, 20 October 2019 are used, which correspond to the time of an Aeolus pass that intersects with the GOES-16 coverage. Three different experiments are checked with Aeolus data:

- Experiment 2a: AMV producers extract infrared channel cloudy AMVs considering GOES-16/ABI IR Band 14 (11.2 µm) images, and using image times 11:20 to 11:40 UTC, with a 10-minute separation. Aeolus Mie winds are used here for the comparison.

- Experiment 3: AMV producers extract water vapor channel clear-sky AMVs considering GOES-16/ABI IR Band 8 (6.2 µm) images, and using image times 11:20 to 11:40 UTC, with a 10-minute separation. Aeolus Rayleigh winds are used here for the comparison.

- Experiment 4: AMV producers extract water vapor channel clear-sky AMVs considering GOES-16/ABI IR Band 8 (6.2 µm) images, and using image times 11:10 to 11:50 UTC, with a 20-minute separation. Aeolus Rayleigh winds are used here for the comparison.

JMA did not participate in experiments 3 and 4.

The AMV characteristics and distributions are summarized earlier in this report in Chapters 8, 9 and 10 respectively for Experiments 2a, 3, and 4.

Here it is needed to remark that only the AMV component parallel to the Aeolus horizontal line of sight (HLOS) wind can evaluated. Aeolus is not able to detect the wind, which is perpendicular to this horizontal line of sight.
The following three tables summarize the comparison of the HLOS-equivalent AMV speed with Aeolus HLOS wind speed, for these three experiments: Cloudy AMVs with 10-minute time interval, Clear AMVs with 10-minute time interval, and Clear AMVs with 20-minute time interval. They all are considered with CQI >= 80%. The producer with better result is BRZ in experiment 2a, and NOA in experiments 3 and 4. The producer with worse results is EUM in all of them.

For Experiment 2a (Table 11-1; cloudy, 10-minute time interval) the RMSE ranges from 4.2 to 5.2 ms^{-1}, with EUM having the largest value of 6.5 ms^{-1}. The greatest contributor to the higher RMSE is the larger standard deviation (Table

11-1), which is evident in the larger scatter of the EUM comparison wind speeds (Figure 11-4). Also, similarly higher RMSE values for EUM were seen in the rawinsonde comparisons (Table 8-17) with a value of 7.8 ms^{-1}, respectively.

The number of clear sky AMVs is greatly reduced compared to cloudy AMVs for all centres (between 3 times less for BRZ and 250 times less for NOA), so the statistics may not be meaningful. However, the trends in the statistics indicate:

- When compared to Aeolus HLOS winds, clear sky AMVs have generally larger RMSE values (Table 11-2) than cloudy AMVs (Table 11-1), which is expected as the water vapor features being tracked are more diffuse (less defined) than the cloud features.
- When the time interval between water vapor images is increased to 20 minutes, there is generally a slight decrease in RMSE (Table 11-3), which can be convenient for a better calculation of clear air water vapour AMVs.

Table 11-1: Experiment 2a. Statistics for cloudy 10-minute interval AMVs compared to Aeolus, with CQI >= 80. N = total number of AMVs and matched Aeolus; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N Aeolus	Mean	StdDev	RMSE
BRZ	1061	1075	1.40	4.03	4.26
EUM	4554	4570	0.19	6.56	6.56
JMA	9017	9043	-0.11	4.55	4.55
KMA	3576	3605	-0.28	5.06	5.07
NOA	2746	2754	-0.43	4.31	4.33
NWC	7347	7384	-0.38	5.20	5.21

Table 11-2: Experiment 3. Statistics for clear 10-minute interval AMVs compared to Aeolus, with CQI >= 80. N = total number of AMVs and matched Aeolus; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N Aeolus	Mean	StdDev	RMSE
BRZ	347	347	-1.25	5.56	5.70
EUM	325	325	0.47	7.89	7.90
JMA	-	-	-	-	-
KMA	676	676	1.16	6.57	6.67
NOA	11	11	-0.21	4.06	4.06
NWC	552	552	-1.28	4.64	4.81

Table 11-3: Experiment 4. Statistics for clear 20-minute interval AMVs compared to Aeolus, with CQI >= 80. N = total number of AMVs and matched Aeolus; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N Aeolus	Mean	StdDev	RMSE
BRZ	552	552	-1.28	4.64	4.81
EUM	260	260	-0.26	6.60	6.60
JMA	-	-	-	-	-
KMA	496	496	0.94	6.04	6.11
NOA	9	9	-1.42	4.33	4.56
NWC	259	259	-0.36	4.55	4.57

Considering the density scatter plots for Experiment 2a (relating for each producer the HLOS Aeolus wind speed with the HLOS-equivalent AMV speed) there are differences because corresponding wind collocations are not located in the same locations (red dots in the maps in following pages). This occurs especially for BRZ, which has very few collocations in the Southern hemisphere (Figure 11-1). A general good correspondence is seen in all producers between both wind components, with maxima in the scatter plot restricted in all cases to the diagonal. However, some producers show a higher dispersion of the data in the graph (EUM, KMA, NWC) than other ones (BRZ, JMA, NOA), which in part of the cases can be related to errors in the tracking process.

Considering the density scatter plots for Experiments 3 and 4, less information can be extracted due to the smaller number of collocations. The differences between the producers are also more significant, with some centres calculating very few AMVs (NOA), and others calculating many more (e.g., KMA). The maxima in the scatter plot are aligned on the diagonal, although there is also some dispersion in the data.

a) Experiment 2a: Cloudy AMVs (10-minute interval)

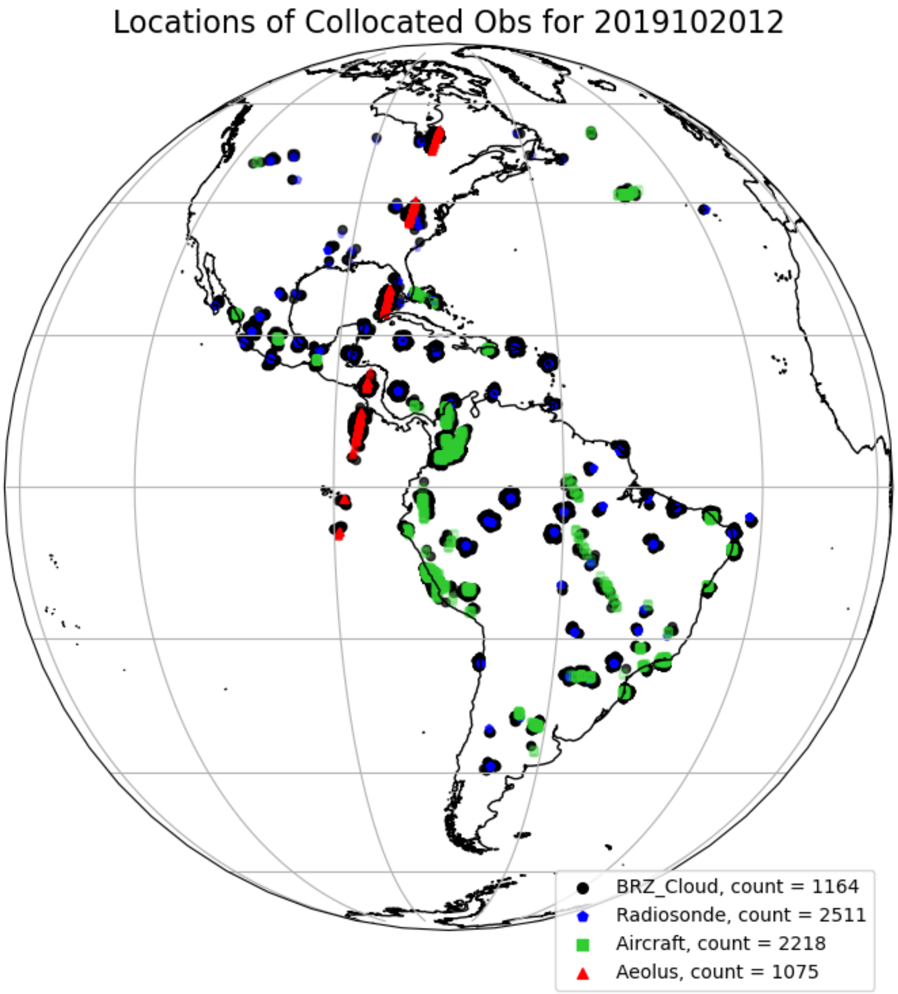

Figure 11-1: Experiment 2a. BRZ cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

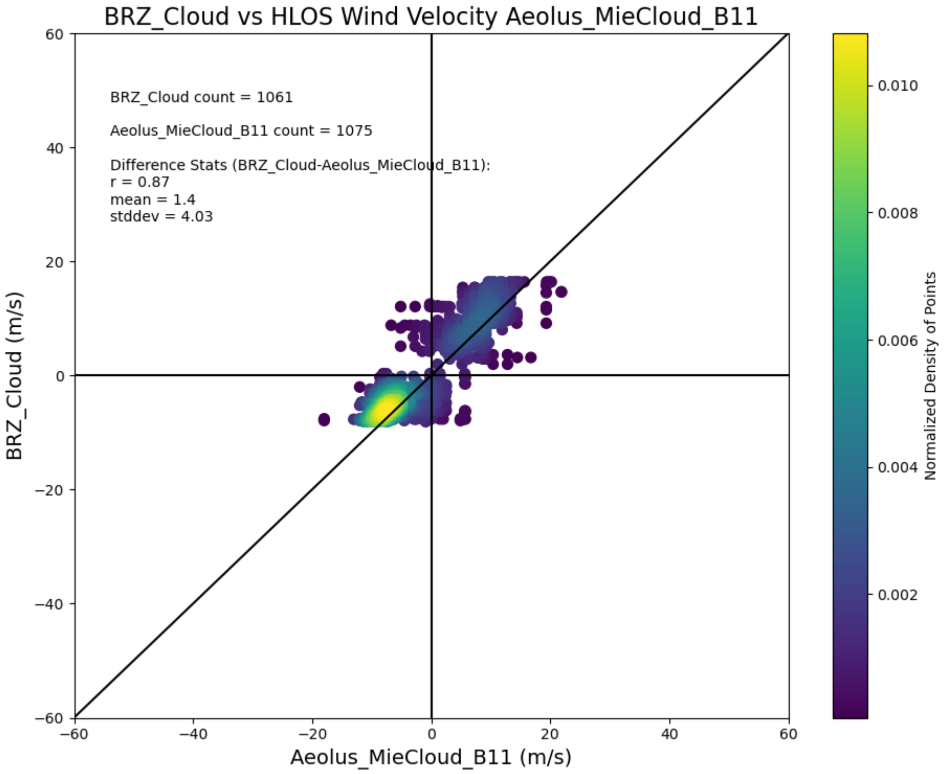

Figure 11-2: Experiment 2a. BRZ cloud AMVs (CQI >= 80): Density scatter plot of BRZ cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

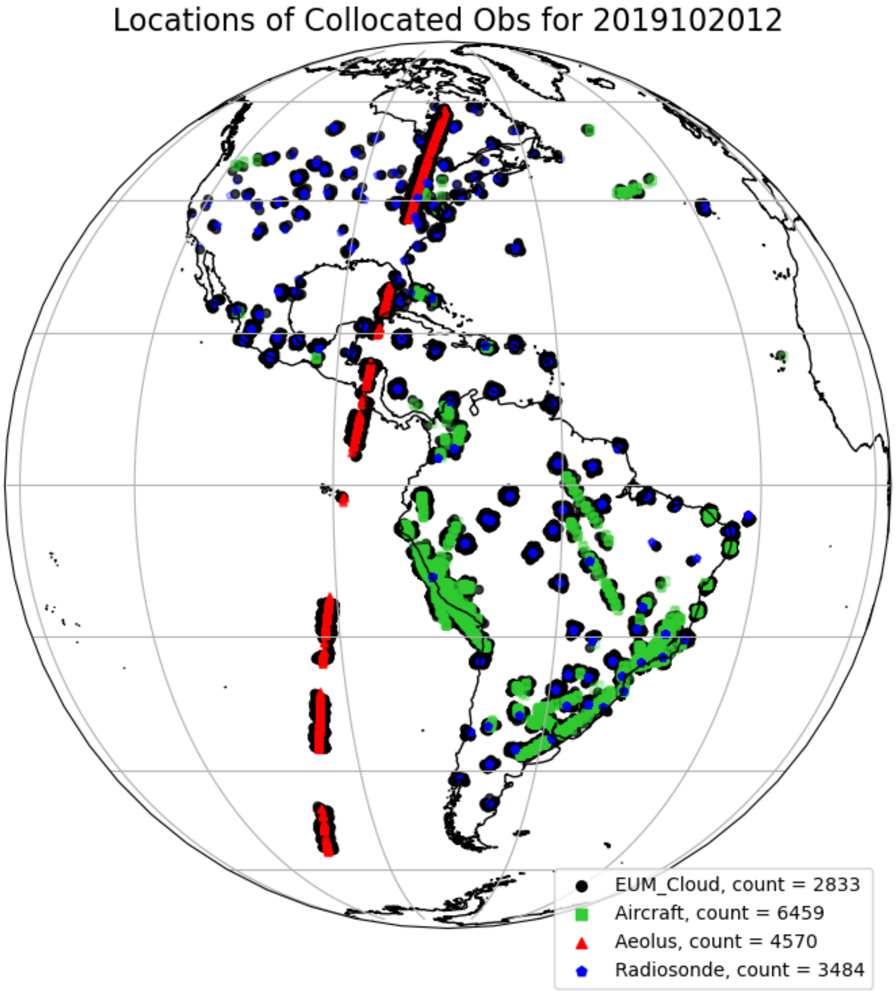

Figure 11-3: Experiment 2a. EUM cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

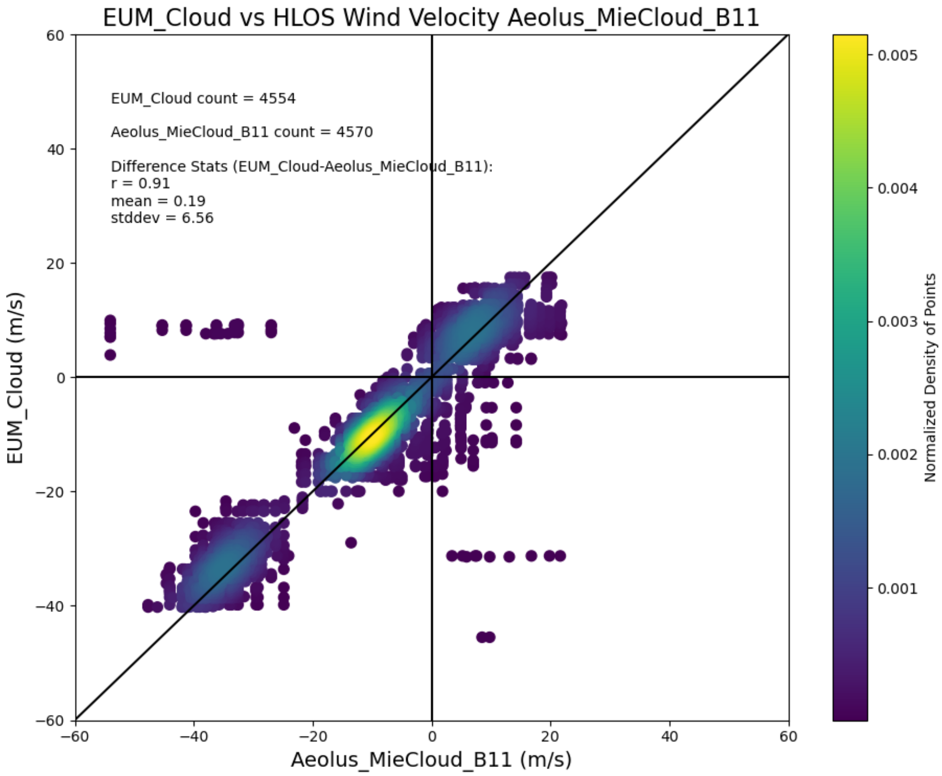

Figure 11-4: Experiment 2a. EUM cloud AMVs (CQI >= 80): Density scatter plot of EUM cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

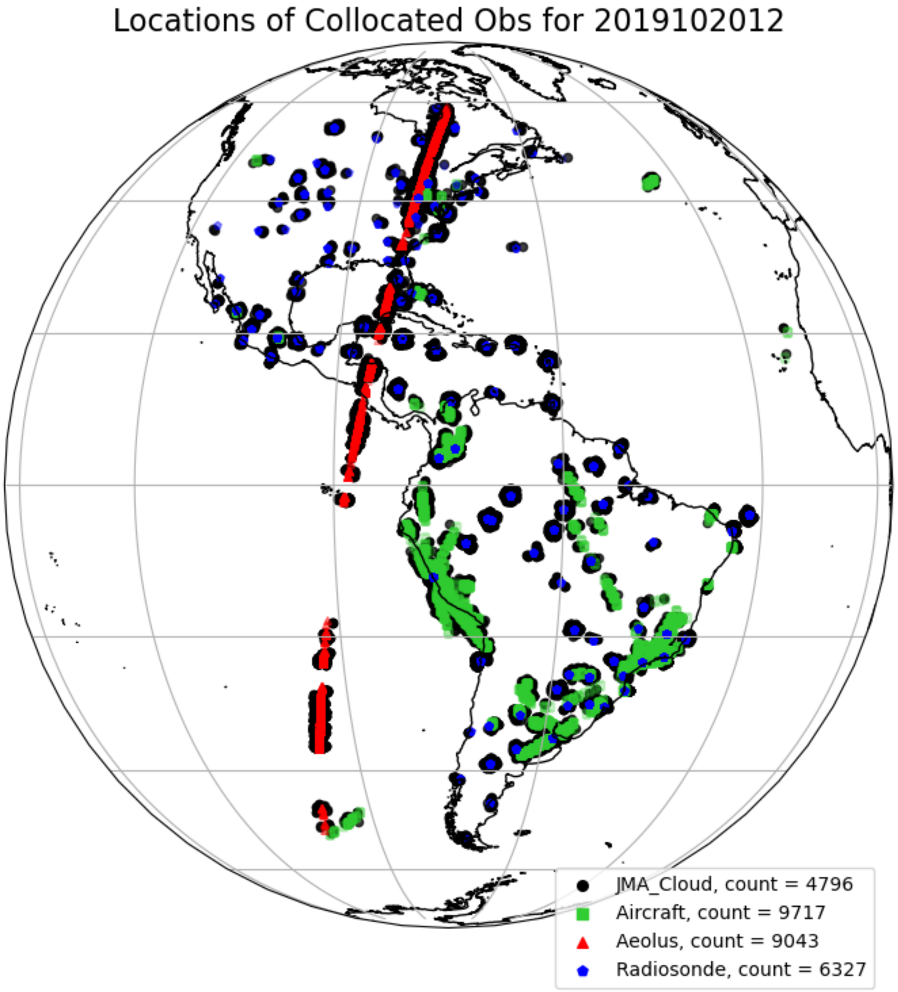

Figure 11-5: Experiment 2a. JMA cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

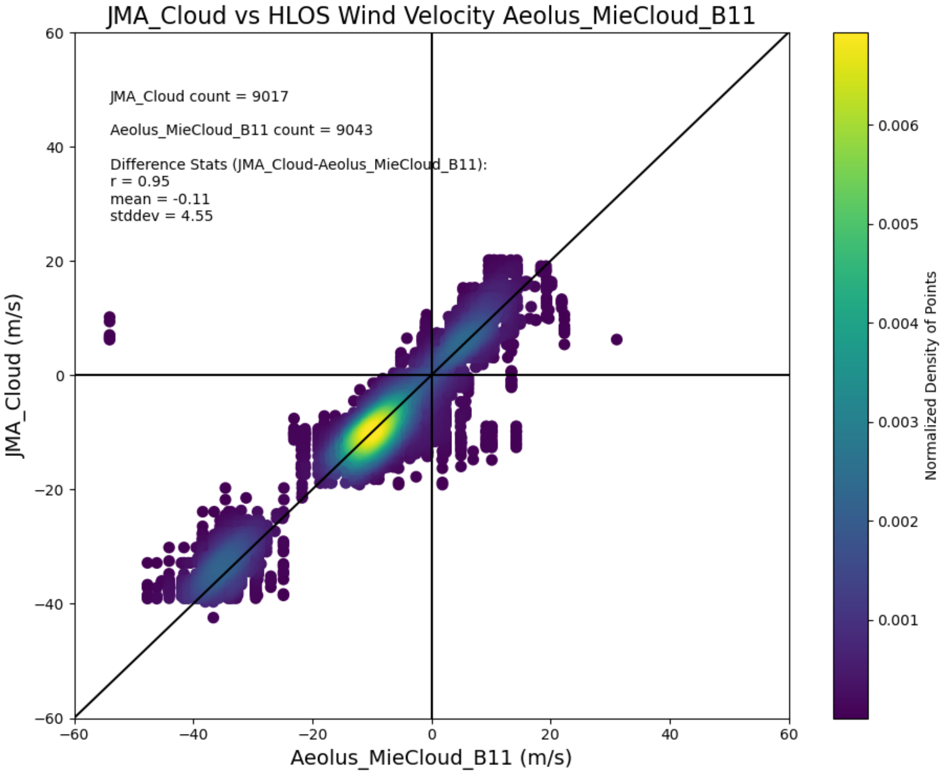

Figure 11-6: Experiment 2a. JMA cloud AMVs (CQI >= 80): Density scatter plot of JMA cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

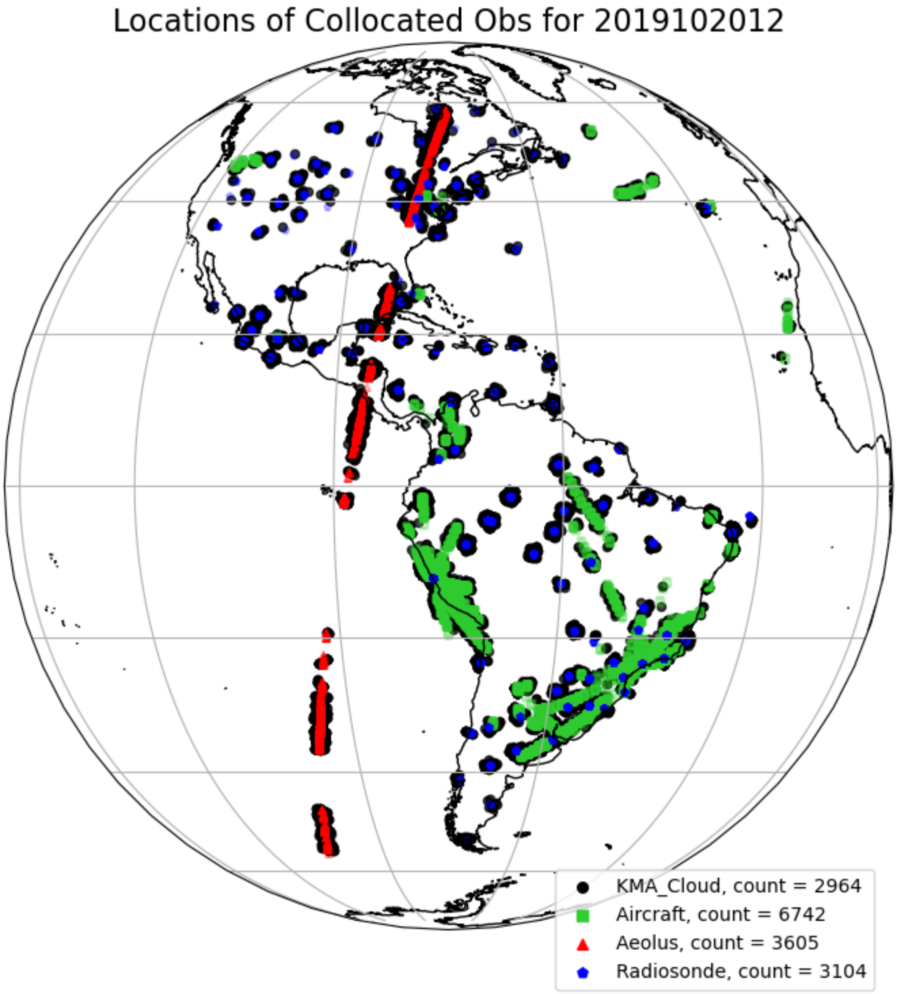

Figure 11-7: Experiment 2a. KMA cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

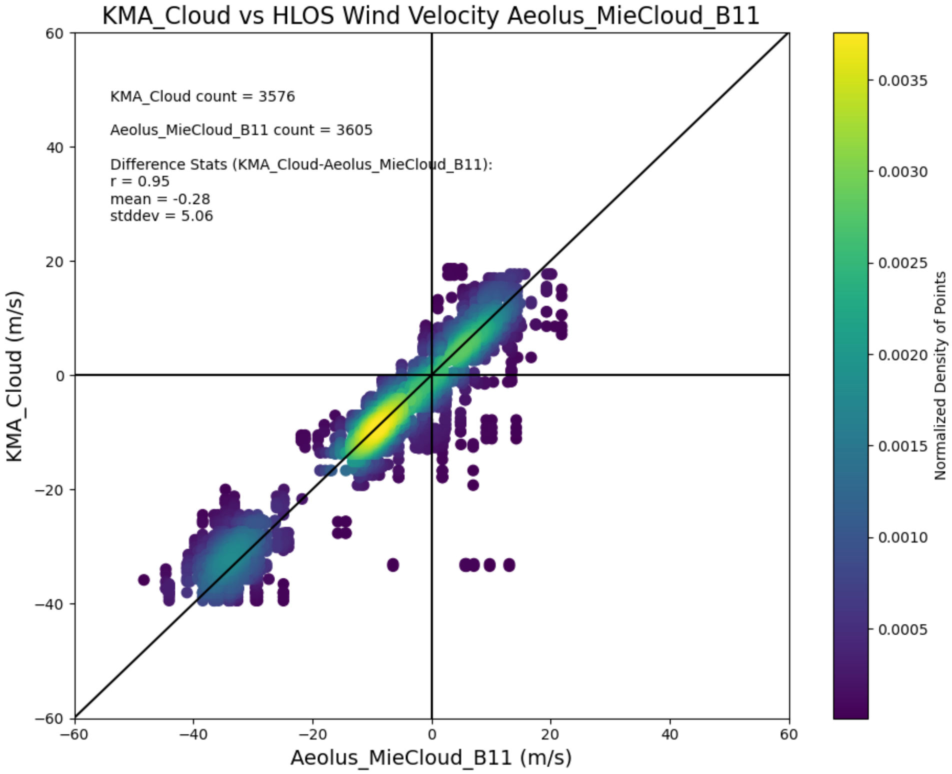

Figure 11-8: Experiment 2a. KMA cloud AMVs (CQI >= 80): Density scatter plot of KMA cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

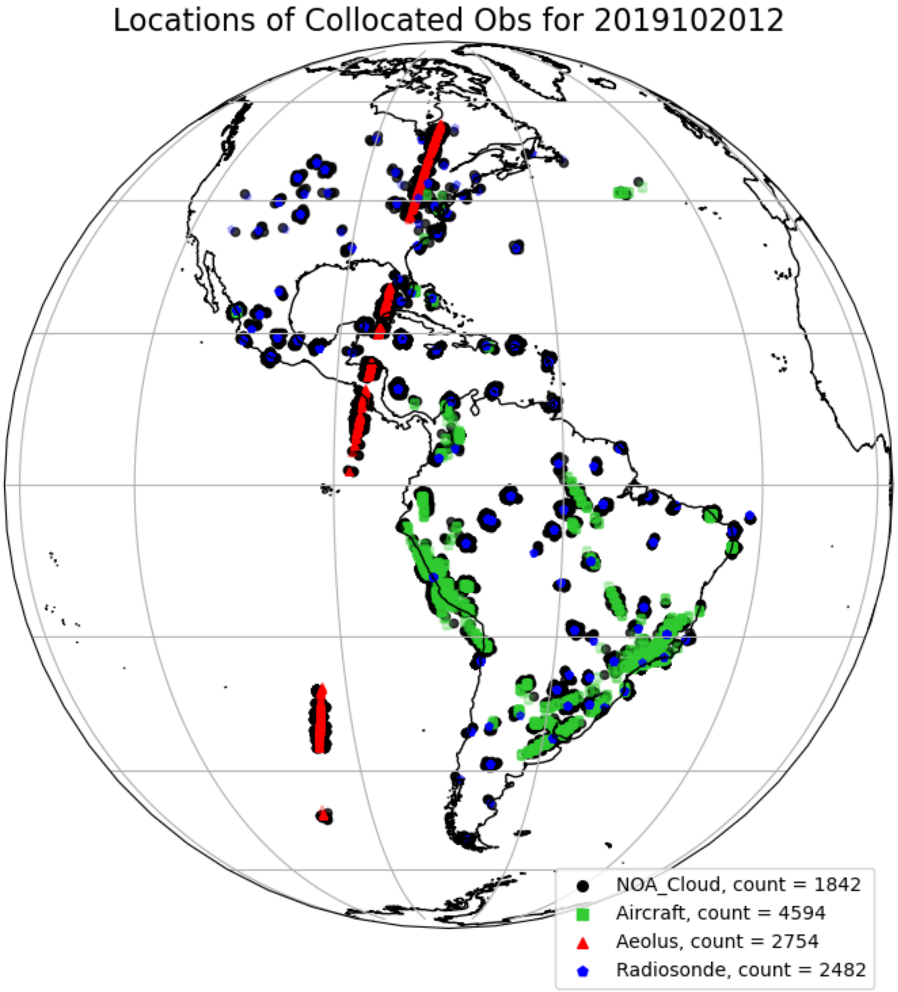

Figure 11-9: Experiment 2a. NOA cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

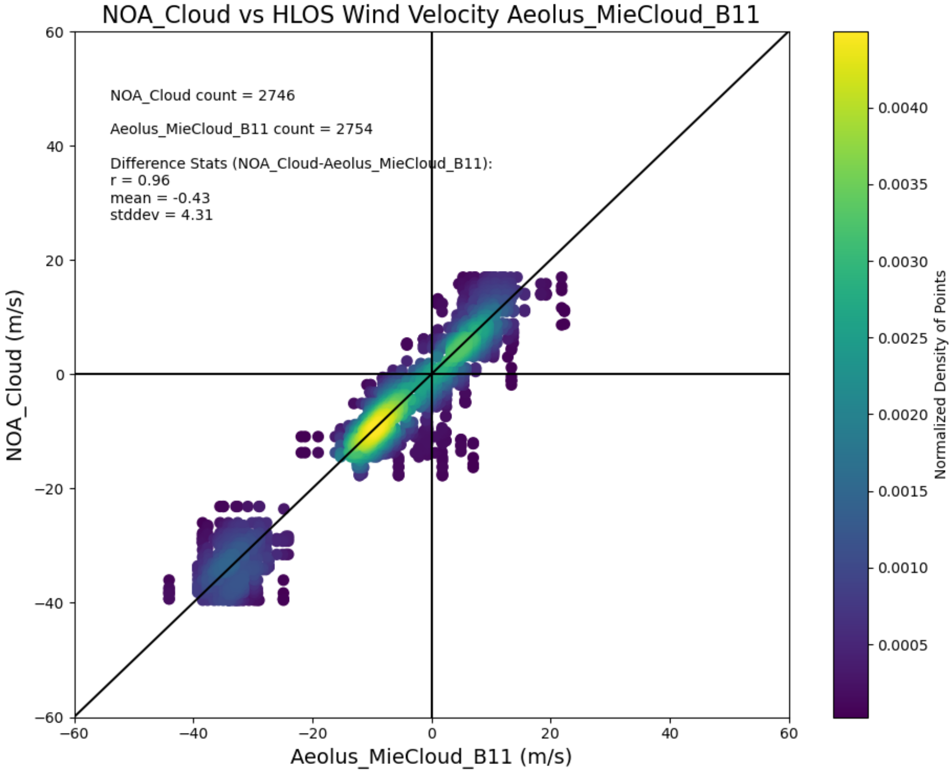

Figure 11-10: Experiment 2a. NOA cloud AMVs (CQI >= 80): Density scatter plot of NOA cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

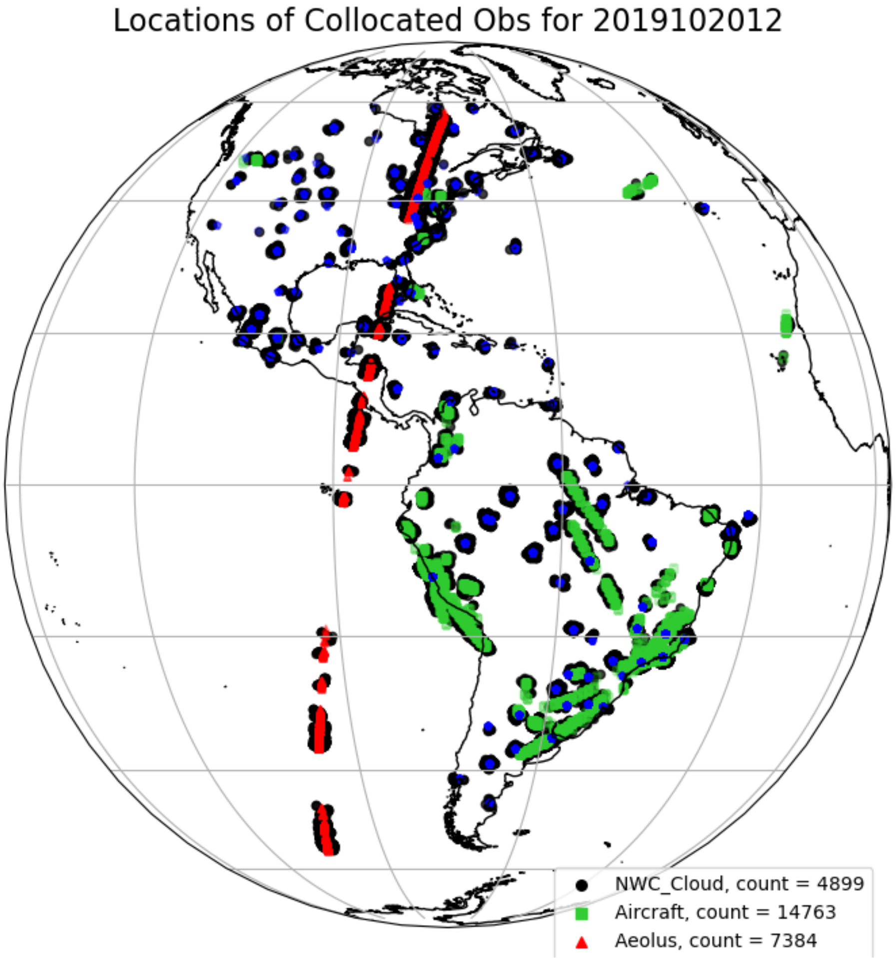

Figure 11-11: Experiment 2a. NWC cloud AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

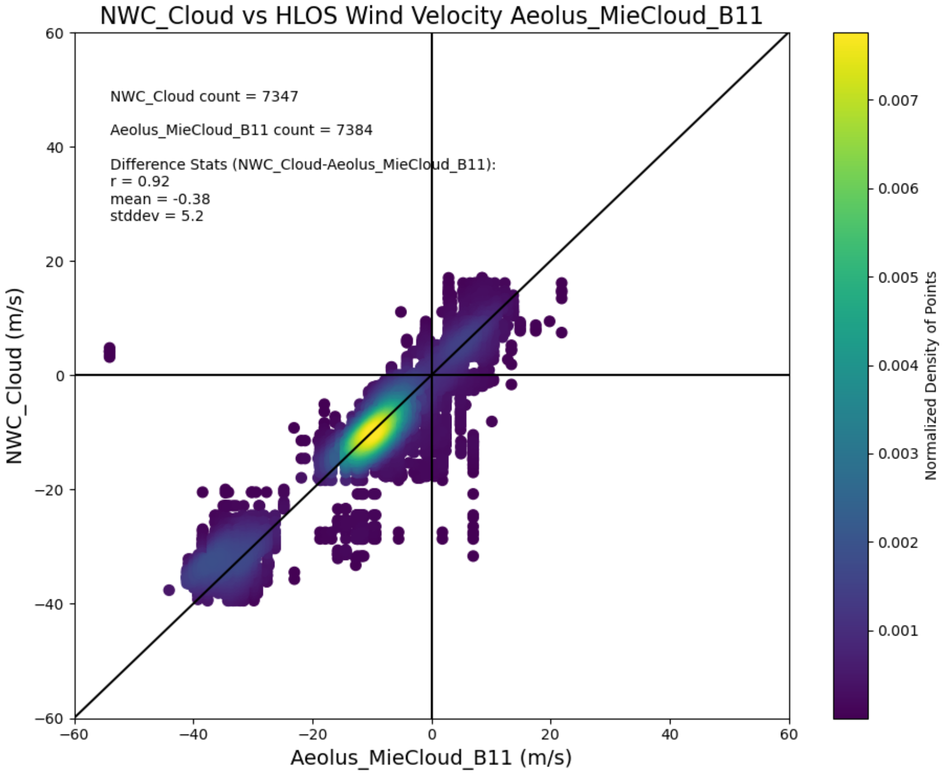

Figure 11-12: Experiment 2a. NWC cloud AMVs (CQI >= 80): Density scatter plot of NWC cloud AMV HLOS-equivalent speed vs Aeolus Mie cloud HLOS speed.

b) Experiment 3: Clear AMVs (10-minute interval)

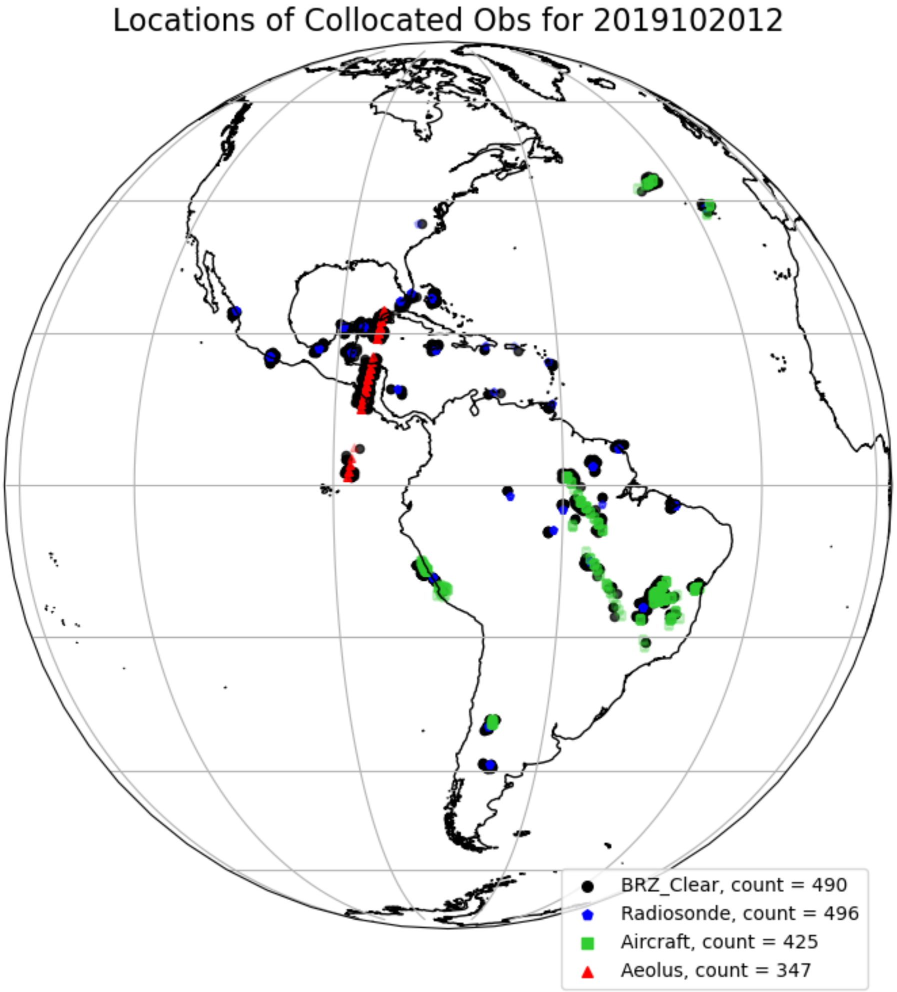

Figure 11-13: Experiment 3. BRZ clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

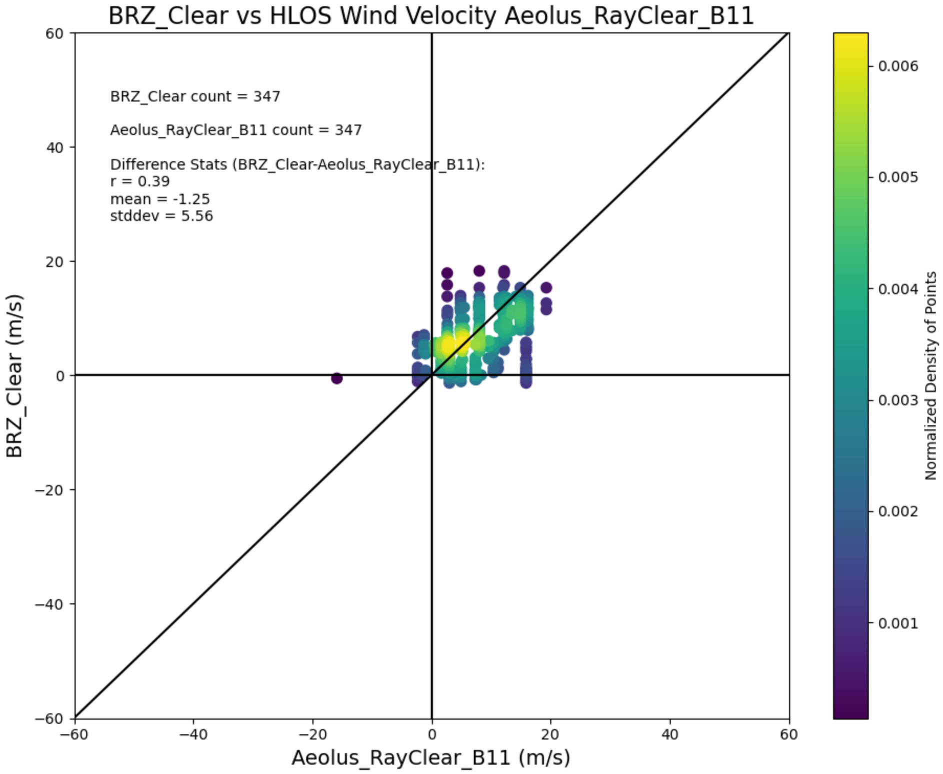

Figure 11-14: Experiment 3. BRZ clear AMVs (CQI >= 80): Density scatter plot of BRZ cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

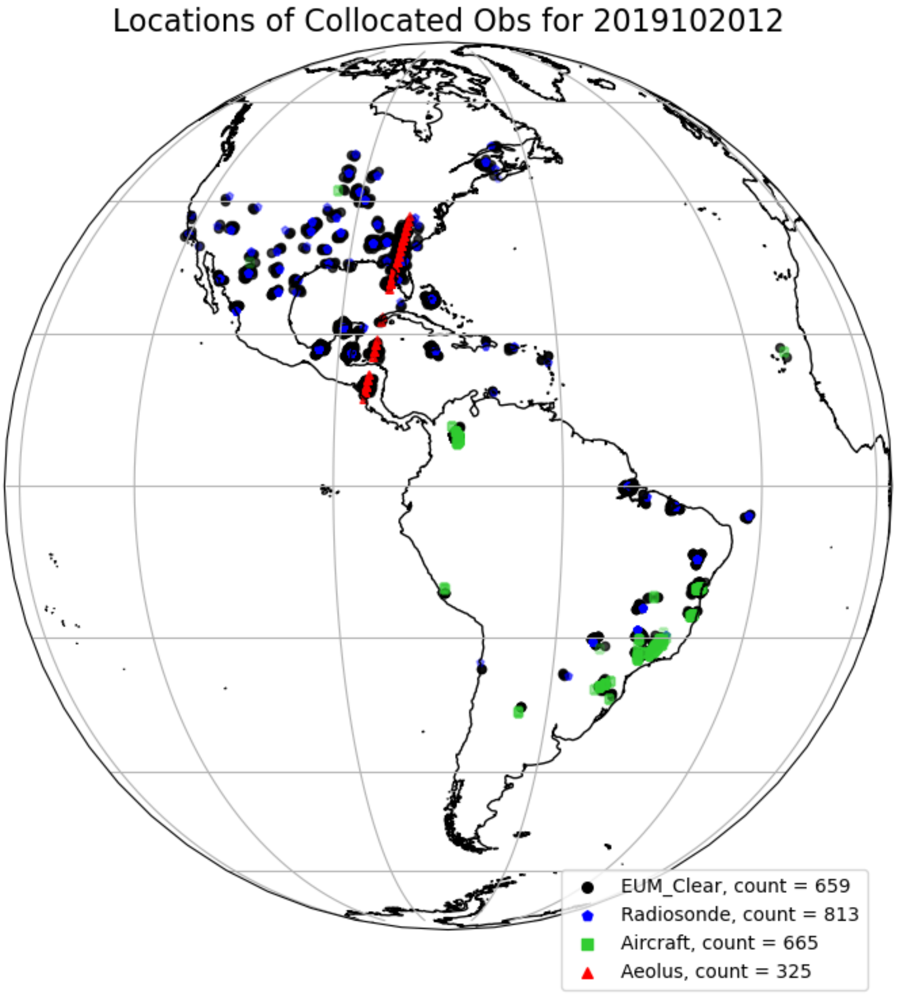

Figure 11-15: Experiment 3. EUM clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

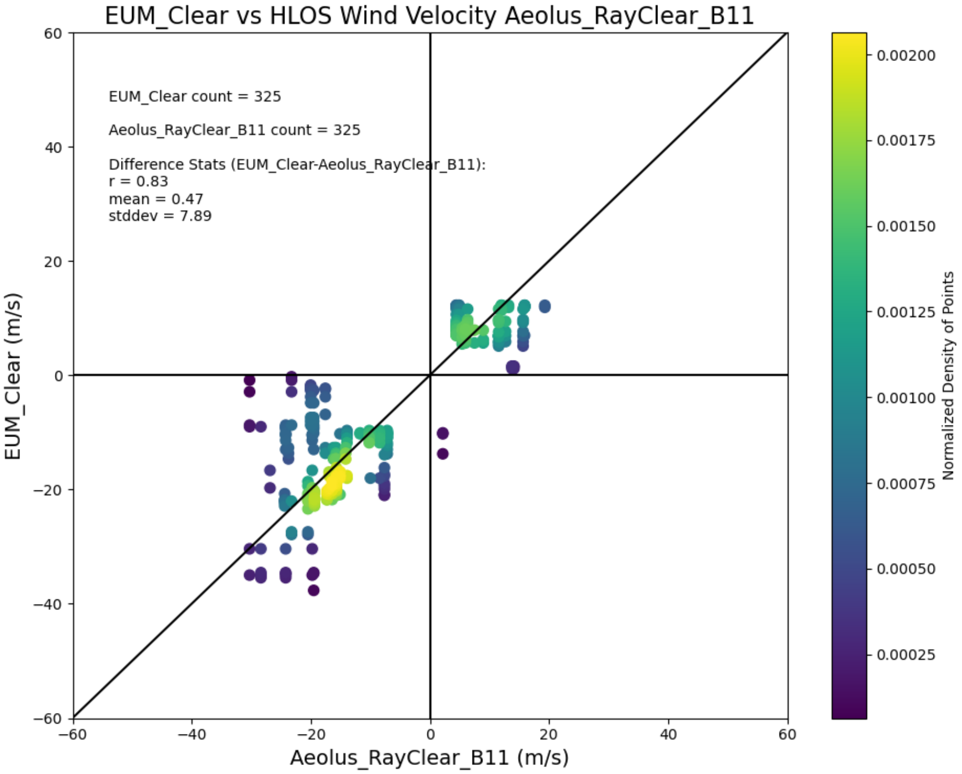

Figure 11-16: Experiment 3. EUM clear AMVs (CQI >= 80): Density scatter plot of EUM cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

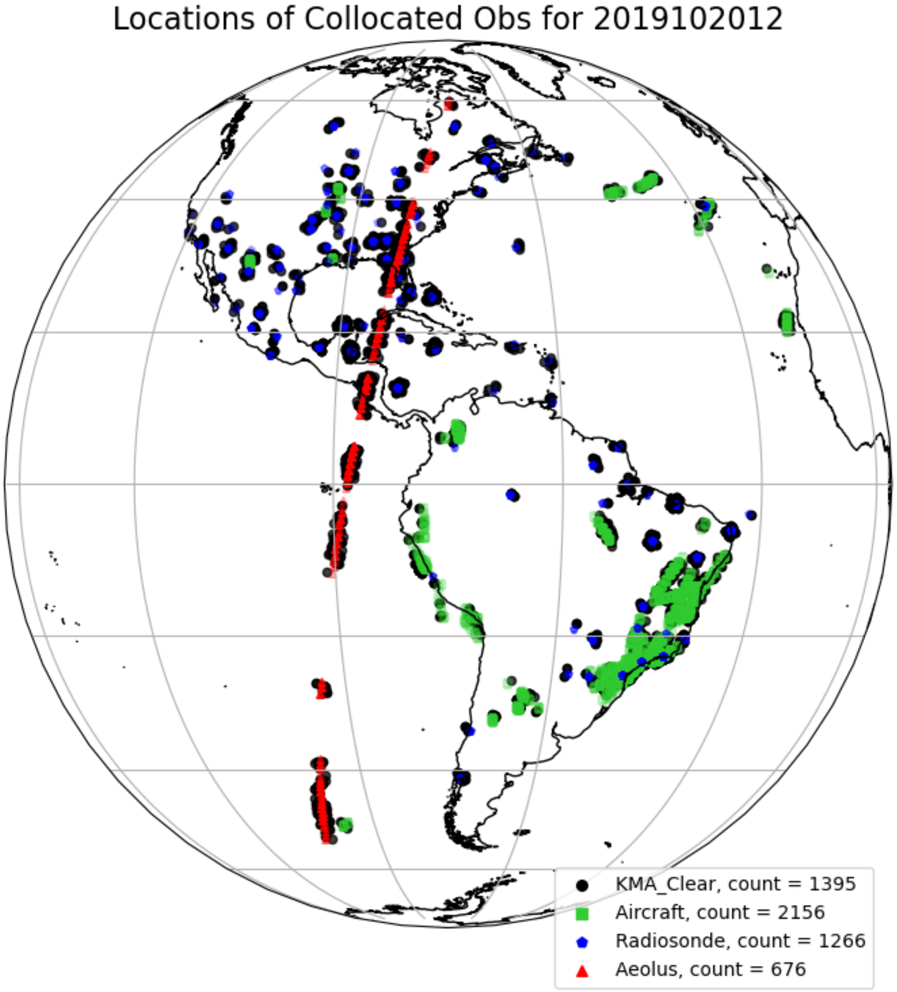

Figure 11-17: Experiment 3. KMA clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

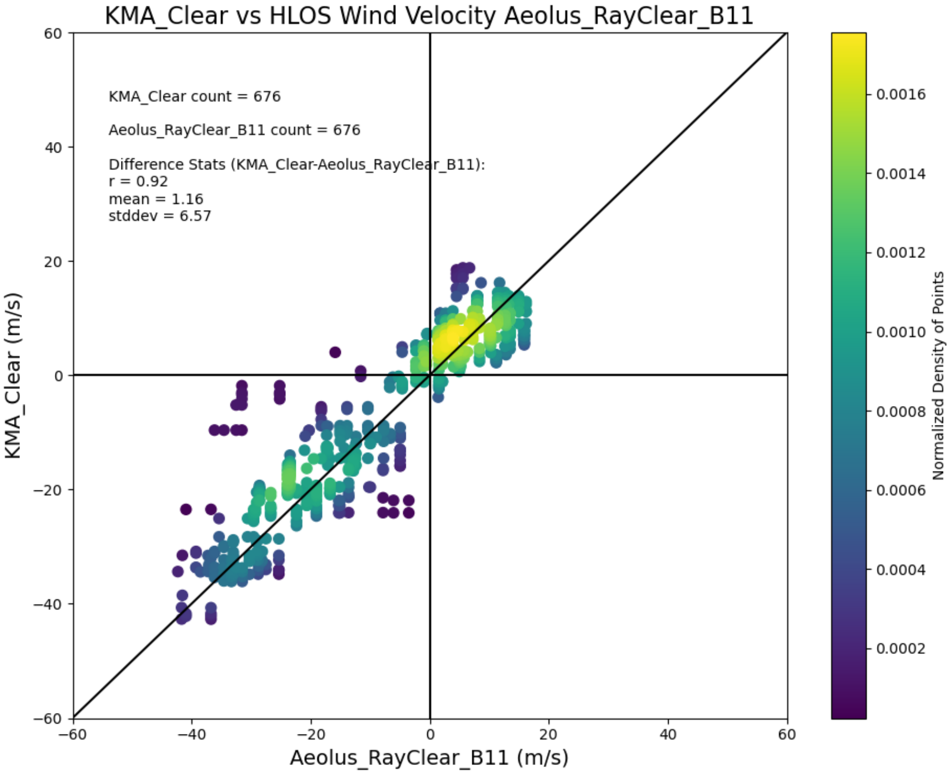

Figure 11-18: Experiment 3. KMA clear AMVs (CQI >= 80): Density scatter plot of KMA cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

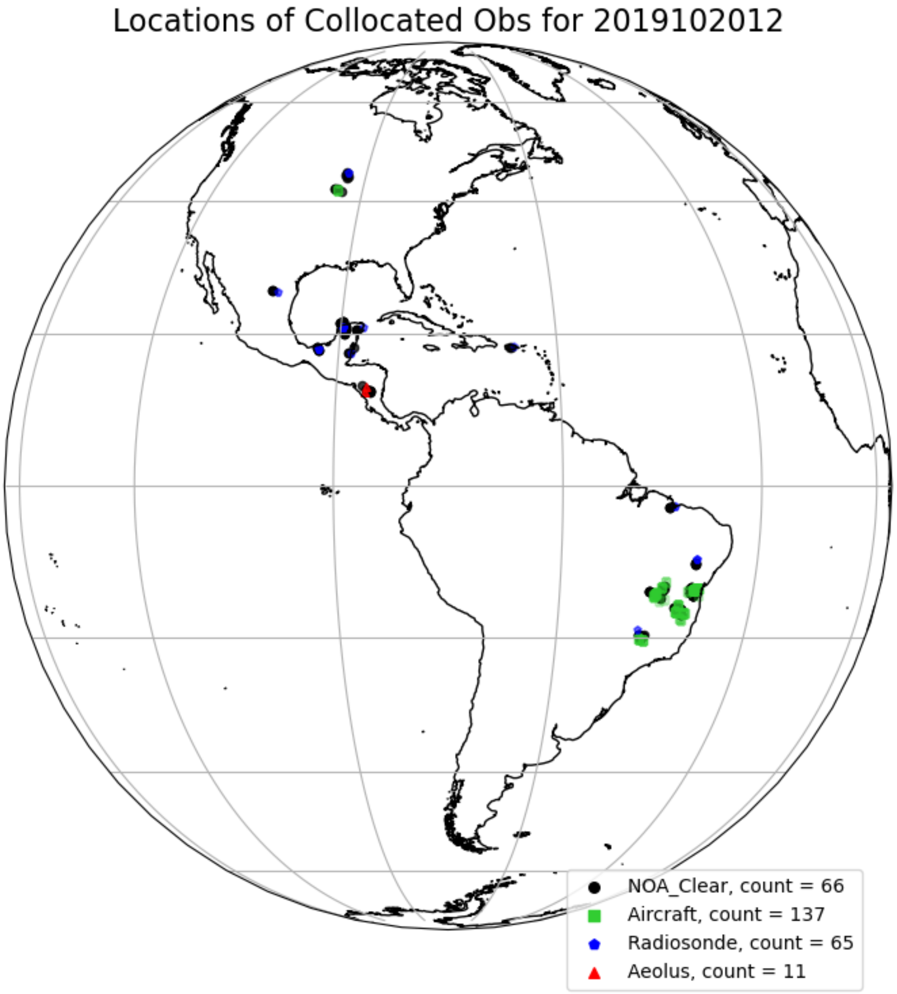

Figure 11-19: Experiment 3. NOA clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

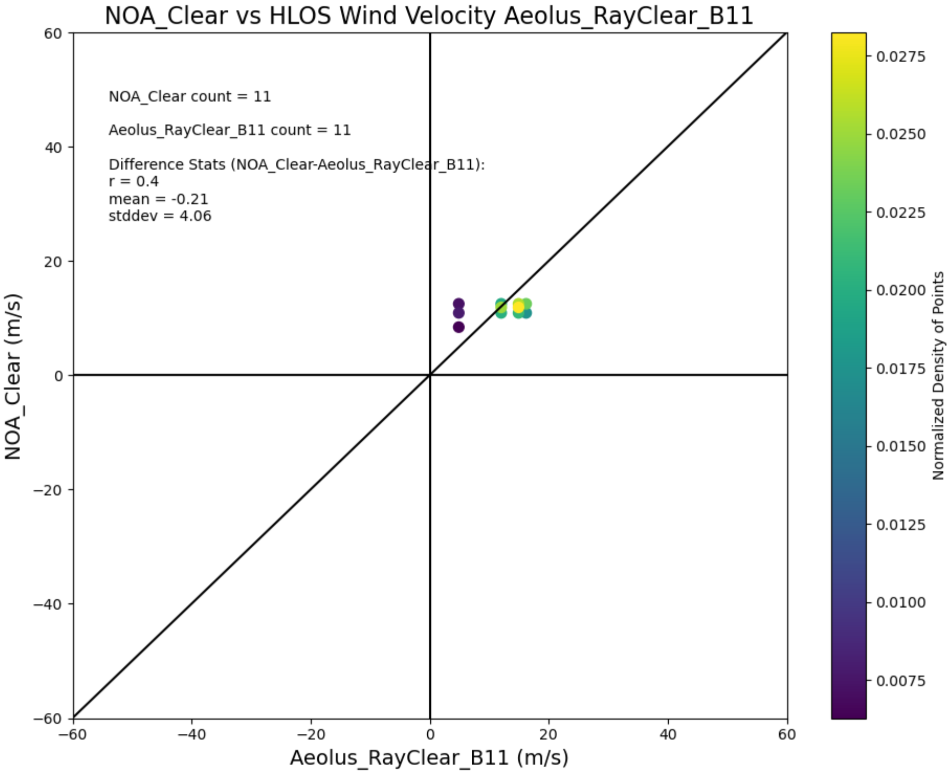

Figure 11-20: Experiment 3. NOA clear AMVs (CQI >= 80): Density scatter plot of NOA cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

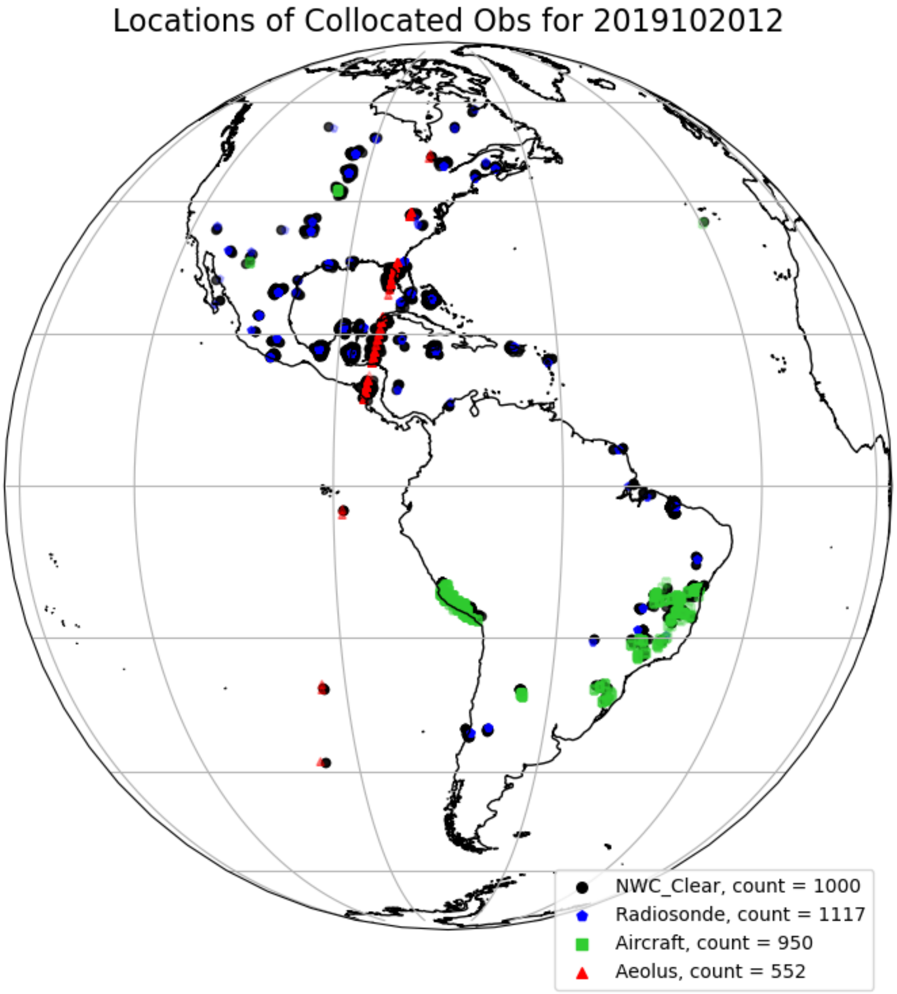

Figure 11-21: Experiment 3. NWC clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

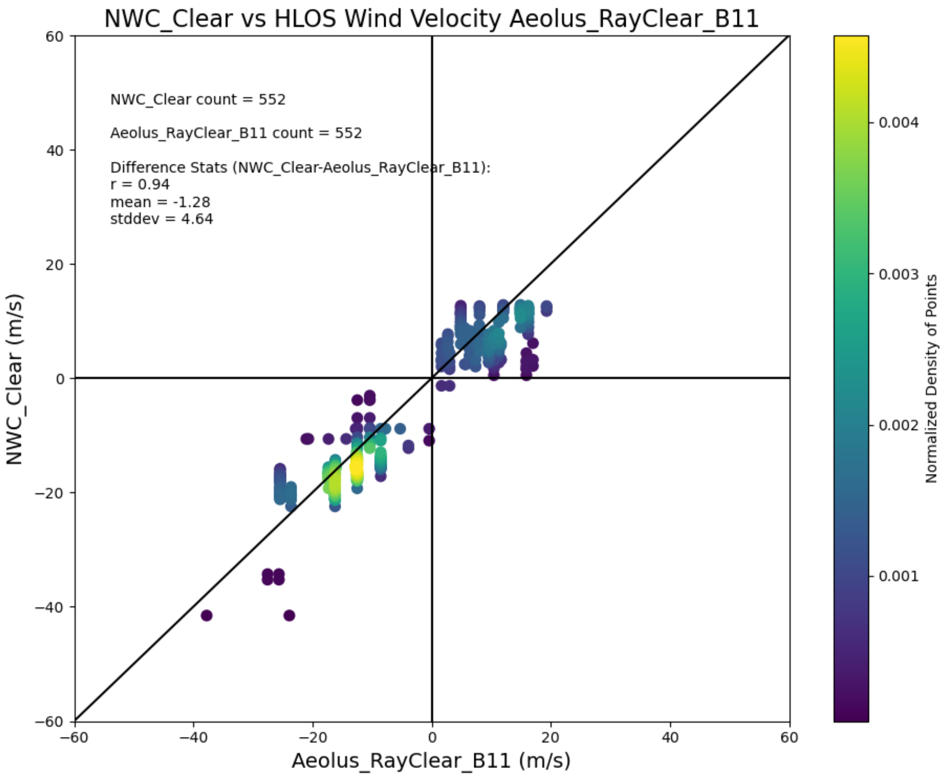

Figure 11-22: Experiment 3. NWC clear AMVs (CQI >= 80): Density scatter plot of NWC cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

c) Experiment 4: Clear AMVs (20-minute interval)

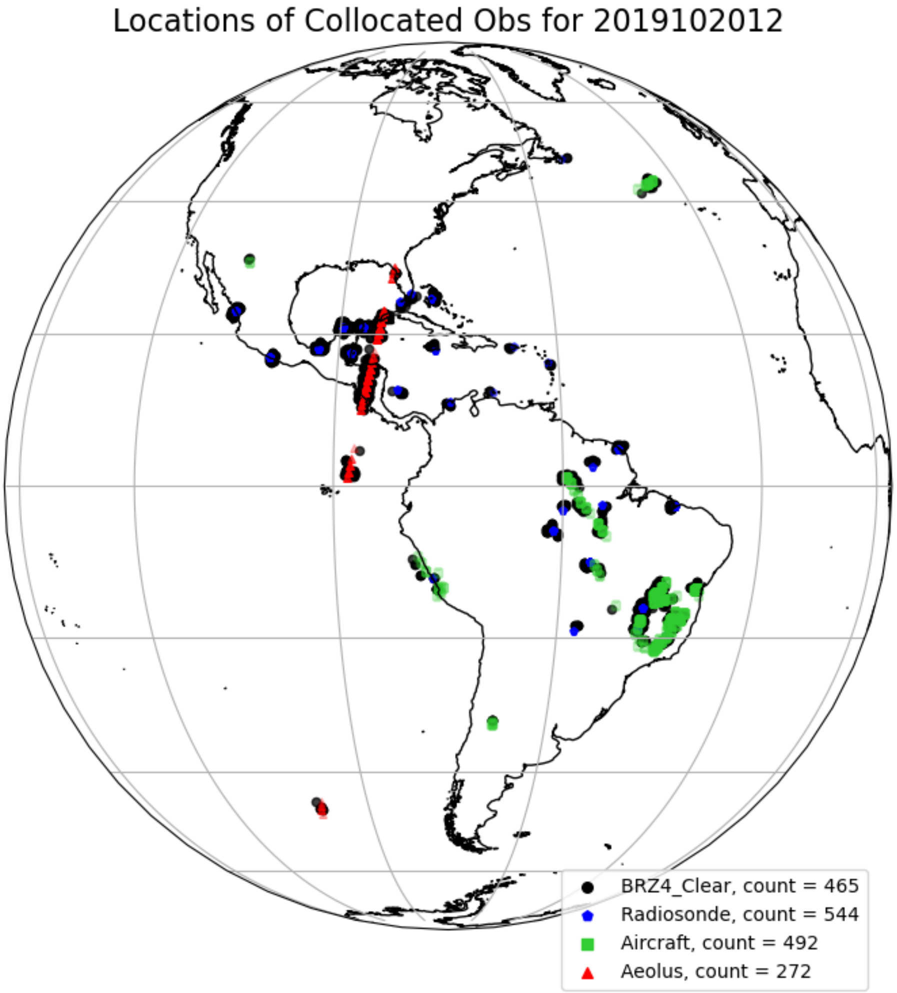

Figure 11-23: Experiment 4. BRZ clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

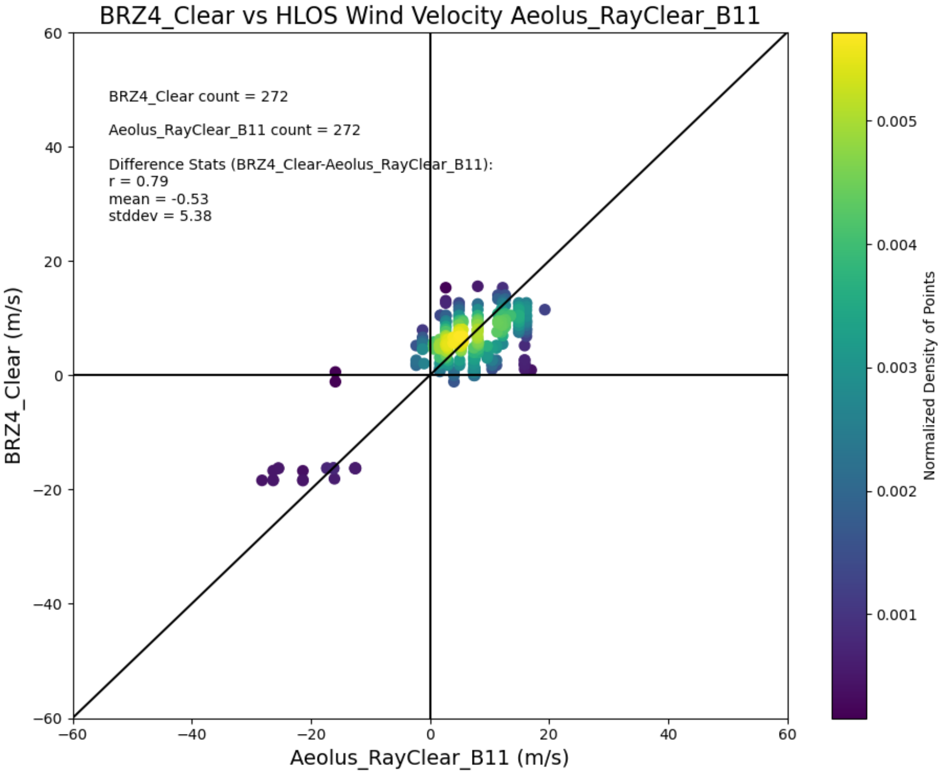

Figure 11-24: Experiment 4. BRZ clear AMVs (CQI >= 80): Density scatter plot of BRZ cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

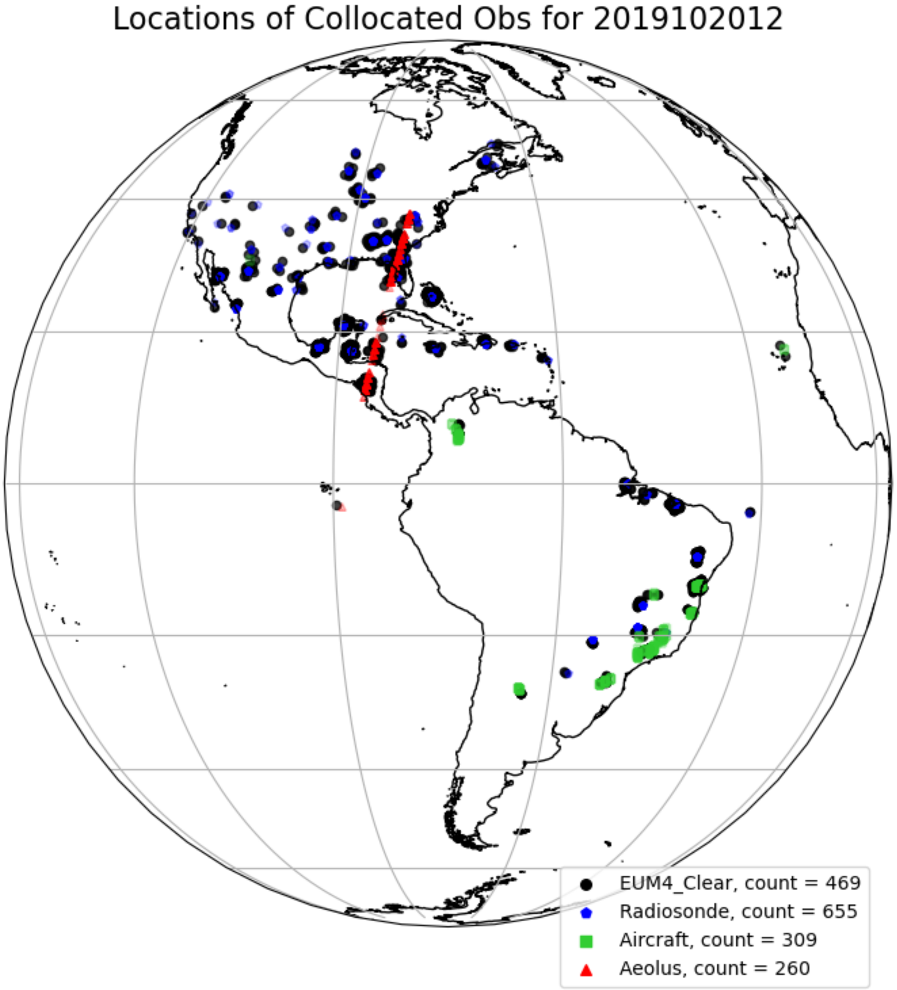

Figure 11-25: Experiment 4. EUM clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

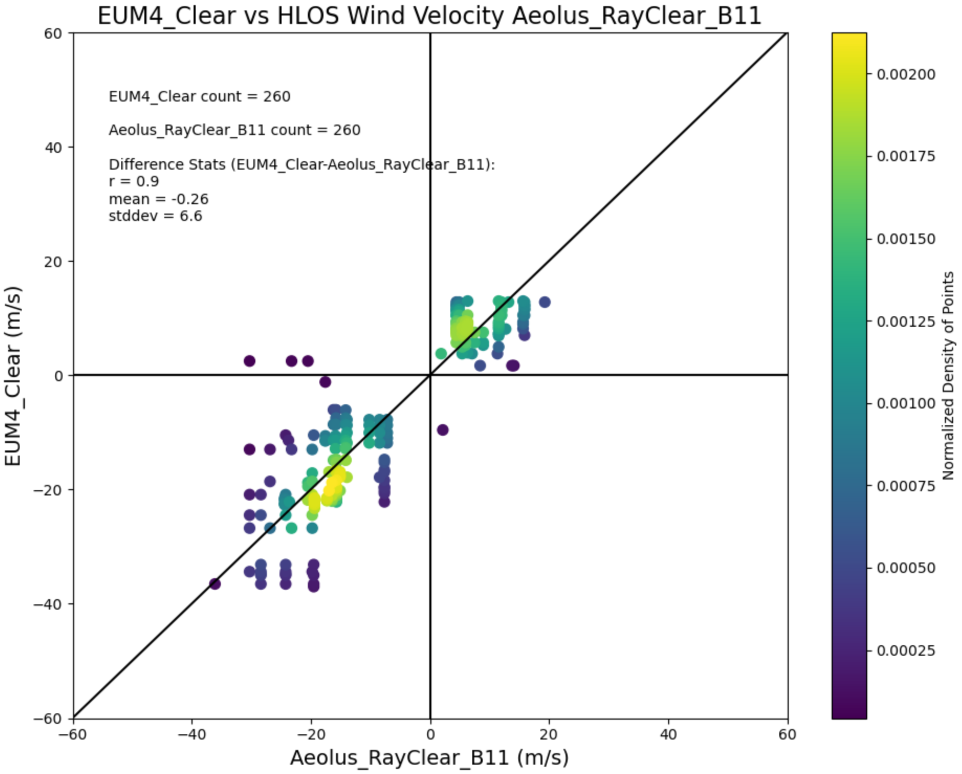

Figure 11-26: Experiment 4. EUM clear AMVs (CQI >= 80): Density scatter plot of EUM cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

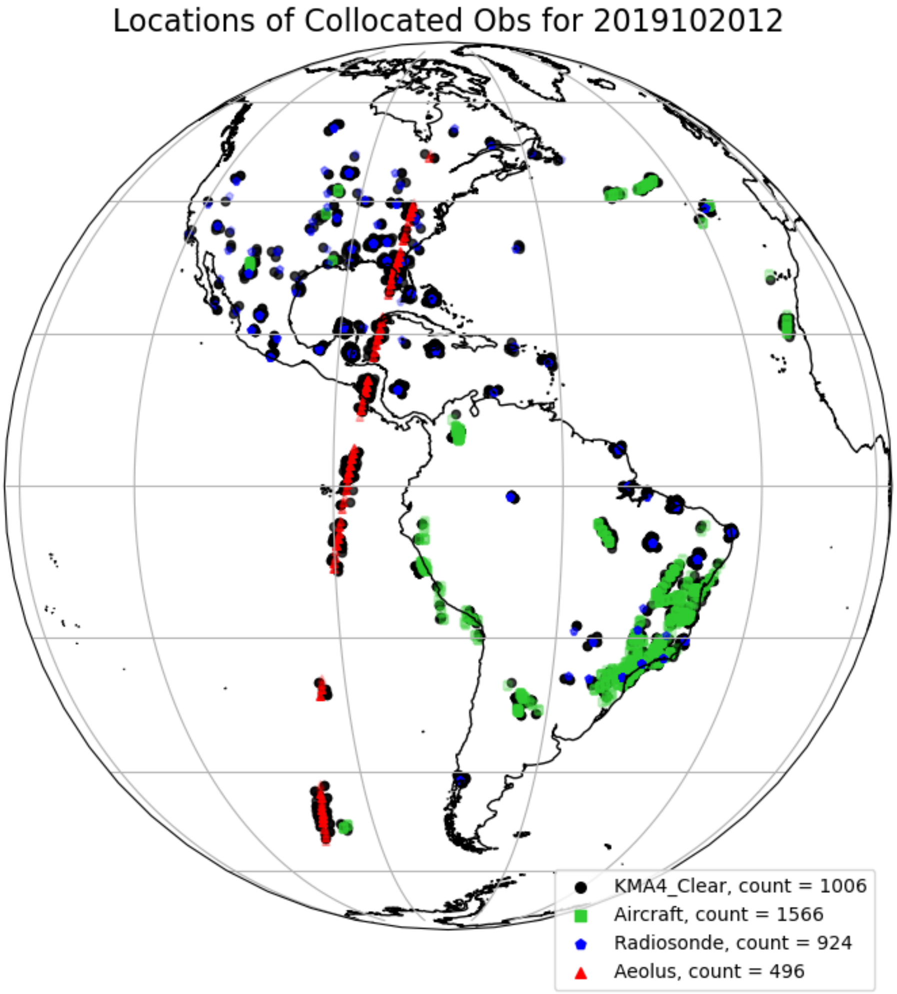

Figure 11-27: Experiment 4. KMA clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

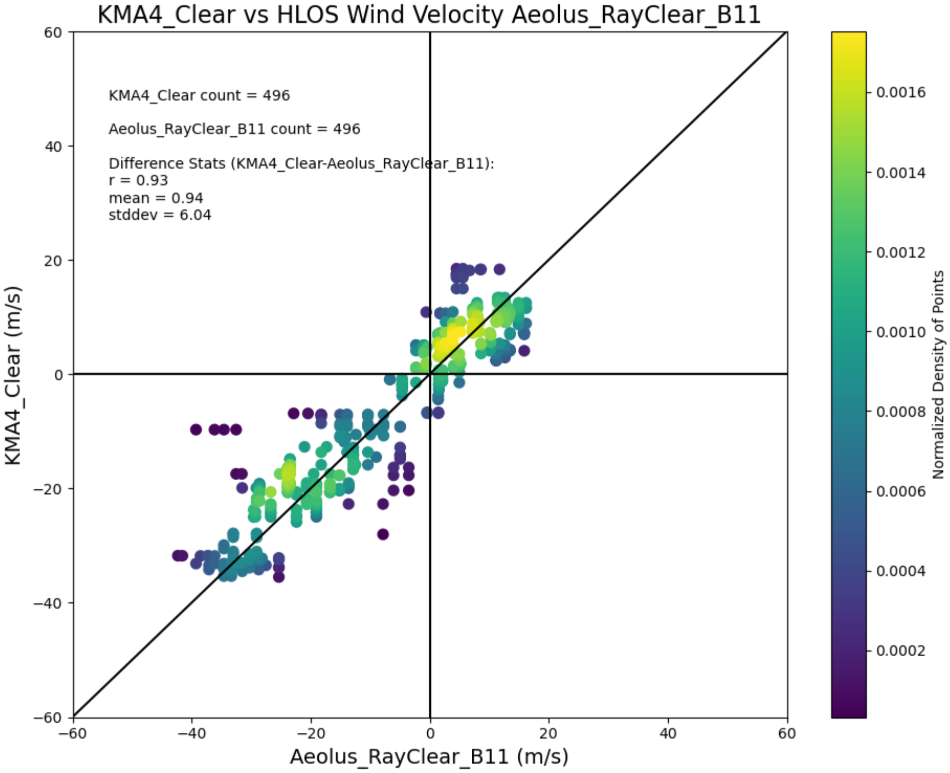

Figure 11-28: Experiment 4. KMA clear AMVs (CQI >= 80): Density scatter plot of KMA cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

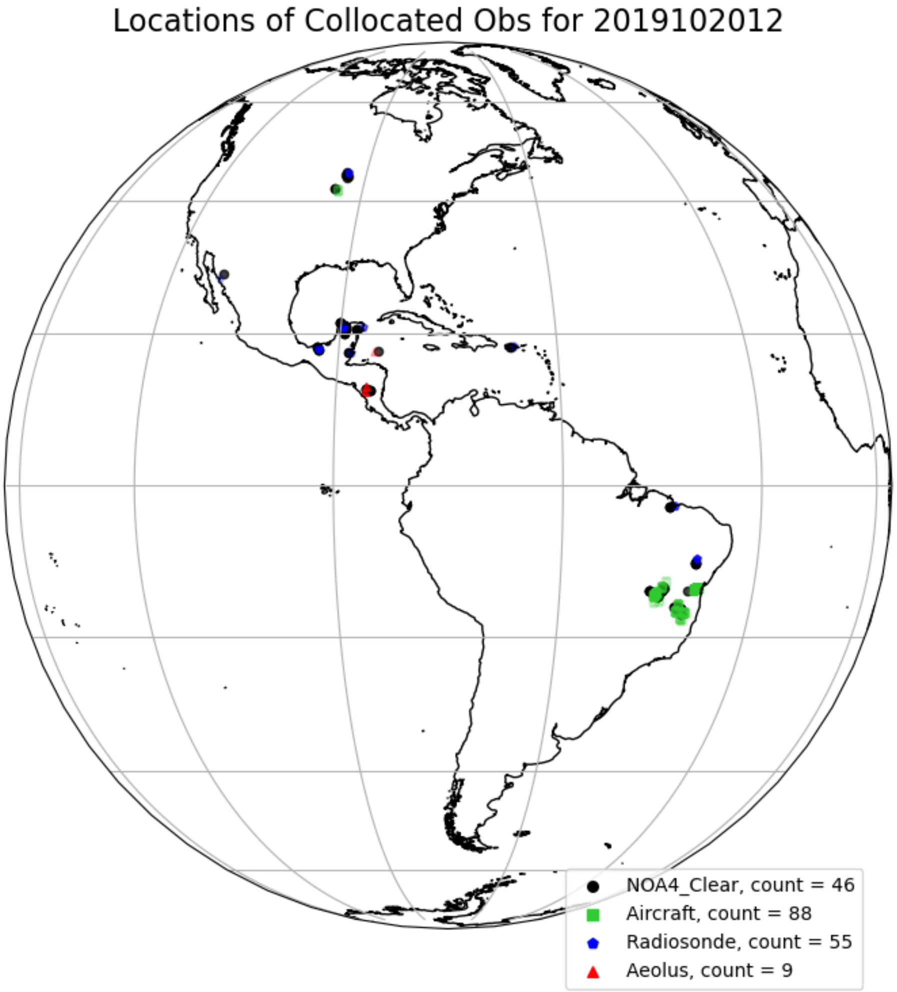

Figure 11-29: Experiment 4. NOA clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

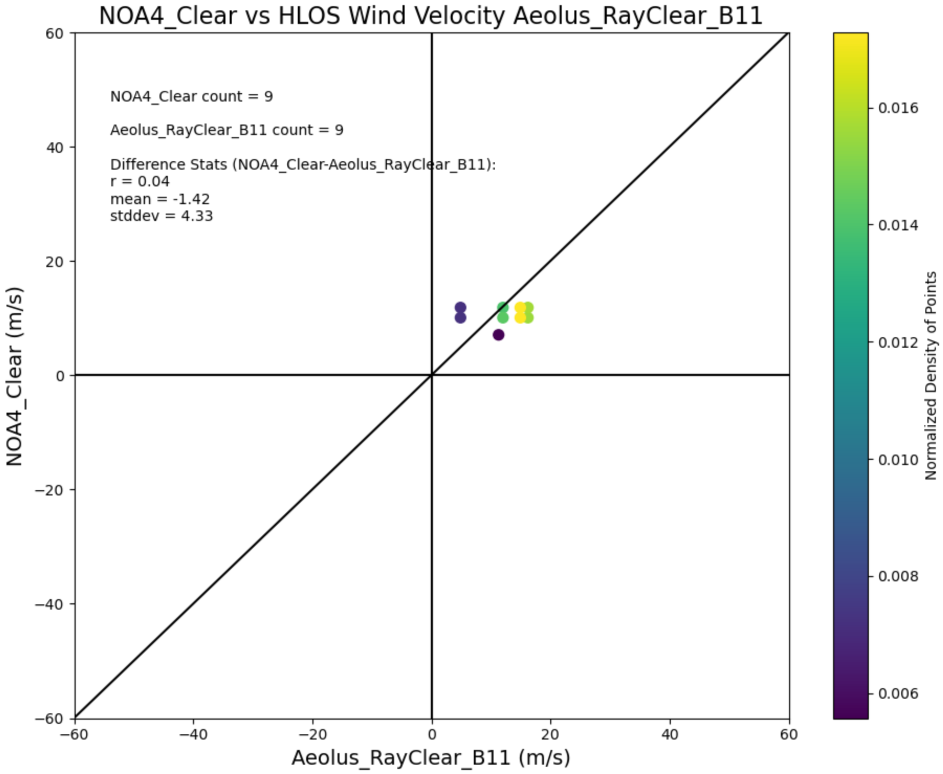

Figure 11-30: Experiment 4. NOA clear AMVs (CQI >= 80): Density scatter plot of NOA cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

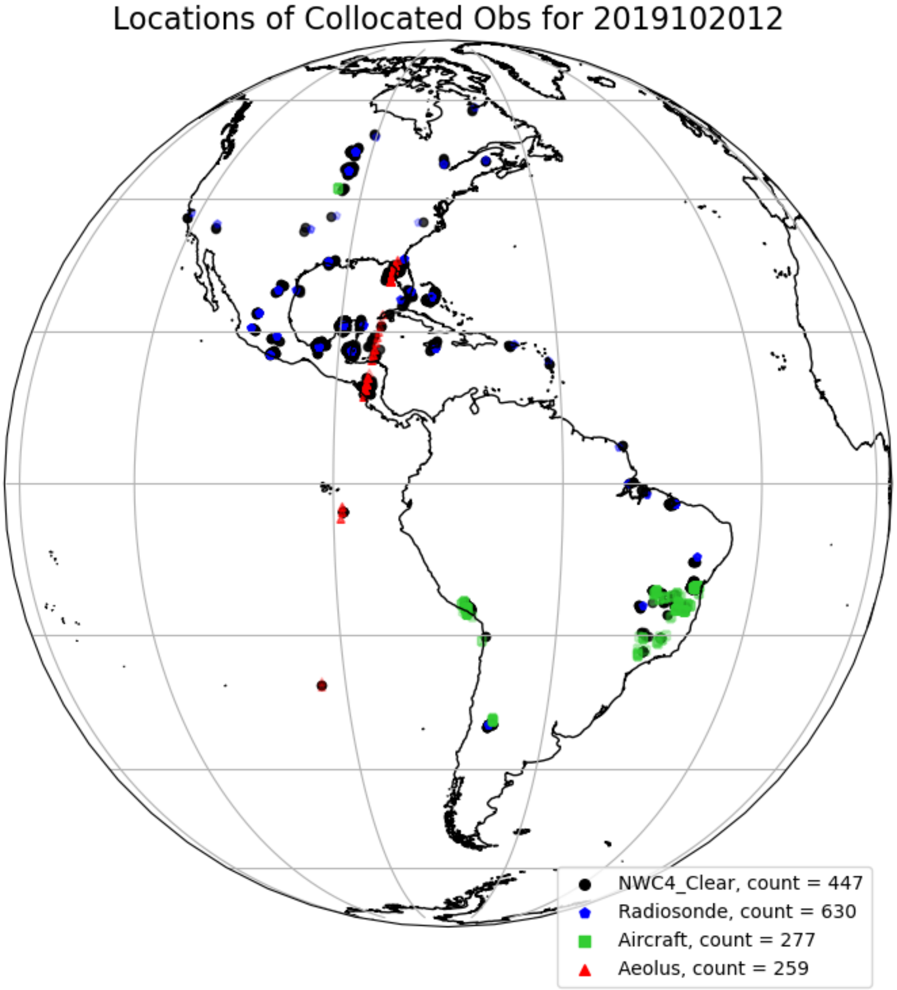

Figure 11-31: Experiment 4. NWC clear AMVs (CQI >= 80): Location of collocated observations. AMVs (black), rawinsondes (blue), aircraft (green), Aeolus (red).

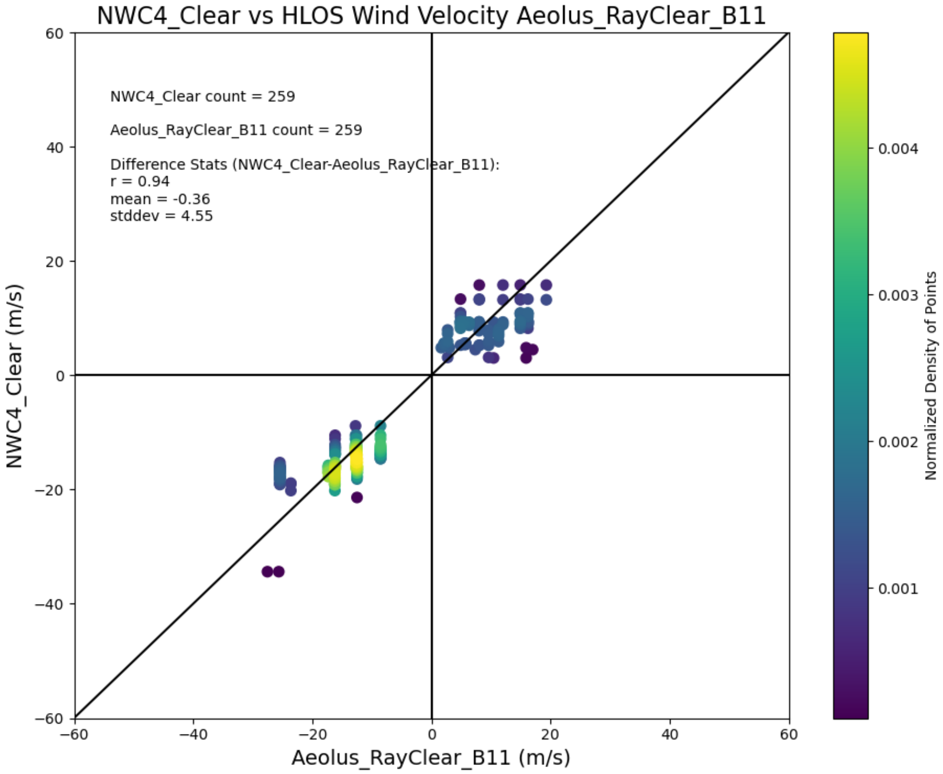

Figure 11-32: Experiment 4. NWC clear AMVs (CQI >= 80): Density scatter plot of NWC cloud AMV HLOS-equivalent speed vs Aeolus Rayleigh clear HLOS speed.

12. Aircraft comparison

a) Approach

A comparison against aircraft winds has been added in this intercomparison, although it was not specifically requested in its tasks. The thresholds for determining collocation between the AMV winds and the aircraft winds are a distance of 0.1° of latitude and longitude, and within one hour.

The comparison against aircraft winds uses the same experiments 2a, 3 and 4 used in the comparison against Aeolus winds, using image data with central image at 11:30 UTC, 20 October 2019:

- Experiment 2a: AMV producers extract infrared channel cloudy AMVs considering their standard AMV algorithm configuration, using the GOES-16/ABI IR Band 14 (11.2 µm) images, with image times 11:20 to 11:40 UTC.
- Experiment 3: AMV producers extract water vapor channel clear-sky AMVs considering their standard AMV algorithm configuration, using the GOES-16/ABI IR Band 8 (6.2 µm) images, with image times 11:20 to 11:40 UTC.
- Experiment 4: AMV producers extract water vapor channel clear-sky AMVs considering their standard AMV algorithm configuration, using the GOES-16/ABI IR Band 8 (6.2 µm) images and the height assignment of their choice, with image times 11:10 to 11:50 UTC.

This time frame was chosen as the comparison dataset and scripts for the aircraft wind data are integrated with those for Aeolus wind data. As in the previous case, JMA did not participate in experiments 3 and 4.

By using their standard AMV configuration, this experiment gives the producers a best-case evaluation of their AMV winds algorithm, as compared to an independent measurement of winds from aircraft reports.

b) Comparison to aircraft

The following three tables summarize the comparison of the AMVs (Cloudy AMVs with 10-minute time interval, Clear AMVs with 10-minute time interval, and Clear AMVs with 20-minute time interval) with aircraft winds. The producer with better result is BRZ in experiments 2a and 3, and NOA in experiment 4. The producer with worse results is KMA in experiments 2a and 4, and EUM in experiment 3.

For Experiment 2a (Table 12-1; cloudy, 10-minute time interval) the RMSE generally range from 3.5 to 4.4 ms^{-1}, with EUM (6.8 ms^{-1}) and KMA (8.3 ms^{-1}) exhibiting much larger values. The greatest contributor to the higher RMSE is the larger standard deviation (Table 12-1), which is evident in the larger scatter of the comparison wind speeds (Figure 12-2 and Figure 12-4). Also, similarly higher RMSE values for EUM and KMA were seen in the rawinsonde comparisons (Table 8-17) with values of 7.8 and 8.1 ms^{-1}, respectively.

Again, the number of clear sky AMVs is greatly reduced for all centres compared to cloudy AMVs (between 3 times less for KMA and 27 times less for NOA), so the statistics may not be so meaningful. However, the trends in the statistics indicate:

- When compared to aircraft winds, clear sky AMVs have larger RMSE values (Table 12-2) than cloudy AMVs (Table 12-1), which is again expected as the water vapor features being tracked are more diffuse (less defined) than the cloud features.
- When the time interval between water vapor images is increased from 10 to 20 minutes, there is generally a slight decrease in RMSE (Table 12-3) which can be convenient for a better calculation of clear air water vapour AMVs. This was also evident in comparing the clear sky AMVs to Aeolus HLOS wind speed (Table 11-2 and Table 11-3).

Table 12-1: Experiment 2a. Statistics for cloudy 10-minute interval AMVs compared to aircraft, with CQI >= 80. N = total number of AMVs and matched aircraft; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N aircraft	Mean	StdDev	RMSE
BRZ	1311	2141	0.04	3.46	3.46
EUM	4191	6430	1.54	6.59	6.77
JMA	5899	9702	-0.05	3.77	3.77
KMA	4492	6738	-0.14	8.31	8.31
NOA	2722	4576	0.78	4.24	4.32
NWC	8765	14760	0.88	4.28	4.37

Table 12-2: Experiment 3. Statistics for clear 10-minute interval AMVs compared to aircraft, with CQI >= 80. N = total number of AMVs and matched aircraft; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N aircraft	Mean	StdDev	RMSE
BRZ	351	425	2.25	3.80	4.41
EUM	325	325	0.47	7.89	7.90
JMA	-	-	-	-	-
KMA	1626	2131	2.12	6.16	6.51
NOA	100	137	-1.06	4.70	4.82
NWC	778	947	0.89	4.89	4.97

Table 12-3: Experiment 4. Statistics for clear 20-minute interval AMVs compared to aircraft, with CQI >= 80. N = total number of AMVs and matched aircraft; Mean, Standard Deviation, and RMSE (m s^{-1}).

Site	N AMVs	N aircraft	Mean	StdDev	RMSE
BRZ	400	490	1.57	3.84	4.15
EUM	441	664	2.16	6.07	6.44
JMA	-	-	-	-	-
KMA	1179	1547	2.94	6.15	6.82
NOA	62	88	0.79	3.89	3.97
NWC	230	277	-0.99	4.86	4.96

Considering the density scatter plots for Experiment 2a (relating for each producer the aircraft wind speed with the AMV speed, with corresponding collocations shown as green dots in the maps in Chapter 11) there are less differences caused by corresponding wind collocations being located in different locations. A general good correspondence is seen in all producers between both wind sources, with maxima in the scatter plot restricted in all cases to the diagonal. Some producers show a higher dispersion of the data in the graph (EUM, KMA), which includes secondary maxima outside the diagonal possibly related to tracking errors in some cases. Additionally, BRZ is much less able to calculate AMVs with speeds larger than 15 ms^{-1}, which does not occur in the rest of datasets; this element should also be checked, surely in relationship with similar results obtained in Chapters 7 and 8 (maybe the use of “tracking areas” not large enough for the speediest winds?).

Considering the density scatter plots for Experiments 3 and 4, less information can be extracted due to the smaller number of collocations. The differences between the producers are also more significant, with some centres calculating very few AMVs (NOA), and others calculating many more (e.g., KMA). Additionally, the maxima in the scatter plot are outside the diagonal for all centres: it is below the diagonal for NOA meaning AMVs tend to be slower than the aircraft winds, and above the diagonal for the rest of centres meaning AMVs tend to be faster than the aircraft winds. The main cause for this will surely be a wrong height assignment of the Clear air AMVs in all centres; the AMVs should be at lower levels for NOA and at higher levels for the rest of AMV centres.

c) Cloudy AMVs (10-minute interval)

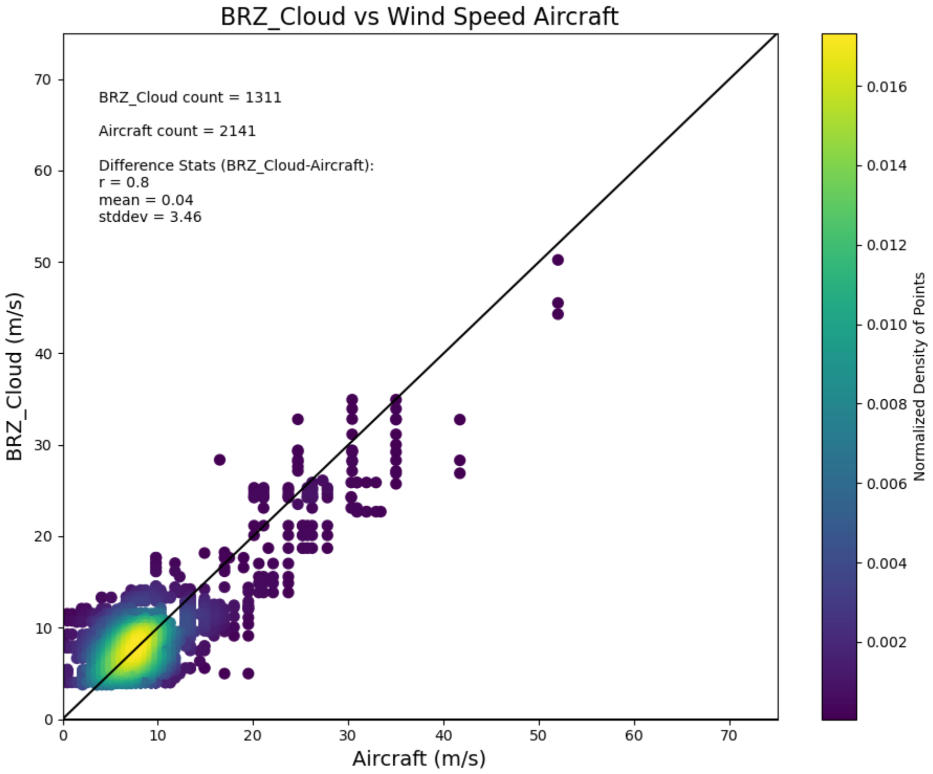

Figure 12-1: Experiment 2a. BRZ cloud AMVs (CQI >= 80): Density scatter plot of BRZ cloud AMV wind speed vs aircraft wind speed.

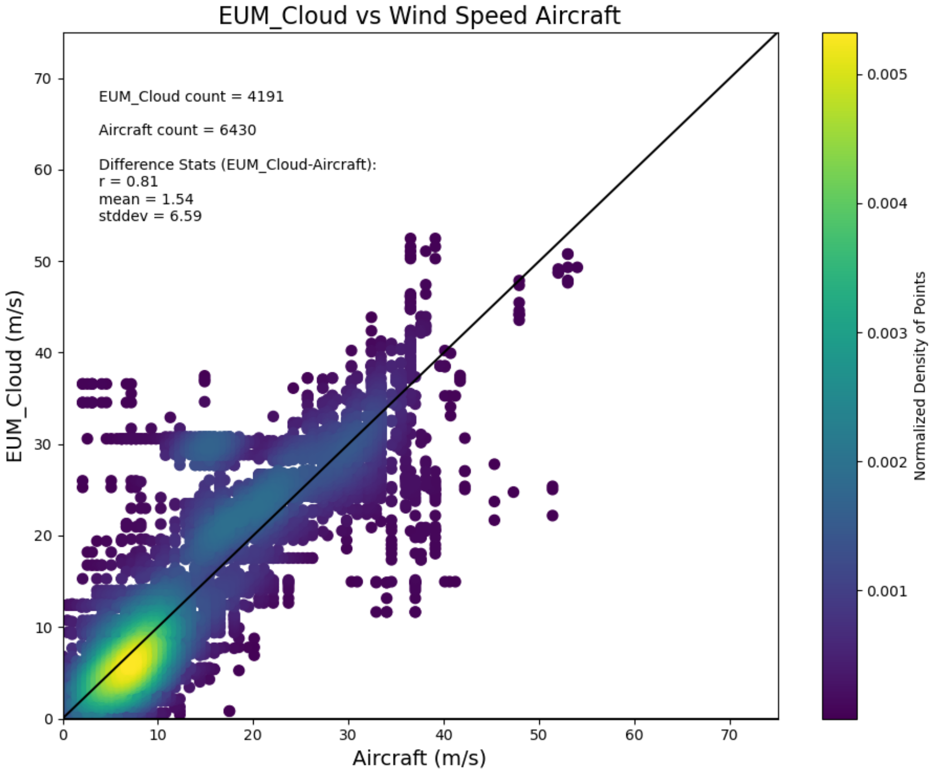

Figure 12-2: Experiment 2a. EUM cloud AMVs (CQI >= 80): Density scatter plot of EUM cloud AMV wind speed vs aircraft wind speed.

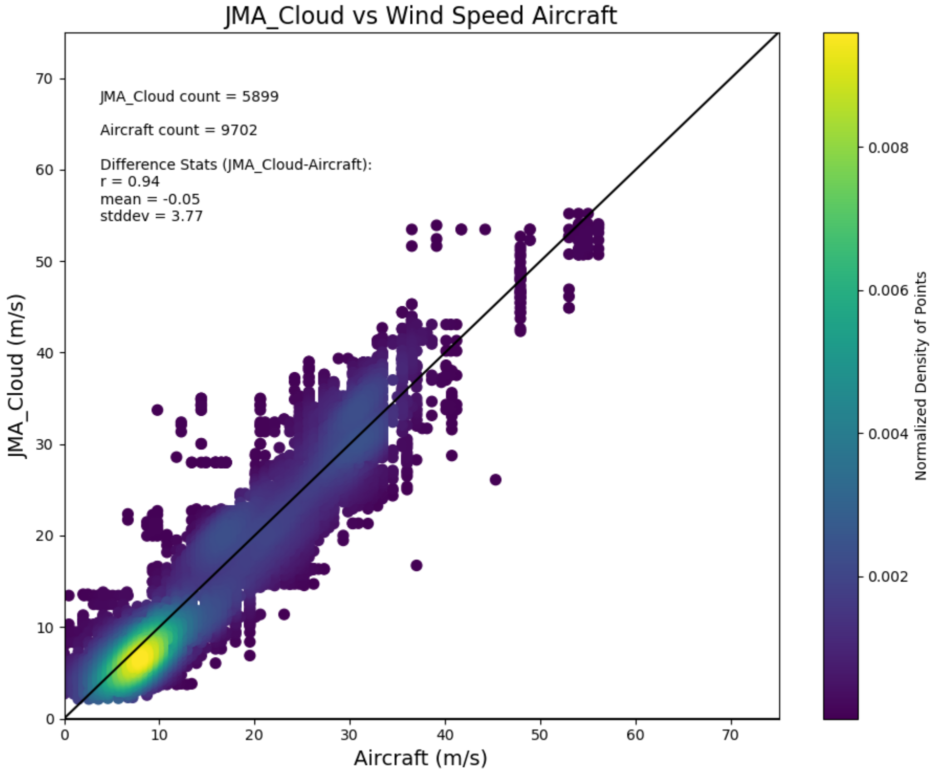

Figure 12-3: Experiment 2a. JMA cloud AMVs (CQI >= 80): Density scatter plot of JMA cloud AMV wind speed vs aircraft wind speed.

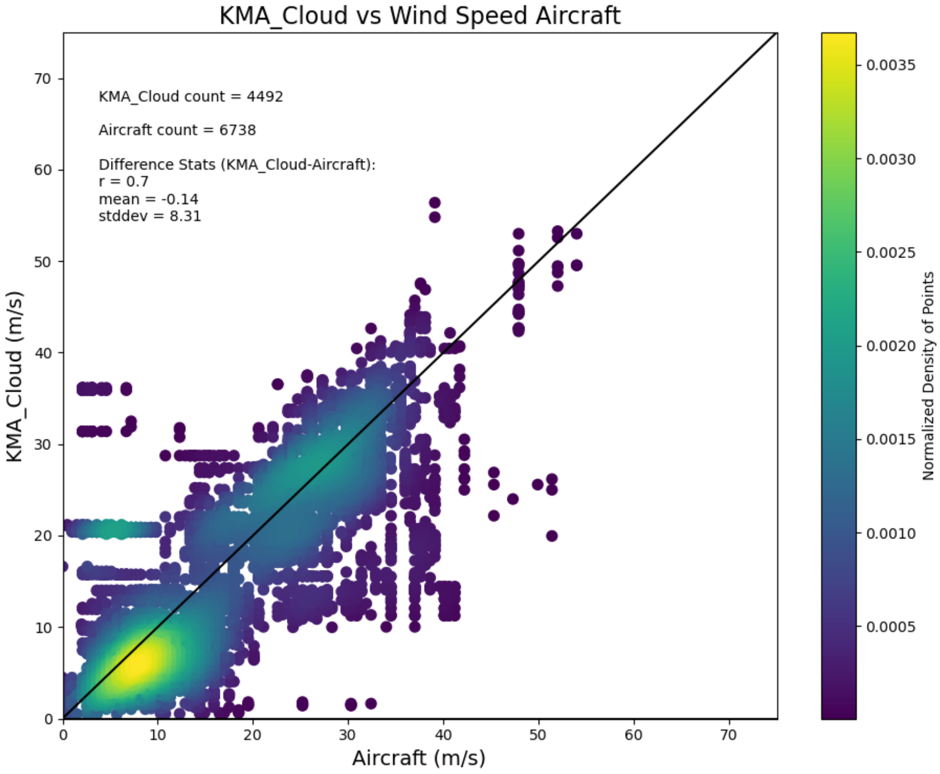

Figure 12-4: Experiment 2a. KMA cloud AMVs (CQI >= 80): Density scatter plot of KMA cloud AMV wind speed vs aircraft wind speed.

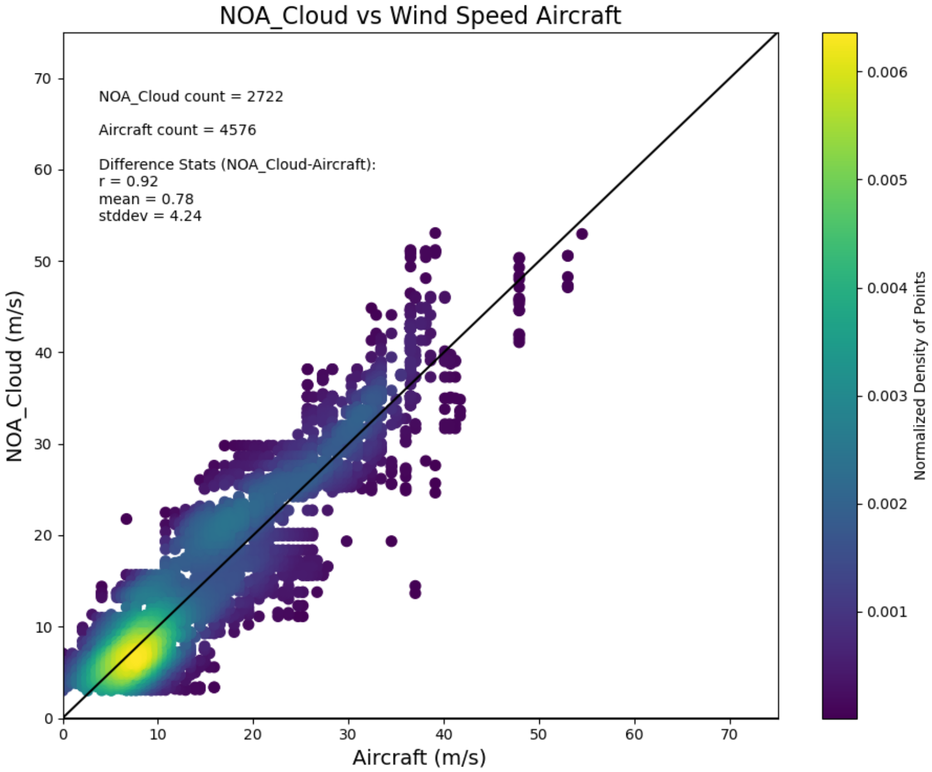

Figure 12-5: Experiment 2a. NOA cloud AMVs (CQI >= 80): Density scatter plot of NOA cloud AMV wind speed vs aircraft wind speed.

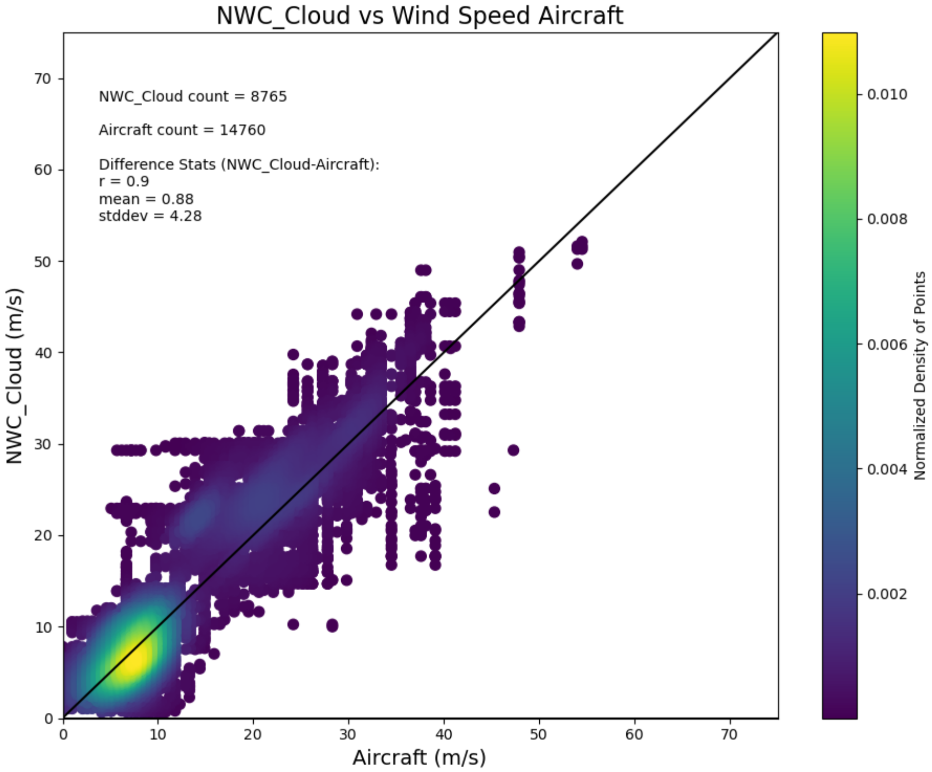

Figure 12-6: Experiment 2a. NWC cloud AMVs (CQI >= 80): Density scatter plot of NWC cloud AMV wind speed vs aircraft wind speed.

d) Clear AMVs (10-minute interval)

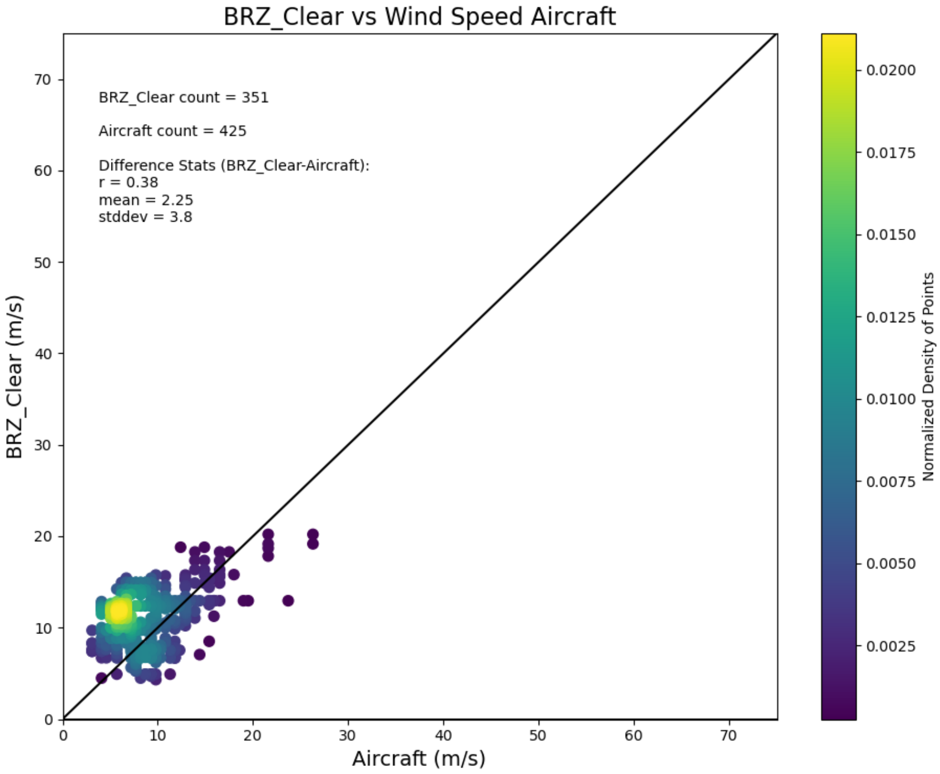

Figure 12-7: Experiment 3. BRZ clear AMVs (CQI >= 80): Density scatter plot of BRZ clear AMV wind speed vs aircraft wind speed.

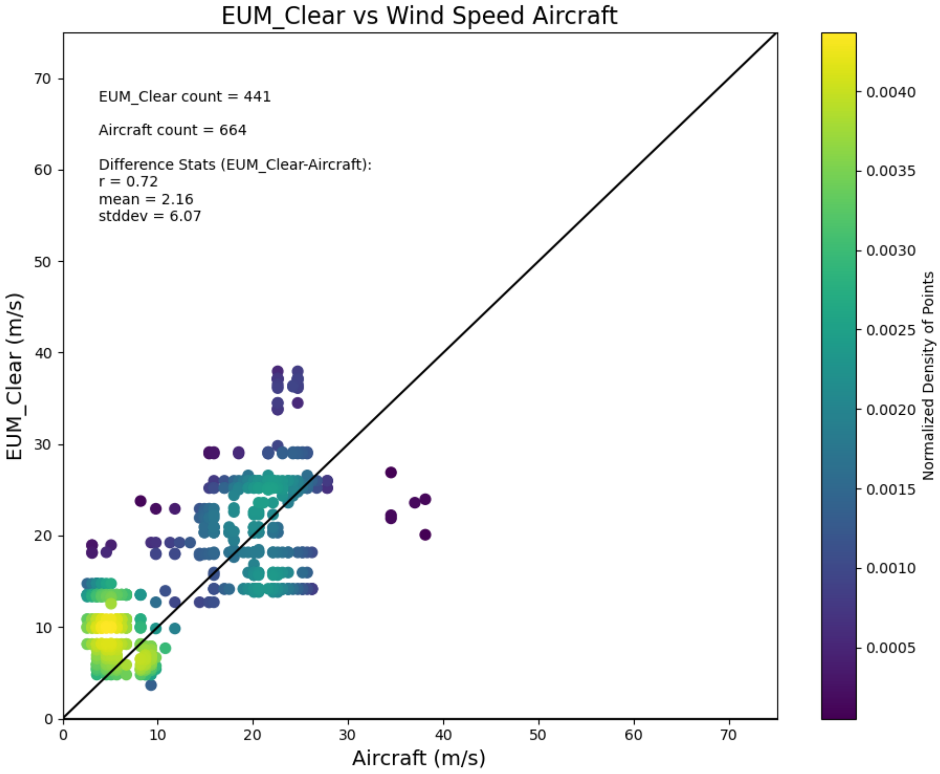

Figure 12-8: Experiment 3. EUM clear AMVs (CQI >= 80): Density scatter plot of EUM clear AMV wind speed vs aircraft wind speed.

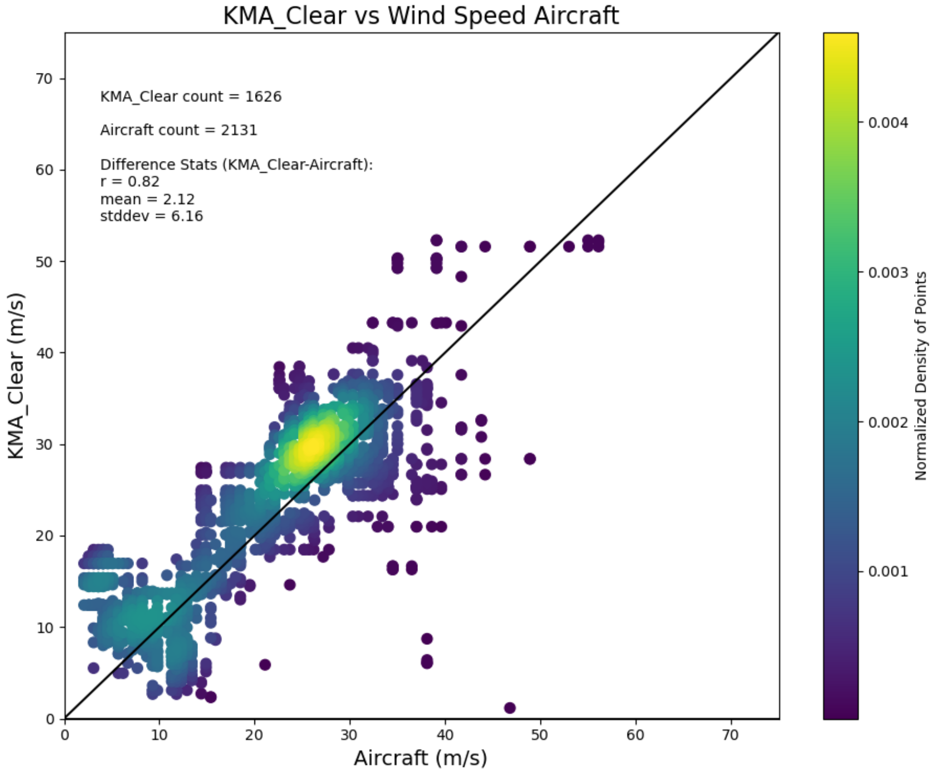

Figure 12-9: Experiment 3. KMA clear AMVs (CQI >= 80): Density scatter plot of KMA clear AMV wind speed vs aircraft wind speed.

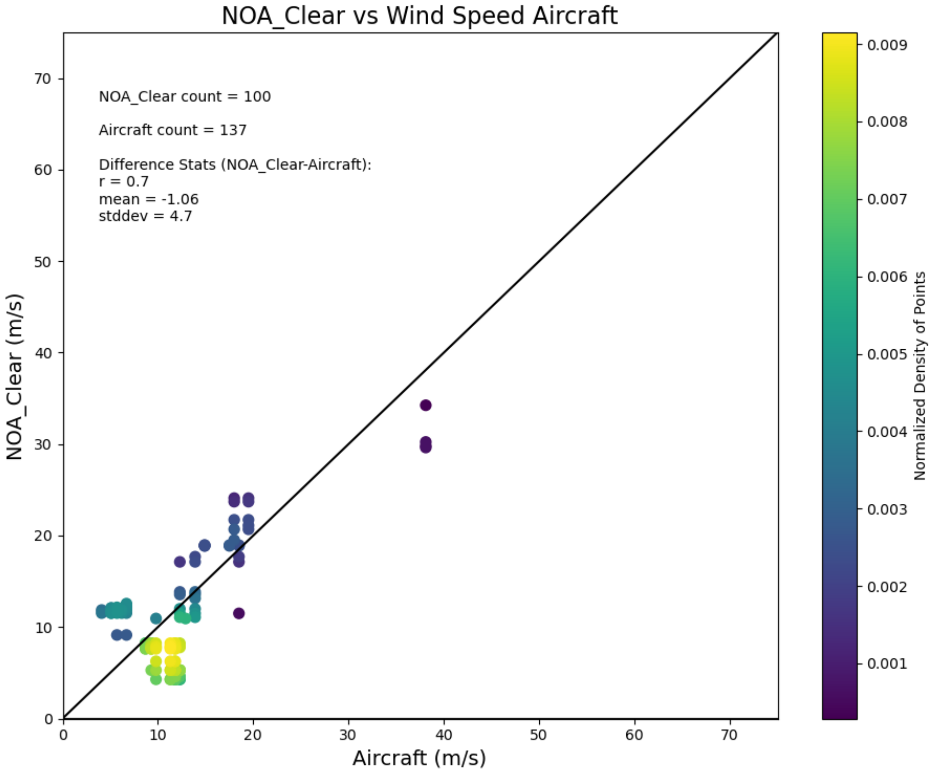

Figure 12-10: Experiment 3. NOA clear AMVs (CQI >= 80): Density scatter plot of NOA clear AMV wind speed vs aircraft wind speed.

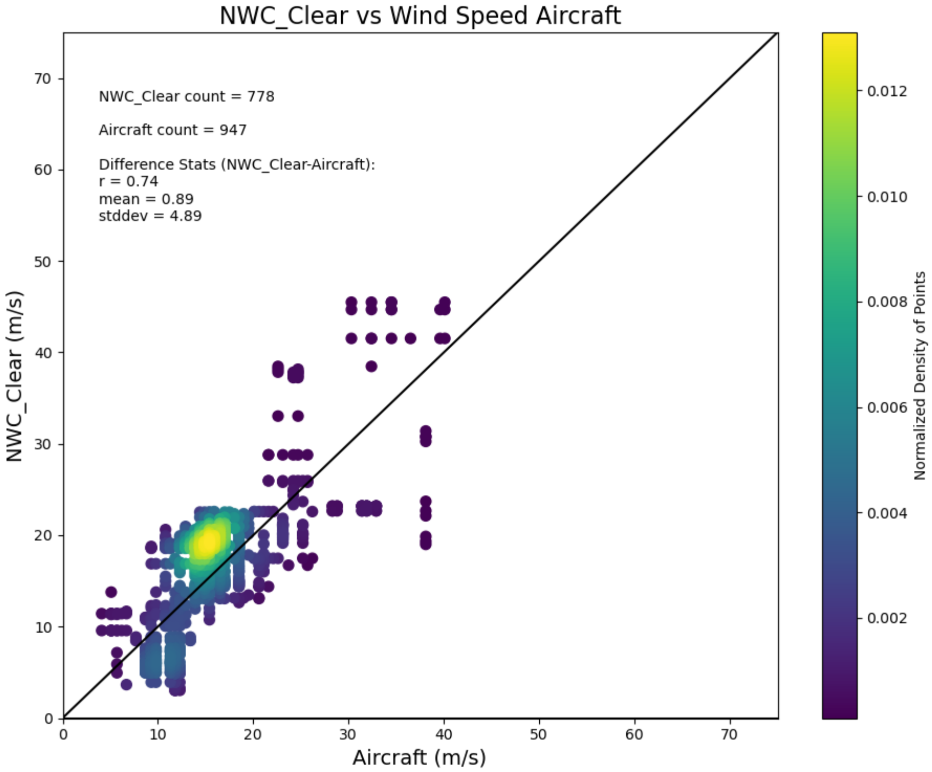

Figure 12-11: Experiment 3. NWC clear AMVs (CQI >= 80): Density scatter plot of NWC clear AMV wind speed vs aircraft wind speed.

e) Clear AMVs (20-minute interval)

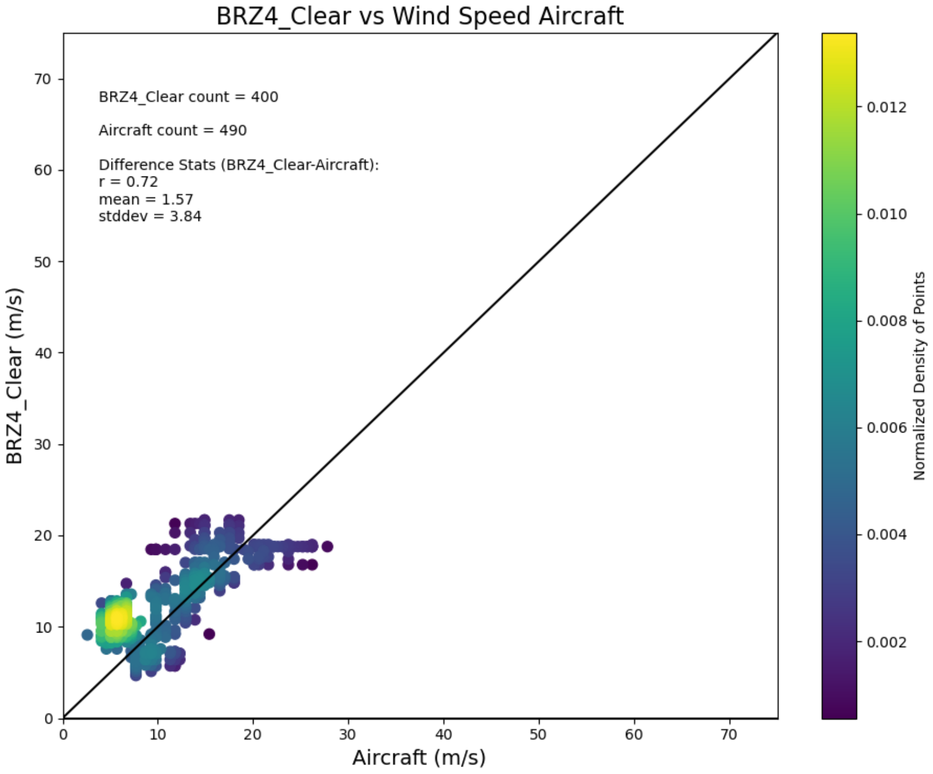

Figure 12-12: Experiment 4. BRZ clear AMVs (CQI >= 80): Density scatter plot of BRZ clear AMV wind speed vs aircraft wind speed.

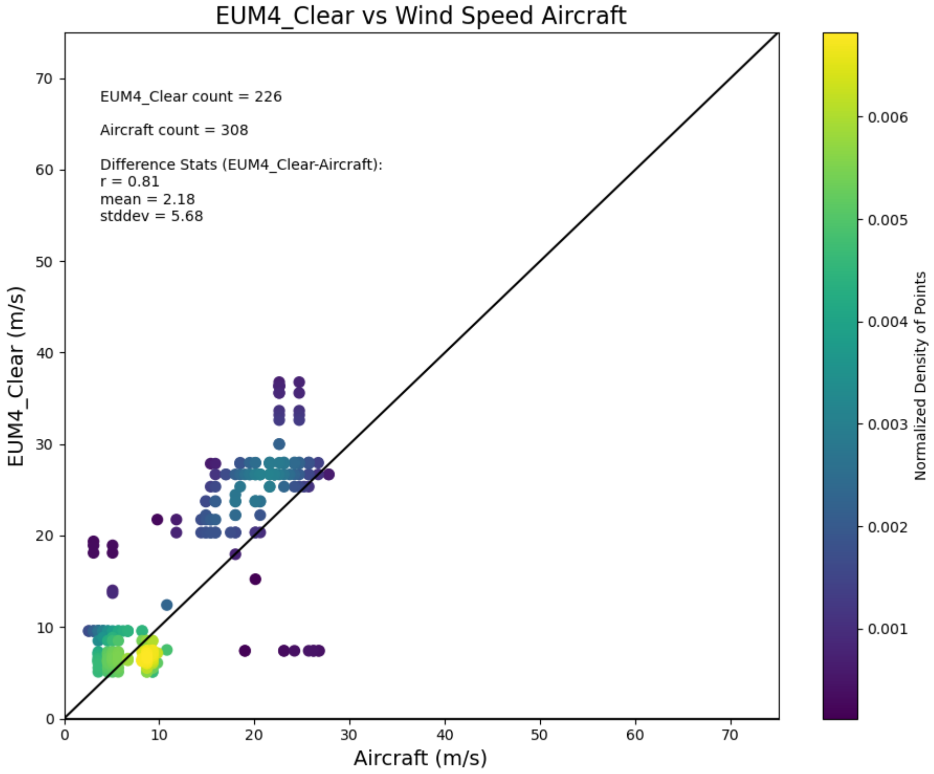

Figure 12-13: Experiment 4. EUM clear AMVs (CQI >= 80): Density scatter plot of EUM clear AMV wind speed vs aircraft wind speed.

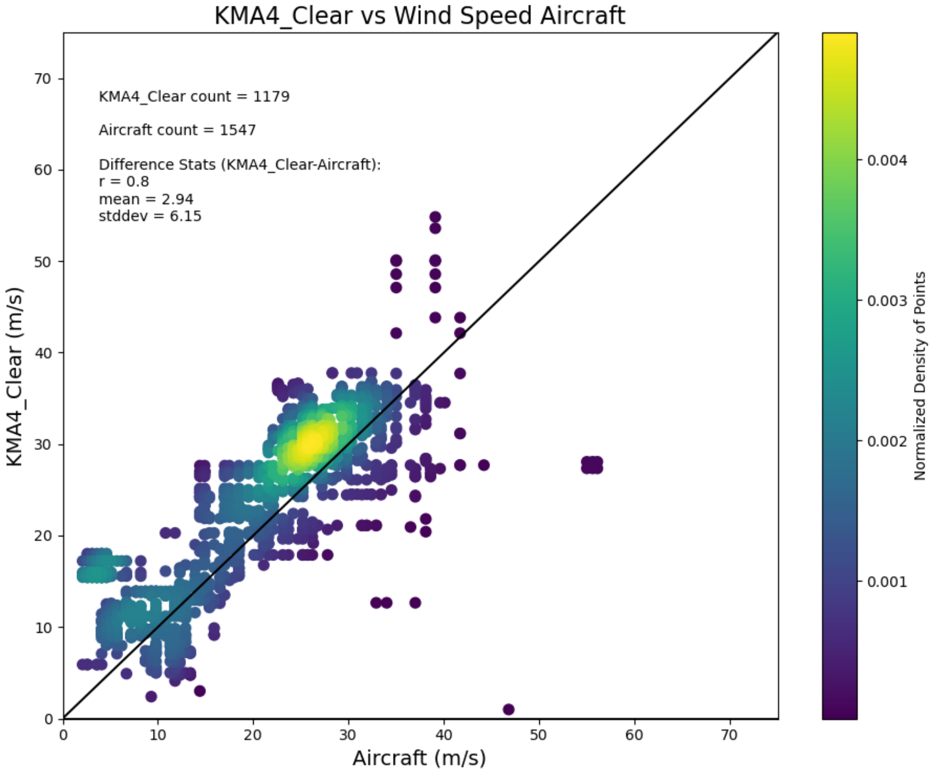

Figure 12-14: Experiment 4. KMA clear AMVs (CQI >= 80): Density scatter plot of KMA clear AMV wind speed vs aircraft wind speed.

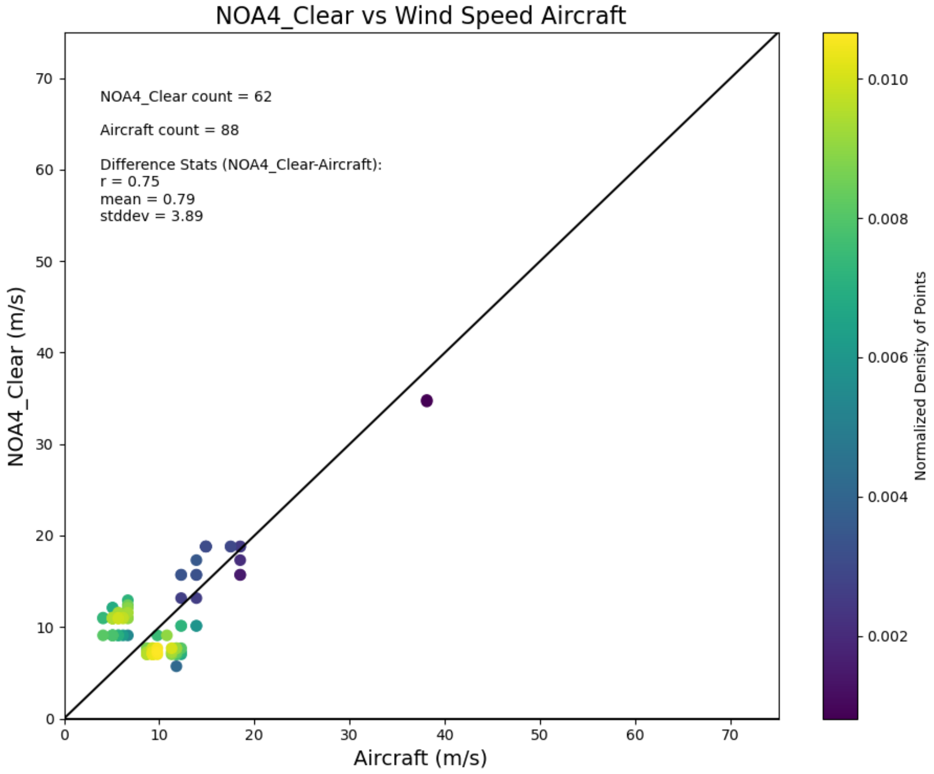

Figure 12-15: Experiment 4. NOA clear AMVs (CQI >= 80): Density scatter plot of NOA clear AMV wind speed vs aircraft wind speed.

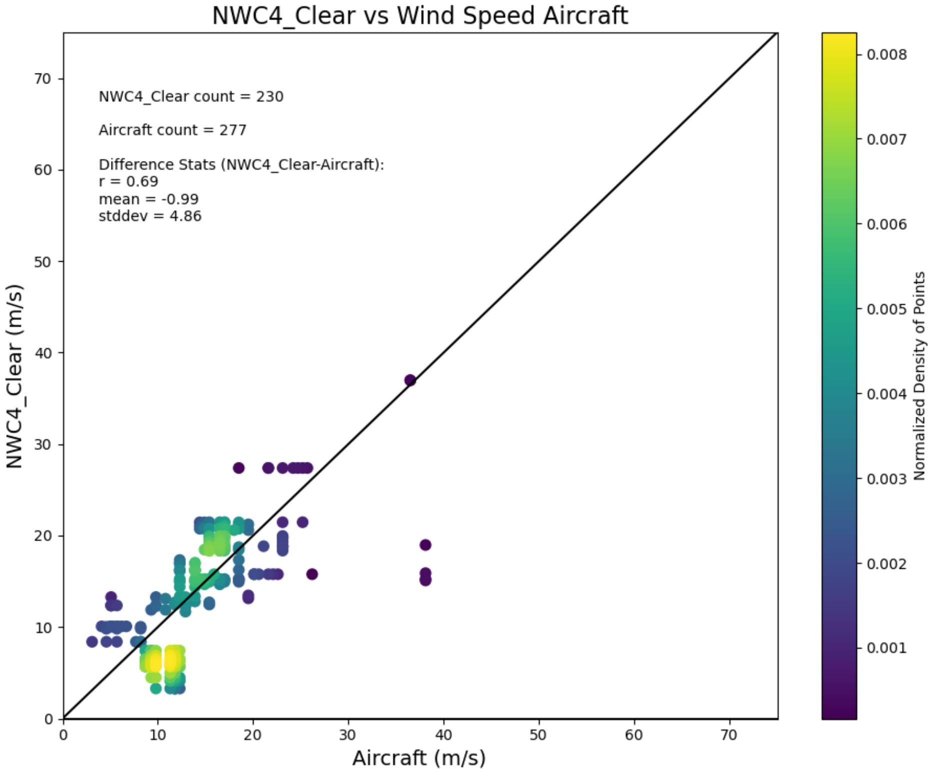

Figure 12-16: Experiment 4. NWC clear AMVs (CQI >= 80): Density scatter plot of NWC clear AMV wind speed vs aircraft wind speed.

13. CALIPSO comparison

a) Approach

This comparison uses the configuration of Experiment 2c, corresponding to the time of a CALIPSO pass that intersects with the GOES-16 coverage.

AMV producers extract infrared channel cloudy AMVs considering their standard AMV configuration, using their typical settings for target selection, target box size and search box size and the height assignment of their choice, with GOES-16/ABI IR Band 14 (11.2 µm) images from 18:50 to 19:10 UTC, 20 October 2019. The AMV characteristics and distributions for Experiment 2c are summarized earlier in this report in Chapter 8.

By using their standard AMV configuration, this experiment gives the producers a best-case evaluation of their AMV height assignment algorithm, as compared to an independent measurement of cloud height from CALIPSO.

For each one of the AMV producer's datasets, AMVs are collocated with CALIPSO measurements of cloud top. The thresholds for determining collocation are a distance of 0.1° of latitude and longitude, and within one hour.

b) Comparison to CALIPSO

Observations from NASA's Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) provide an independent measurement of cloud top heights, which can be used to validate and compare to the satellite-derived AMVs.

Since CALIPSO is a line-of-site measurement, considering the match thresholds defined above, there are very few collocated observations with AMVs. Therefore, this evaluation is qualitative as illustrated in the following figures.

The figures contain the following plots, graphs, and information, starting with the upper left panel:

- The first panel shows the CALIPSO groundtrack (red line) over a map of South America
- The second panel depicts the segment of the groundtrack used in the comparison cross-section (lower half of figure), superimposed over an RGB image of the corresponding GOES-16 ABI IR image,

- The third panel is similar to panel 2, except the underlying image is the ABI-derived cloud top height product,
- The lower half of the figure depicts the clouds (gray) as detected by CALIPSO. The tropopause height is designated by the black line across the top of the graph (above the top of the cirrus clouds). The topography of the Earth's surface is the light blue line in the lower part of the graph. The collocated AMVs are the red symbols, primarily located primarily in the the upper and lower troposphere. There are few AMVs in the mid-troposphere.

From a qualitative perspective, the AMV heights are scattered throughout the high-level and thin cirrus clouds (depending on the centre), and in and below the low-level clouds. These results are in general agreement with Experiment 2 Best fit height analysis, as high-level AMVs need to be adjusted higher in the atmosphere, while varied adjustments are needed for low-level cloud height.

One example illustrates this variation at low levels, relating on one side BRZ, EUM and JMA, for which the CALIPSO comparison shows the AMV height of many low-level clouds is below the clouds and near the ground (Figure 13-1, Figure 13-2, Figure 13-3), and corresponding red shading in the Best Fit analysis (Figure 8-6, Figure 8-8, Figure 8-10) correctly indicates the AMV heights of these lowest clouds should be adjusted upward. On the other hand, the CALIPSO comparison for KMA depicts the AMV heights for these low clouds within the cloud (Figure 13-4), and the corresponding Best Fit analysis (Figure 8-11) has blue shading denoting heights should be adjusted downward. These cases agree for example with Hasler et al. (1979), showing that low clouds move with the speed of the cloud base.

The other example relates the AMVs at high levels for all centres. In all of them, and especially in BRZ (Figure 13-1), the AMVs at highest levels (above 200 hPa) are located near the top and in cases even over the top of the cloud in the CALIPSO comparison. The Best Fit analysis shows with blue shading that the AMV heights of these highest AMVs should be adjusted downward. The exception to this is NWC, for which no AMVs should be adjusted downward because no AMVs exist over 200 hPa. On the contrary, the rest of high AMVs for all AMV centres seem to be located too low in the clouds in the CALIPSO comparison, and the Best Fit analysis shows also with red shading that the heights of these AMVs should be adjusted upward.

With these encouraging results, it is recommended that a longer case study should be examined in order to quantify the results, which could lead to better height error estimates for AMVs.

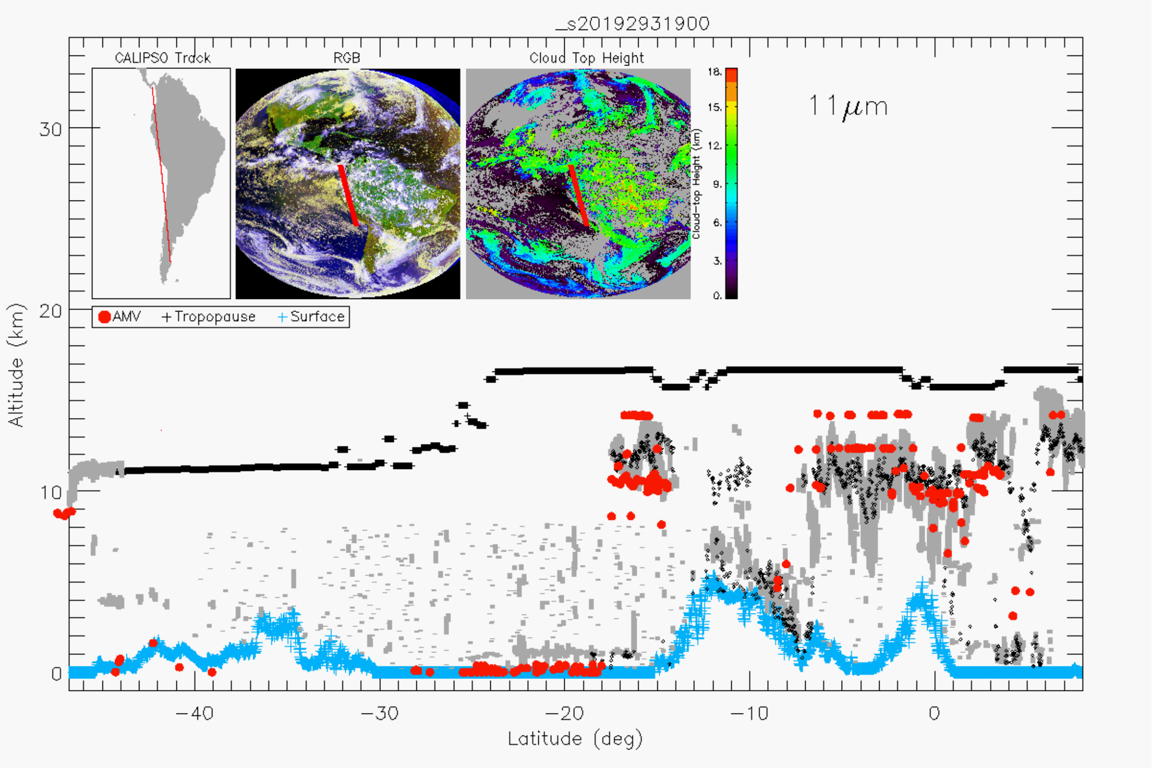

Figure 13-1: Experiment 2c BRZ: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMVs.

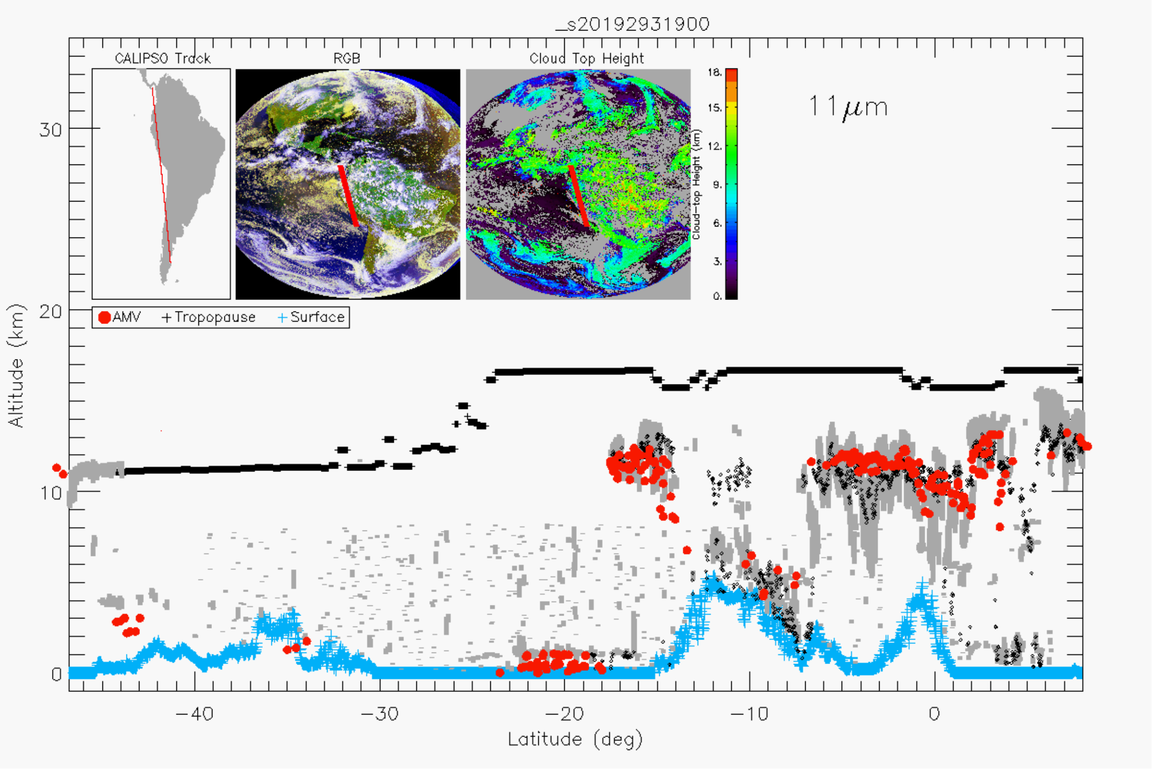

Figure 13-2: Experiment 2c EUM: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMVs.

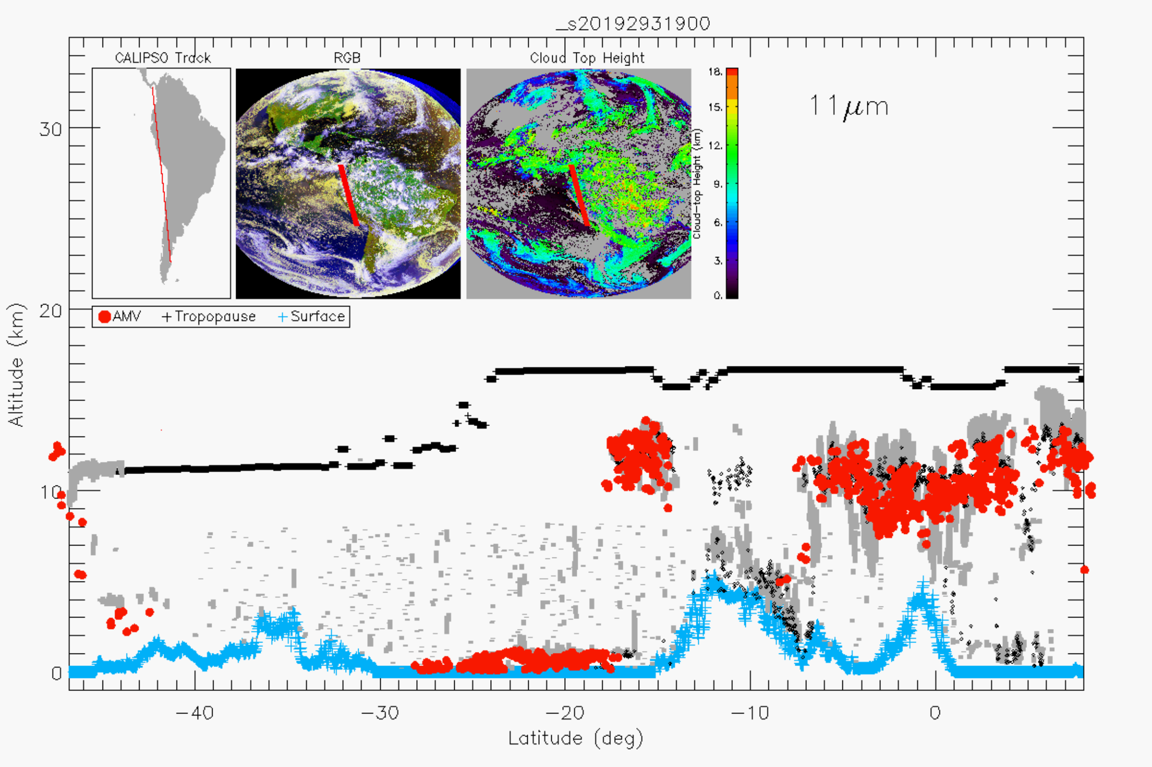

Figure 13-3: Experiment 2c JMA: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMVs.

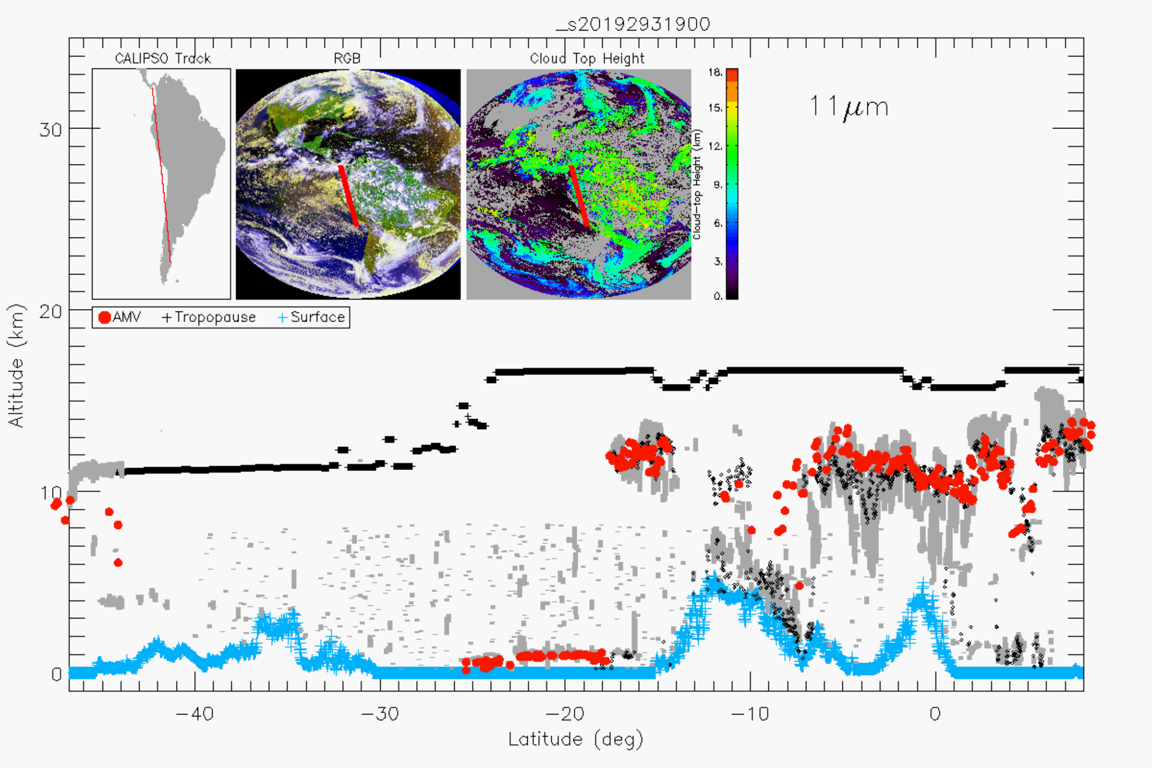

Figure 13-4: Experiment 2c KMA: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMVs.

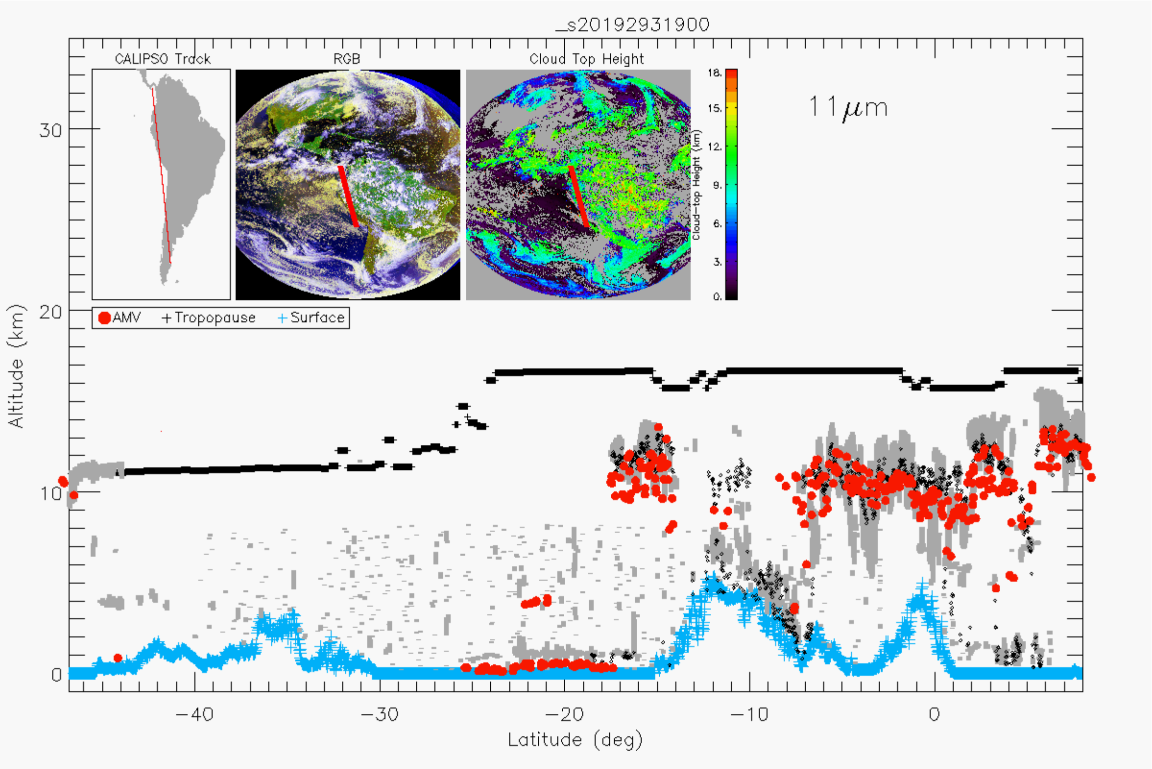

Figure 13-5: Experiment 2c NOA: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMs.

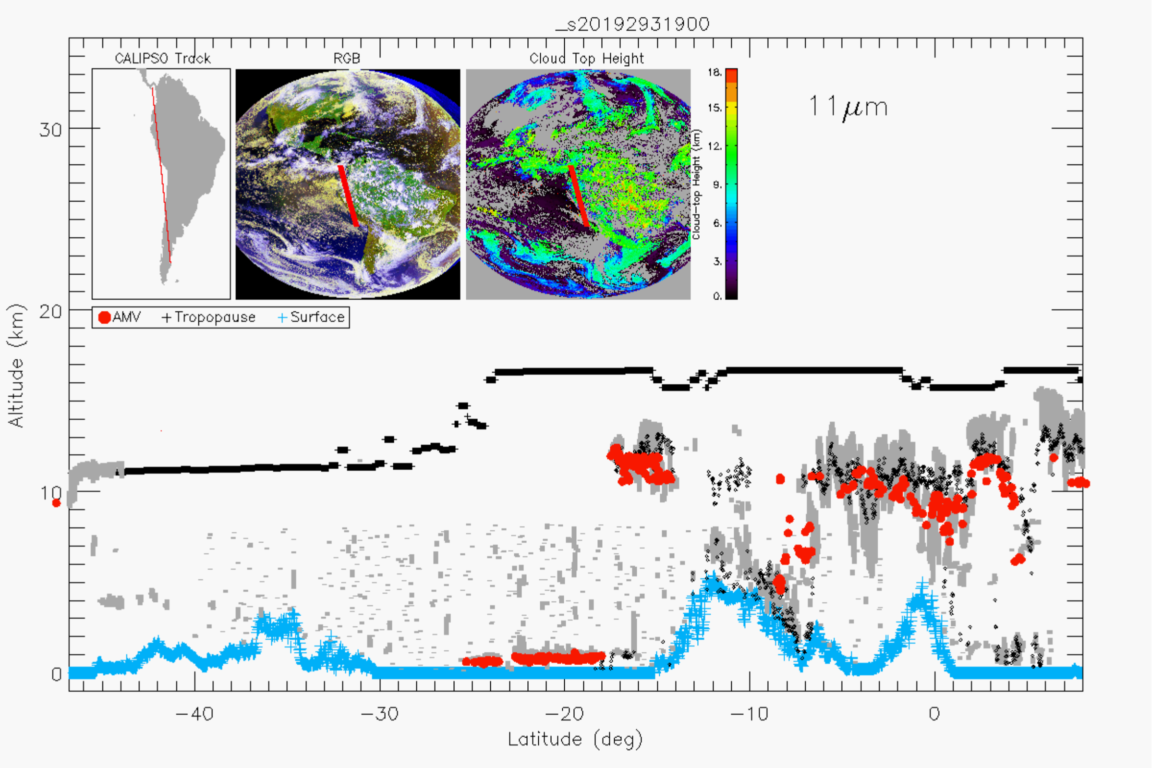

Figure 13-6: Experiment 2c NWC: CALIPSO comparison with collocated AMVs (CQI>=80) at 1900 UTC on 20 October 2019. Red dots represent the AMs.

14. Summary and Conclusions

The following are general observations, conclusions, and recommendations from this AMV Intercomparison Study:

- A homogenization process has occurred in the different AMV algorithm since the AMV intercomparisons started, and now for example AMV layer distributions are more similar, and AMV speed and AMV pressure ranges are smaller than in previous AMV intercomparison.
- The comparisons against rawinsonde winds and NWP analysis winds also show that differences in errors betwen the different AMV datasets are also smaller. Errors for four centres (BRZ, JMA, NOA and NWC) keep in general rather similar values against all references, while KMA and EUM show often higher errors.
- Through the new comparisons in this AMV intercomparison against Aeolus HLOS (horizontal line of sight) winds and aircraft winds, similar errors and differences in errors between the different centres are found, so being results against all references consistent.
- Part of the convergence is related to the fact that the specific operational configuration for some AMV centres is converging to the prescribed configuration defined several years for all these AMV intercomparisons (which nevertheless is never meant to be the best one). The KMA case is the most clear one, calculating exactly the same AMV output in Experiments 1) and 2b), using in both cases its specific Cloud product.

Considering all elements together for Cloudy AMVs in Experiments 1) and 2), the main drivers in variability, over any other option defined in the AMV algorithms keep on being:

- The number of AMVs (with differences of 3-4 times between the different centres). But this can simply be caused by the different densities defined for the tracers/AMVs for operation, unrelated to any error.
- The height assignment procedure, and the pressure it defines for each AMV.

Considering the Clear air AMVs in Experiments 3) and 4), the differences are much larger, taking into account that this is the first time that Clear air AMVs are taken into account in the AMV intercomparisons:

- On one side, there is more variation in the number of AMVs for the different centres: up to 5 times between the BRZ smaller dataset and the KMA larger dataset. NOA acts as an outlier here, with a Clear air AMV dataset one order of magnitude smaller than BRZ. NOA should try at least to calculate a number of AMVs in the middle of the range of the others, so that corresponding AMVs are useful.
- Considering Experiment 4, there is in general a slight 1% increase in the number of AMVs and a small reduction in the errors with respect to Experiment 3. With this, a slight optimization in the calculation of water

vapour AMVs with the longer 20-minute separation between images is seen (as other studies have suggested).
- However, in Experiment 4 NOA calculates comparatively 25% less AMVs and NWC 50% less AMVs. This is not logical, as the only change has been the time separation between images. Both centres should check the reason.
- Considering in both cases the AMV speed scatterplot against aircraft winds and Aeolus HLOS winds, it can be seen that for the Clear air AMVs the maxima in the speed scatterplot are outside the diagonal for all centres: below the diagonal for NOA meaning AMVs tend to be slower than these reference winds, and above the diagonal for the rest of centres meaning AMVs tend to be faster than these reference winds. The main cause for this will surely be a wrong height assignment of the Clear air AMVs; the AMVs should be at lower levels for NOA and at higher levels for the rest of AMV centres.

Considering the comparison with CALIPSO cloud top pressure in Experiment 2c:
- For BRZ, EUM and JMA, the CALIPSO comparison shows the AMV height of many low-level clouds is below the clouds and near the ground; the best-fit analysis also indicates the pressure of these low-level AMVs should be adjusted upward. On the other hand, the CALIPSO comparison for KMA low-level AMVs is within the cloud, and the corresponding best-fit analysis also says they should be adjusted downward.
- In general, and especially for BRZ, the AMVs at highest levels (above 200 hPa) are located near the top and in cases even over the top of the cloud in the CALIPSO comparison. The best-fit analysis shows these highest AMVs should be adjusted downward. The exception to this is NWC, for which no AMVs should be adjusted downward because no AMVs exist over 200 hPa. On the contrary, the rest of high-level AMVs for all AMV centres seem to be located too low in the clouds in the CALIPSO comparison, and the best-fit analysis shows that corresponding pressures should be adjusted upward.

The following sections detail the findings from the experiments, in terms of each AMV producer, independently. This includes the strengths and weaknesses as determined from the results of the experiments

a) CPTEC/INPE (Brazil Weather Forecast and Climatic Studies Center)

The performance of the BRZ AMV algorithm has improved due to all changes in the AMV algorithm, and now its comparison against all reference winds is very similar to the best AMV centres.

There is however one remark: the "NWP coherency filtering" they are doing now is not recommended, because although it helps in general to detect AMVs with gross errors, and so it can improve its results until the level of the best AMV centres, it also removes from the AMV output interesting AMVs which are real observations different to the NWP forecast wind, and which would be the most useful in NWP assimilation or nowcasting tasks. BRZ (and any other centre using something like that) should remove this "NWP coherency filtering" as much as possible to keep the usefulness of the AMV product. This surely has an impact in their results.

Considering also that for several parameters (AMV speed and pressure ranges, AMV height assignment, AMV proportion in the different layers, etc.), BRZ AMVs show a different behaviour than the rest of AMV datasets, they should check why these differences occur, and if they could somehow converge with the rest of AMV centres. The most important element here would be the AMV height assignment, due to the big differences found in the AMV pressure scatter plots.

More specifically, it has also been discovered that BRZ is not able to calculate quick AMVs over 45 ms^{-1}, which the other centres do really calculate. This also causes that the mean AMV speed is smaller than for other centres. There might be a problem with the size of the "tracking area" they use, not enough to detect the displacement of corresponding quick tracers.

b) Japan Meteorological Agency (JMA)

The JMA algorithm is using the same algorithm than in the previous AMV intercomparison, and so results are rather similar. But considering for example AMV pressure scatter plots for Experiments 1 and 2, JMA shows a much more random distribution of AMVs, especially with many AMVs which are located in high levels while the rest of centres locate them at low levels. A good exercise here would be to check visually these JMA AMVs and the clouds they are related to, and see in the corresponding satellite image if there are really high clouds or low clouds (such as defined by the other AMV centres) in these locations.

c) NOAA (United States National Oceanic and Atmospheric Administration)

The main difference of NOA cloudy AMV datasets is the vertical distribution, for which there are very few AMVs in middle levels, which is in disagreement with the rest of the centres; this situation also occurred in the previous AMV intercomparison study. Additionally, there seems to be a frontier around 600 hPa, over which AMVs seem to be at higher levels than for the rest, and at lower levels AMVs seem to be at lower levels than for the rest.

Considering Clear air AMVs, NOA should try at least to calculate a number of AMVs in the middle of the range of the others, so that they are useful; current number of calculated AMVs is too short.

d) NWC SAF (Satellite Application Facility on support to Nowcasting)

NWCSAF/HRW algorithm agrees well with other centres in terms of parameter distributions, especially when using the Common QI and their own configuration. Their validation results against rawinsondes and model analysis winds are usually within the top three positions.

One area that warrants additional investigation is in regards to the new clear sky water vapor AMVs. For 10-minute time step between images (Experiment 3), a reasonable number of AMVs are generated. However, when the time step is increased to 20 minutes, the number of AMVs from NWC are reduced by 50%. This is unlike the other centres which saw a similar yield of AMVs in both Experiments 3 and 4.

e) EUMETSAT (EUM)

A specific analysis has been done on the impact of the "Common Quality Control (CQI)" in the AMVs of the different datasets, and it has been discovered that the quality of the AMVs which reach the Quality control process is very different: The RMSE of the lowest quality AMVs is between 6-8 ms-1 for BRZ, JMA, NOA, and NWC, which is rather homogeneous, but it reaches values of 35 ms-1 in KMA and 55 ms-1 in EUM.

With this, although it is a fact that all AMV centres can calculate wrong AMVs, BRZ/JMA/NOA/NWC are able to remove AMVs with gross errors before the quality control, and so the preliminary quality of their AMVs before the quality control is rather good (the way they do this can be very variable and partially based on what AMV centres say in Chapter 6, in the question checking if any filtering is defined in the AMV data provided for the AMV intercomparison; here a special remark is to be done on the "NWP consistency test" by BRZ, which should be avoided in all cases as much as possible).

This does not occur with EUM and KMA, having a part of AMVs with errors bigger than 10 ms-1 (11% for KMA, 19% for EUM), while other centres have none. This could not only imply that their filtering of AMVs with gross errors is weak, but also that there is a real issue in the processing of at least a part their AMVs. Both centres should analyze as much as possible the information in the AMV intercomparison study, to try to extract useful conclusions about this.

f) Korea Meteorological Administration (KMA)

Beyond everything said for EUM, which is also valid for KMA, KMA results have degraded with respect to the previous AMV intercomparison, and this might be caused by the new "CCC height assignment", which depends very much on the quality of the Cloud product used. KMA should keep the older height assignment methods ("EBBT" and "IR/WV intercept"), while the Cloud product it uses with "CCC method" to calculate the AMV pressure does not guarantee better results.

Some ideas for later exercises:

Considering the conclusions of this AMV intercomparison study, some ideas are defined here for later exercises for further information. They will be presented to the following International Winds Workshop in May 2023 for checking, evaluation, and definition of any other further tasks. These exercises can be done exactly with the same AMV input datasets, without the need to calculate any more AMVs. They would so be related to this AMV intercomparison study.

- One one side, it is confirmed, based on what the AMV producer said, that some AMV dataset can have an important dependency on the NWP winds (f.ex. BRZ). But it is also possible that other AMV datasets can also have this dependency. A good way to see this would be to calculate the scatterplot of the "AMV speed" against the "NWP guess wind speed" they could use for the AMV calculation. This way, it would be possible to see if the AMVs have the option to depart visibly from the NWP wind forecast, and so the option to calculate interesting AMVs which are real observations different to the NWP forecast, and which would be the most useful for example in NWP assimilation.

- On the other side, the AMV pressure scatterplots in Experiments 1 and 2 also show that some AMV pressures could be "artificial" (for example in the cases in which all centres define a low-level AMV, while JMA defines a higher level AMV, which is a frequent case). A specific evaluation can be done here, checking for these collocated AMVs what the tracer is specifically seeing: which cloud layers are really inside the tracer, which AMV pressures are defined by the different AMV centres, and see if really all these AMV pressures can be defined with information existing in that tracer.

Some ideas for the calculation of AMVs with the new generation of satellites:

After all these considerations, general and specific for each AMV centre, thinking about the best options for the calculation of AMVs with the new generation of geostationary satellites (Himawari-8/9, GOES-R, MTG-I, etc.), two different elements have to be taken into account:

- On one side, it is a fact that AMV datasets from the different centres have had some homogenization, considering their cloudy AMV outputs and their comparison against several reference wind datasets, and this is a positive result by itself. This has been reached mainly with the use of the "Common Quality Index (CQI)", and with the (at least partial) convergence to a common configuration.
- On the other side, this has been reached in spite of the difference procedures with which the different producers calculate their AMVs. Here, the main difference keeps on being the height assignment process: JMA's height assignment seems to be the best option ("optimal estimation method using observed radiance and NWP vertical profile"), but it still needs to be seen if it implies too much dependence on NWP wind information (some exercises have been defined here to check this). Other centres (like NWC with "CCC method") reach only slightly worse results, but with a method very independent of the NWP wind.
- The other main element having an impact in the improvement of the AMV datasets, seems to be the additional filtering that some centres are doing in the AMV output (BRZ, NOA, NWC), before what is done by the Quality control. It is a fact that these filterings can remove all AMVs with gross errors before the Quality Control, with the consequence that all AMVs that are validated by the Quality control have some extra quality. Here, the report has seen that some of these filterings can be very unrecommended (for example, the "NWP consistency", which is better to be avoided as much as possible), but other filterings can do a good work here, and can be tested by the different AMV centres.

Finally, even though we did not have substantial results from the water vapour channel nor the different time interval between images, it is important to remark these elements (other satellite channels, other time intervals between images) are important for future studies, since they tie into what we can expect from future satellites.

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16. Acknowledgements

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We also thank the AMV producers for their efforts in processing these datasets:

BRZ: Renato Galante Negri
EUM: Régis Borde and Manuel Carranza
NWC: Javier García Pereda
JMA: Kazuki Shimoji
KMA: Kim Hee-ae
NOA: Andrew Bailey, Jaime Daniels and Hongming Qi

17. Appendix A: Parameter Distribution Histograms

Experiment 1: QINF Parameter Distribution Histograms

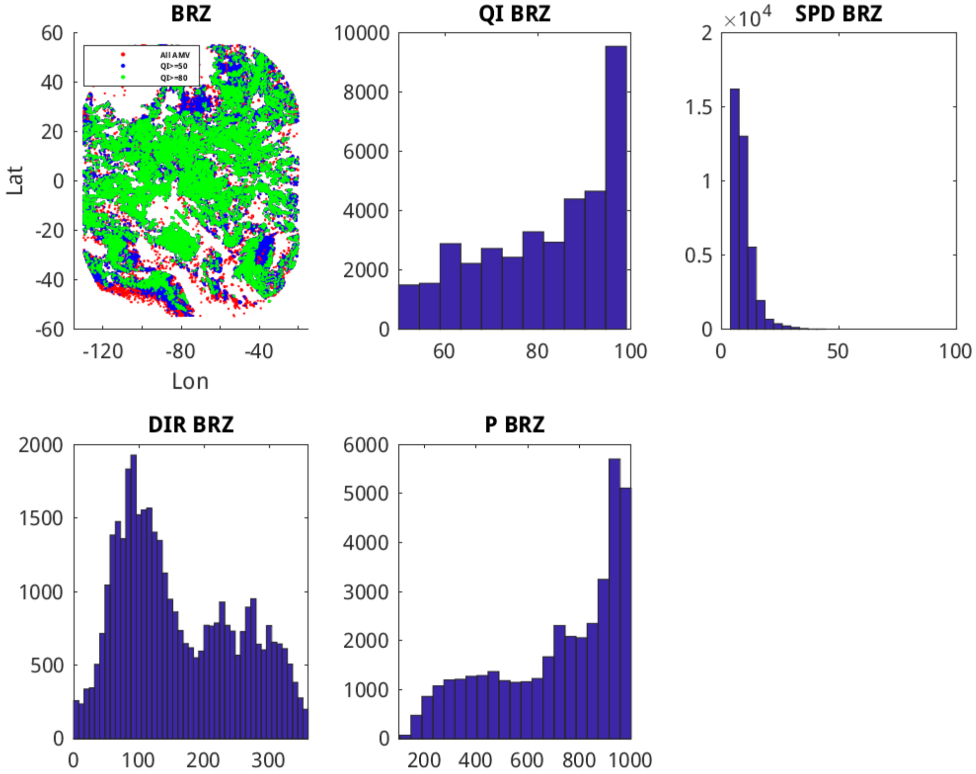

Figure 17-1: Experiment 1, BRZ (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

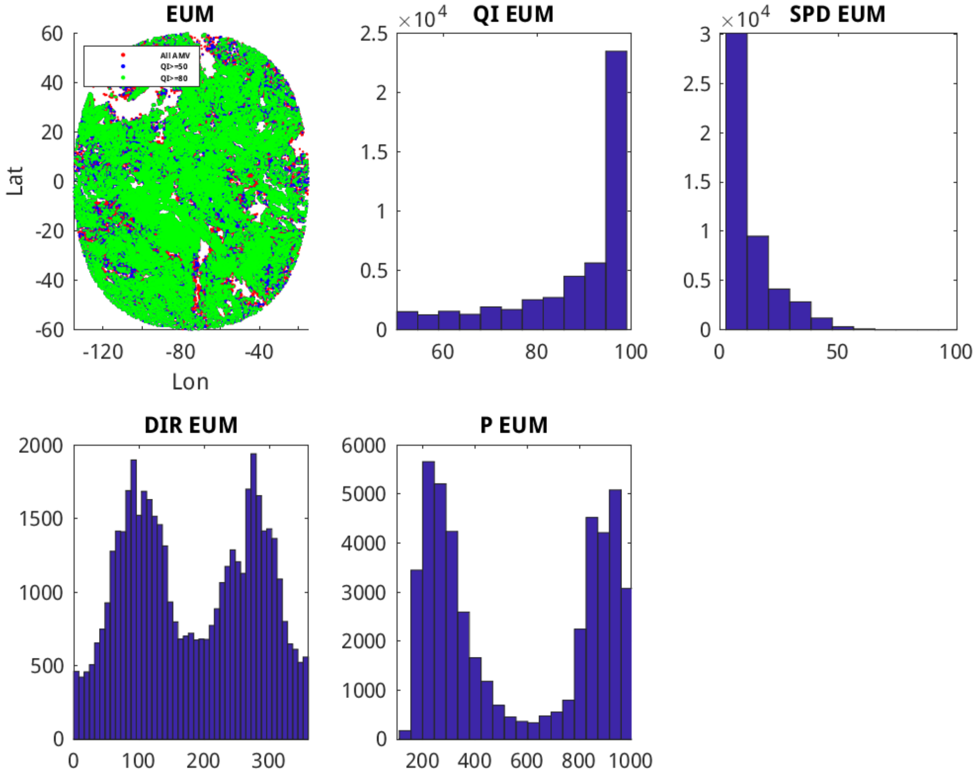

Figure 17-2: Experiment 1, EUM (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

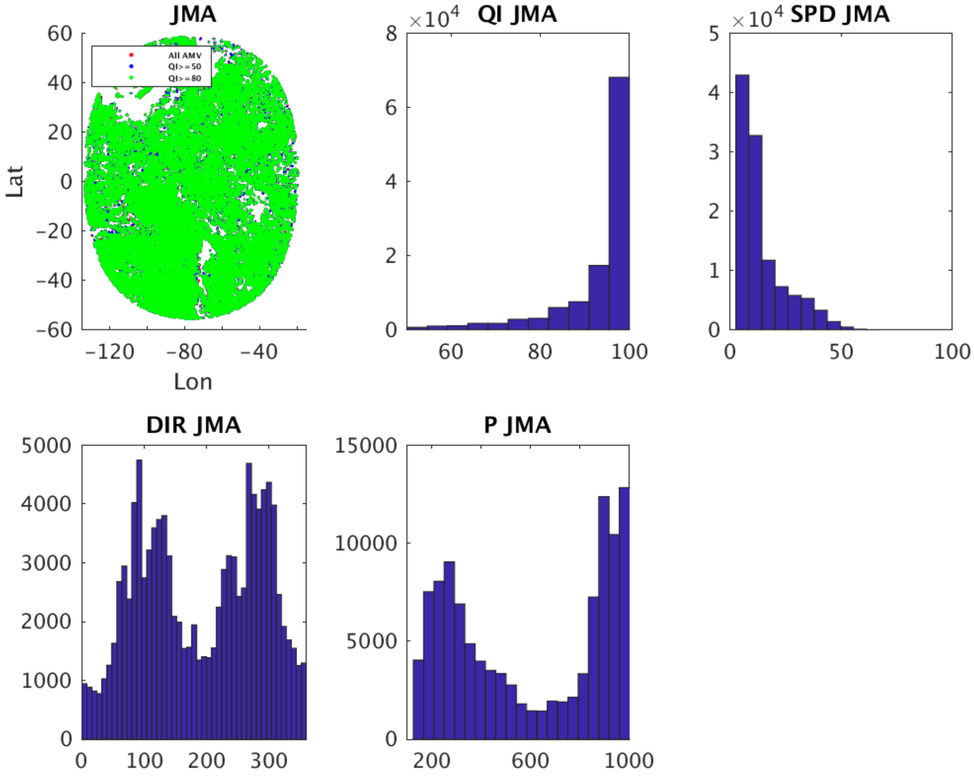

Figure 17-3: Experiment 1, JMA (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

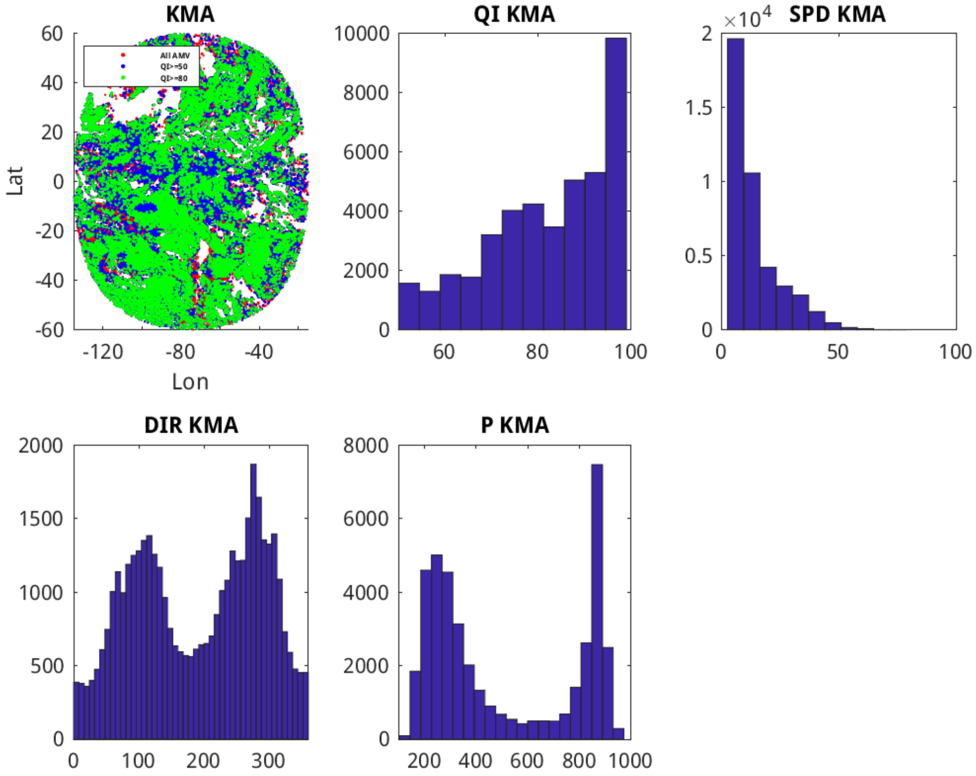

Figure 17-4: Experiment 1, KMA (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

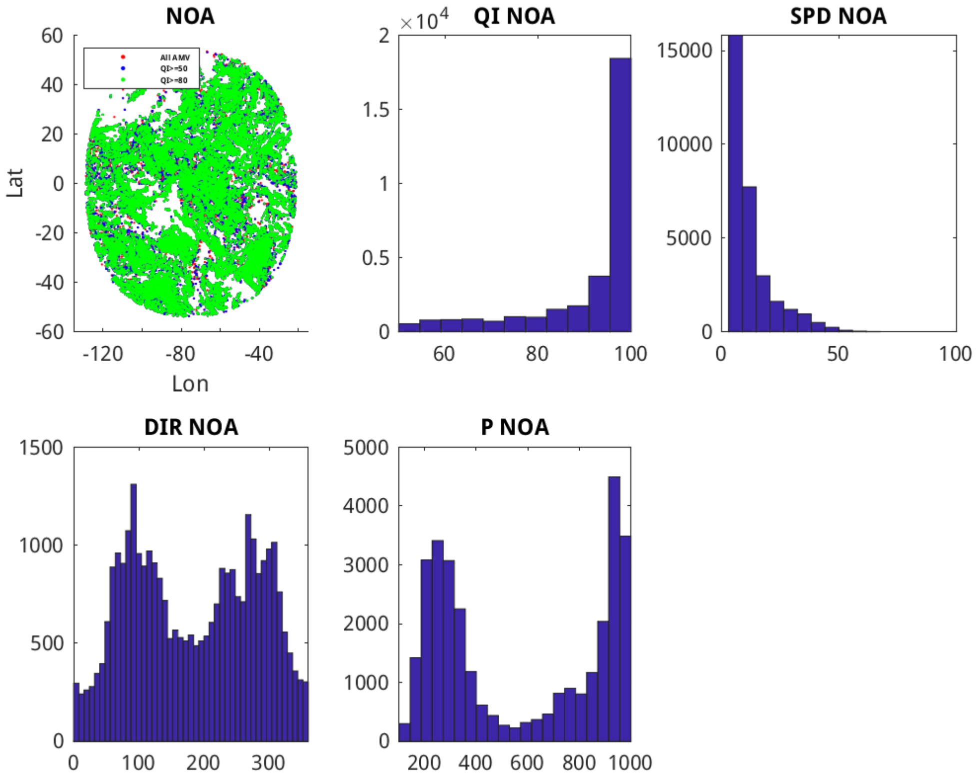

Figure 17-5: Experiment 1, NOA (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

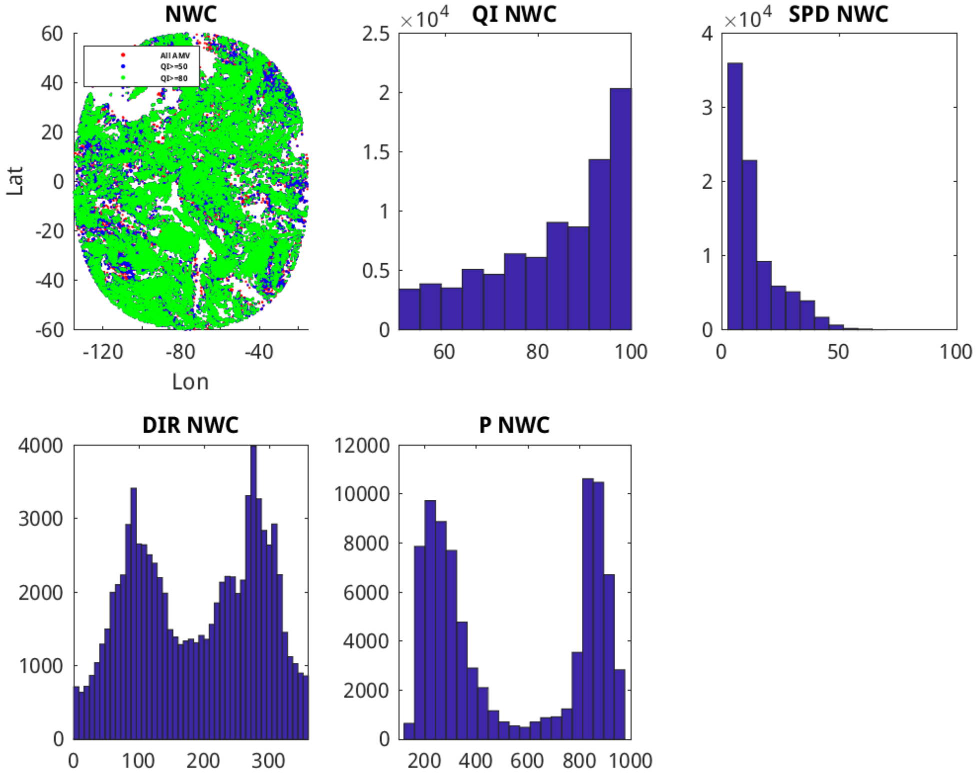

Figure 17-6: Experiment 1, NWC (QINF>=50). Parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 1: CQI Parameter Distribution Histograms

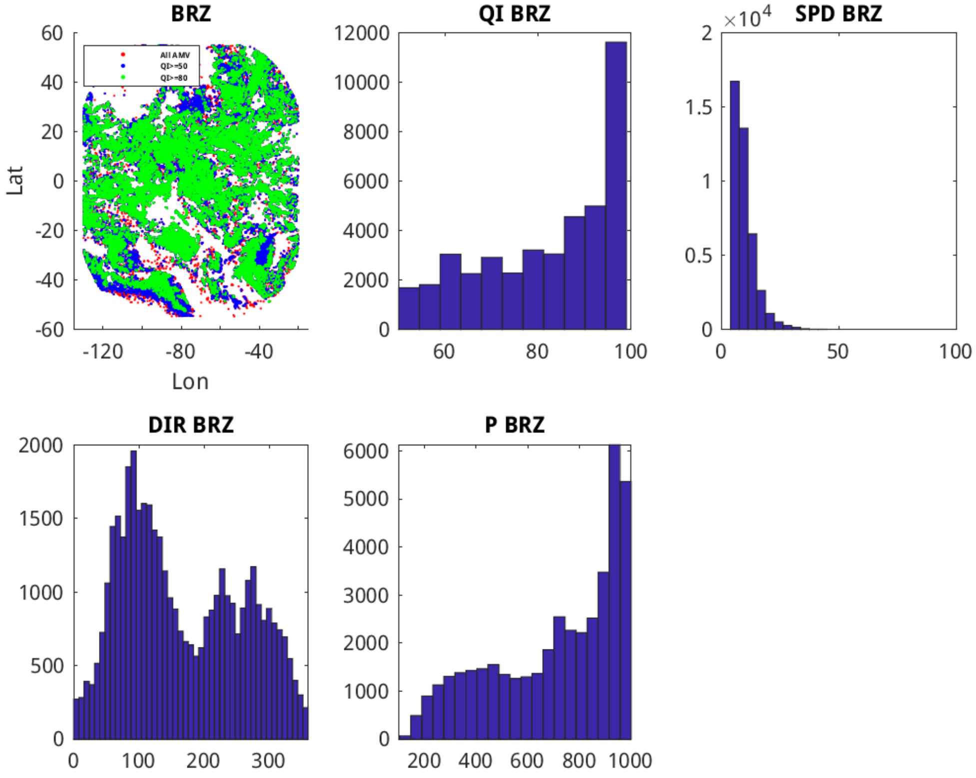

Figure 17-7: Experiment 1 BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

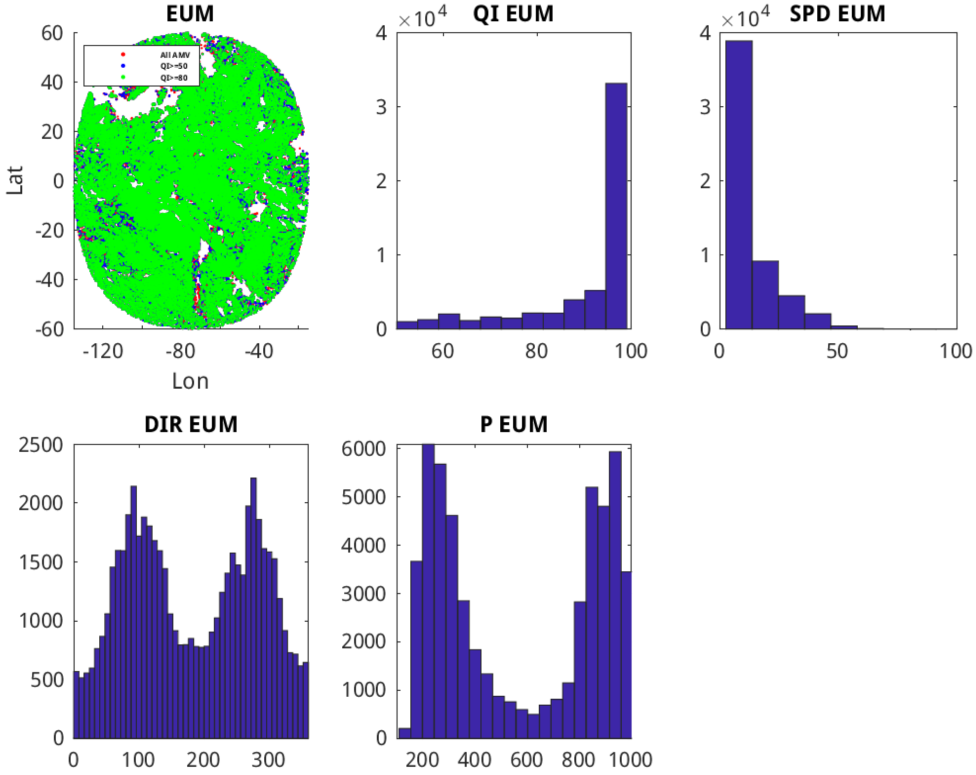

Figure 17-8: Experiment 1 EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

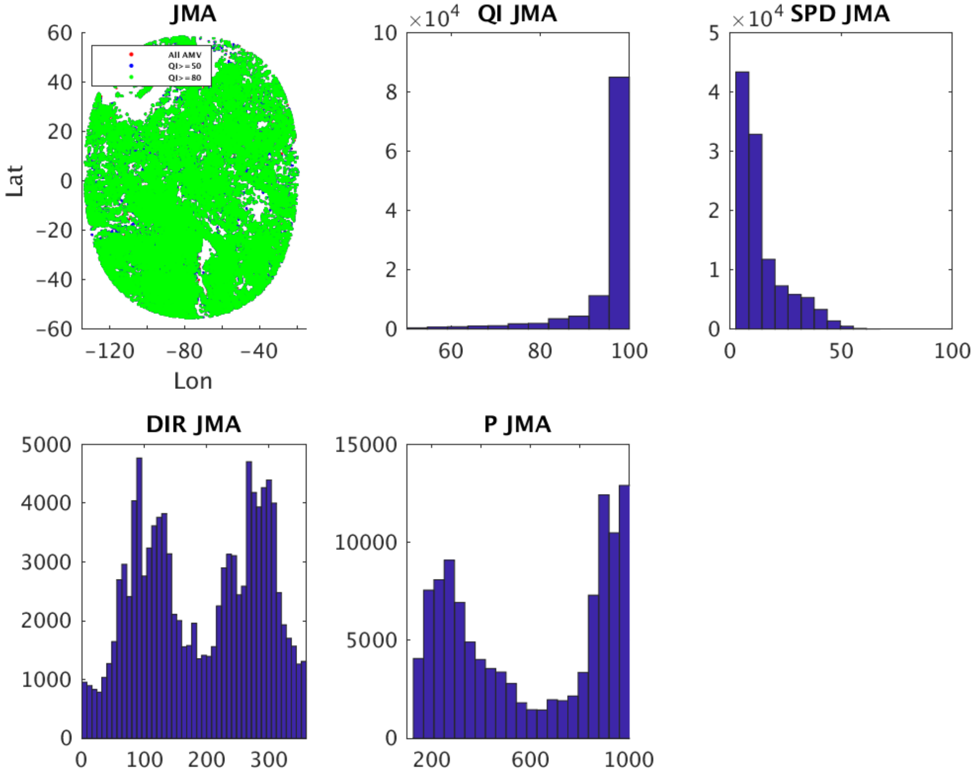

Figure 17-9: Experiment 1 JMA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

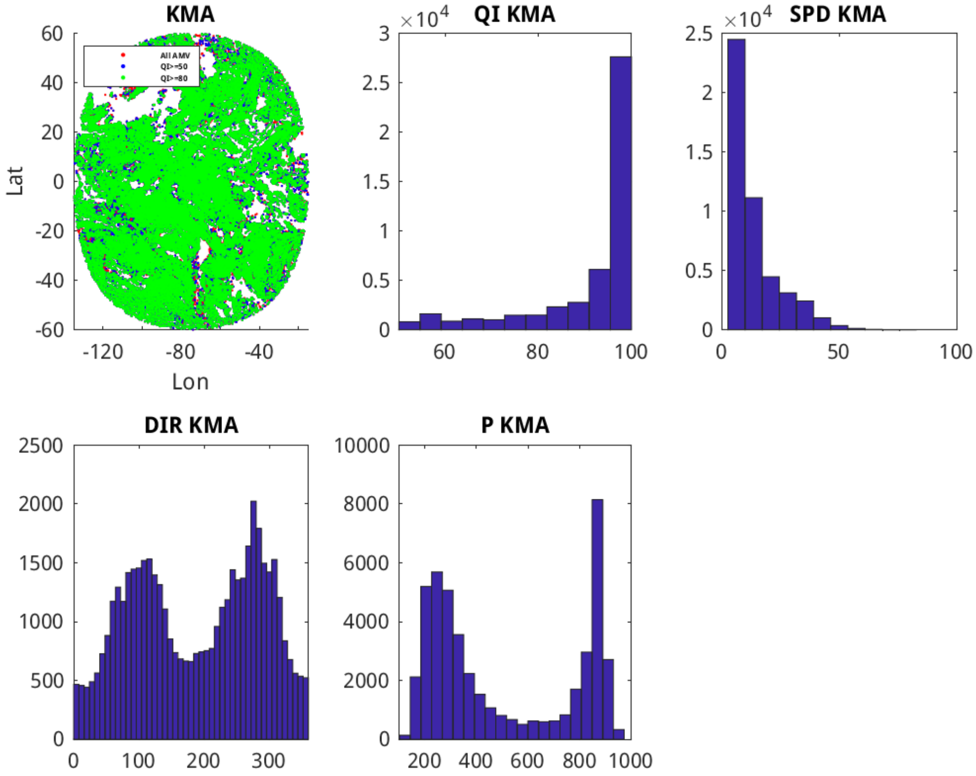

Figure 17-10: Experiment 1 KMA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

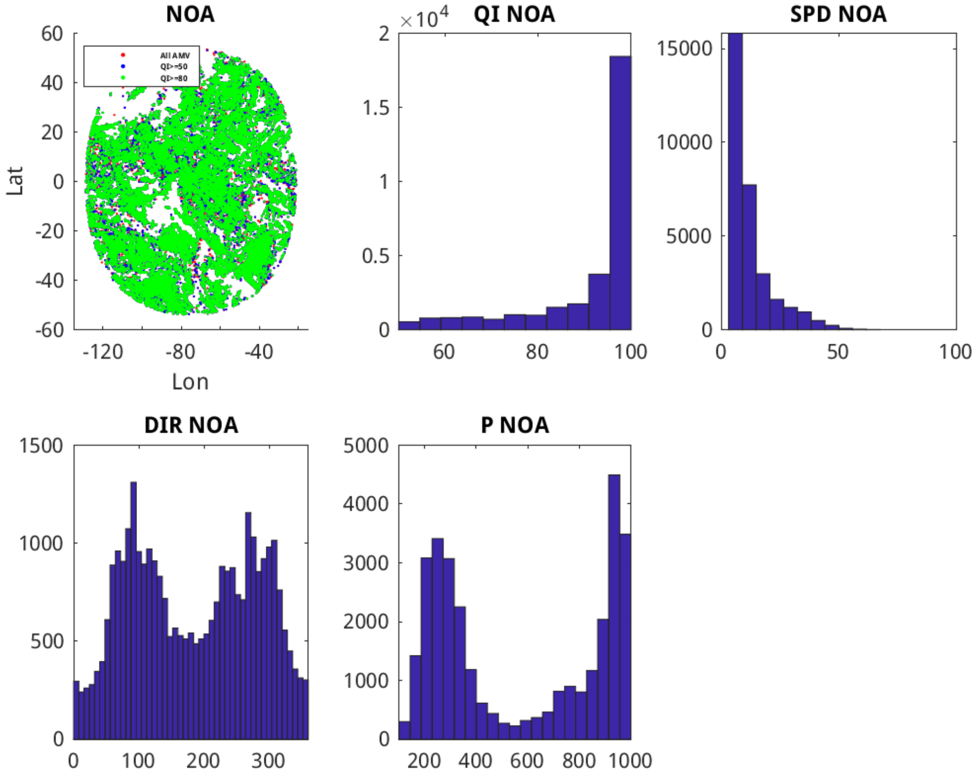

Figure 17-11: Experiment 1 NOA (CQI>=50) NOA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

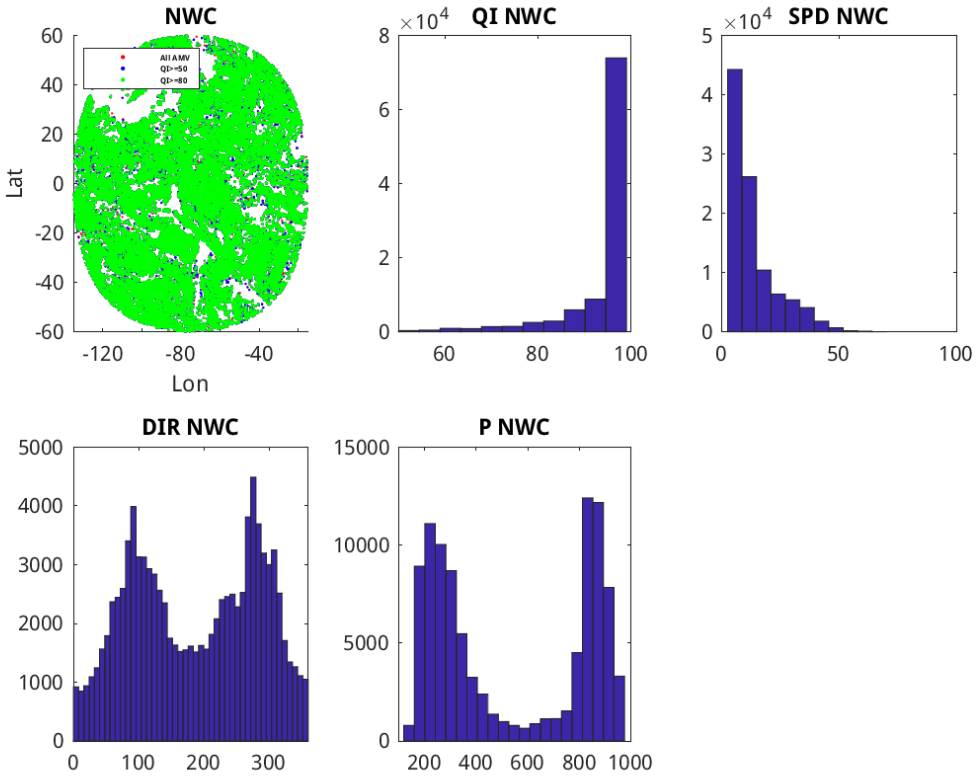

Figure 17-12: Experiment 1 NWC (CQI>=50) NWC parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2a: QINF Parameter Distribution Histograms

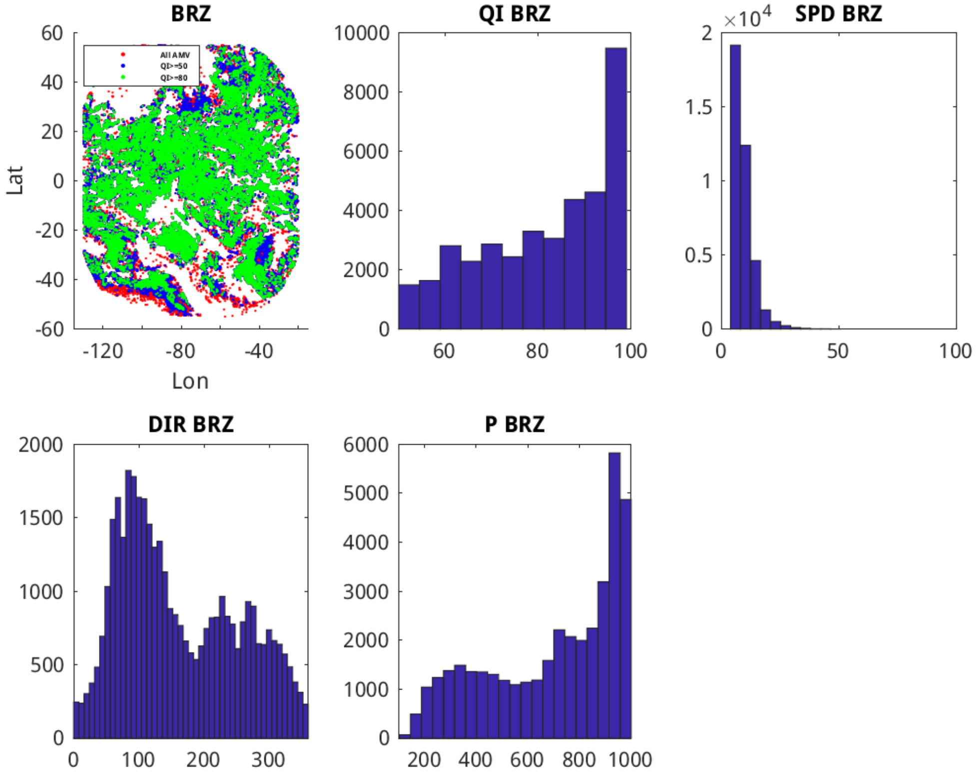

Figure 17-13: Experiment 2a BRZ (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

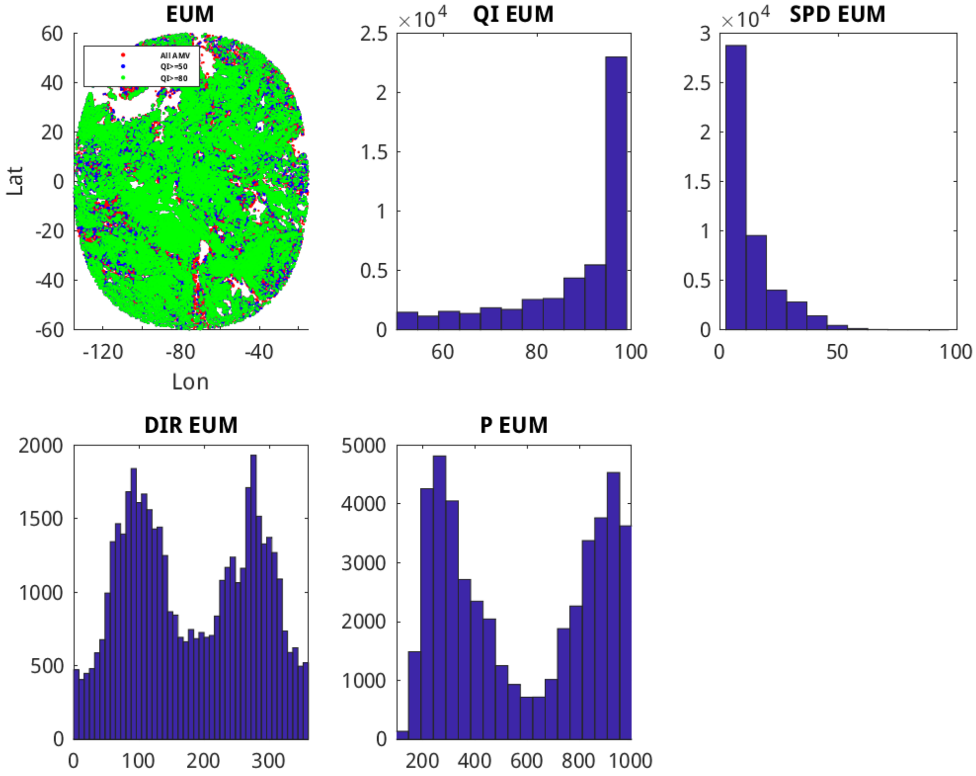

Figure 17-14: Experiment 2a EUM (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

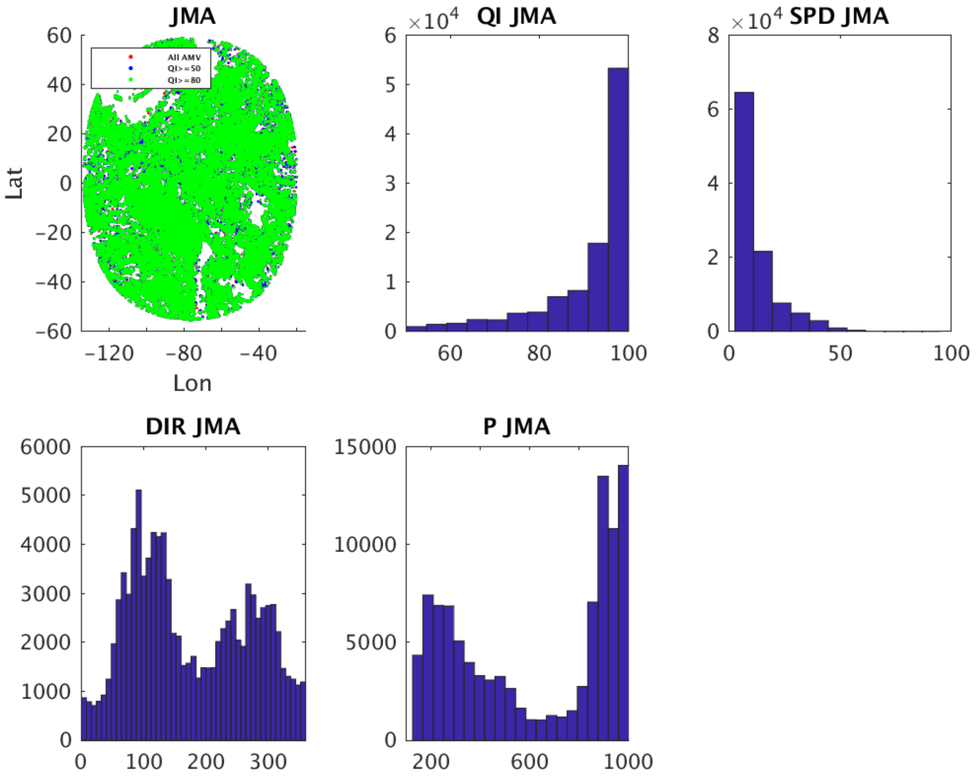

Figure 17-15: Experiment 2a JMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

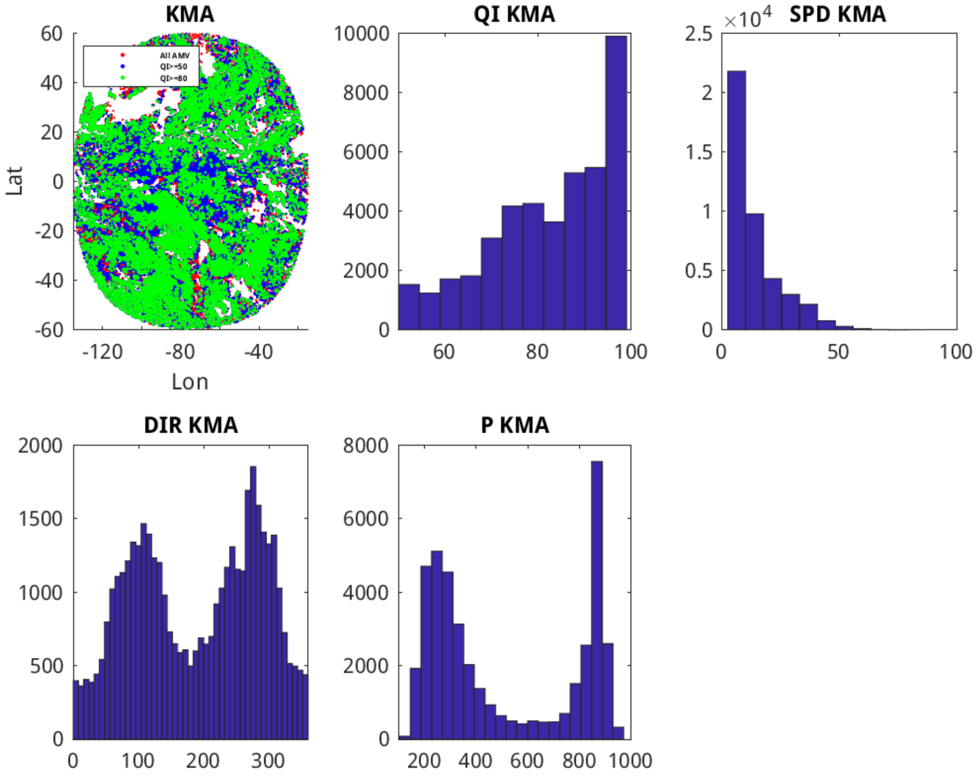

Figure 17-16: Experiment 2a KMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

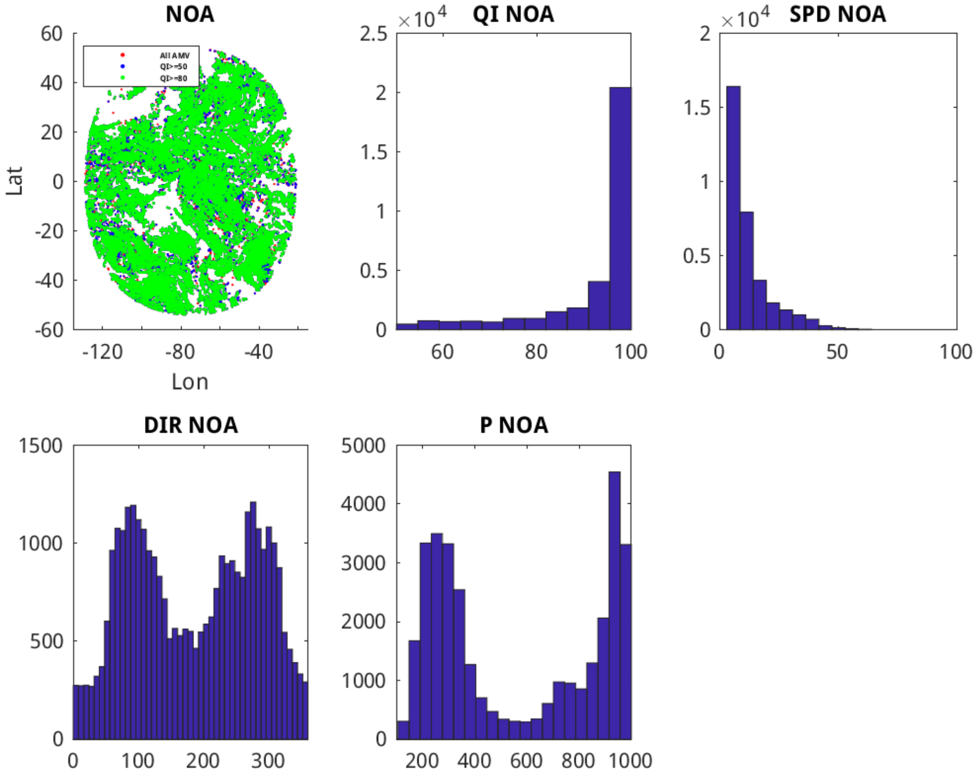

Figure 17-17: Experiment 2a NOA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

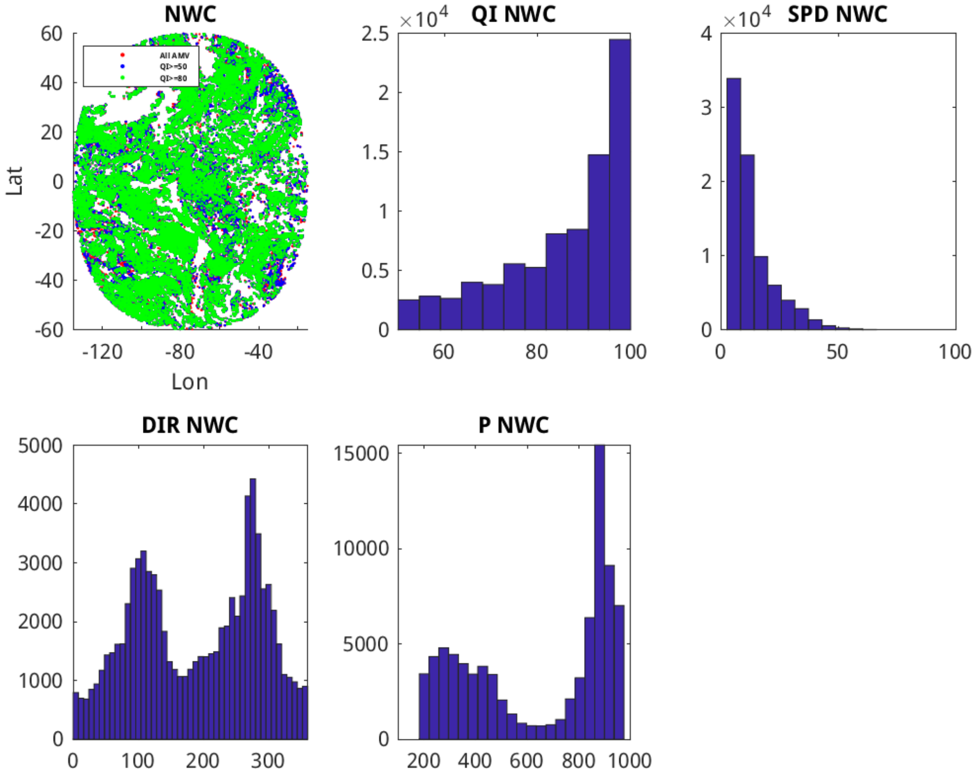

Figure 17-18: Experiment 2a NWC (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2a: CQI Parameter Distribution Histograms

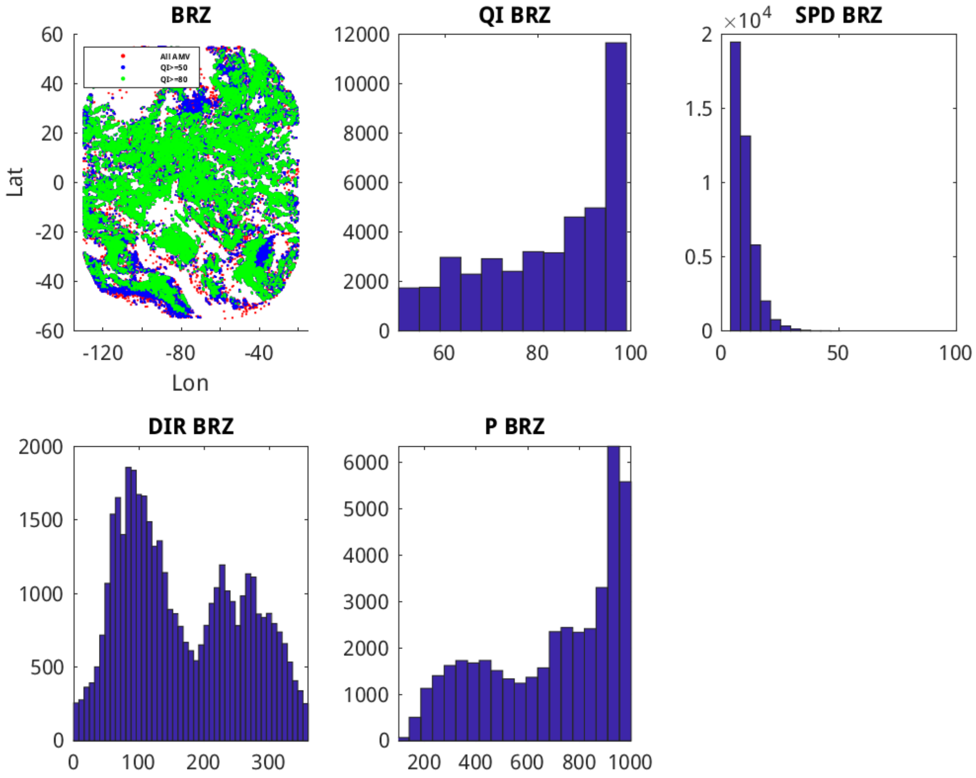

Figure 17-19: Experiment 2a BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

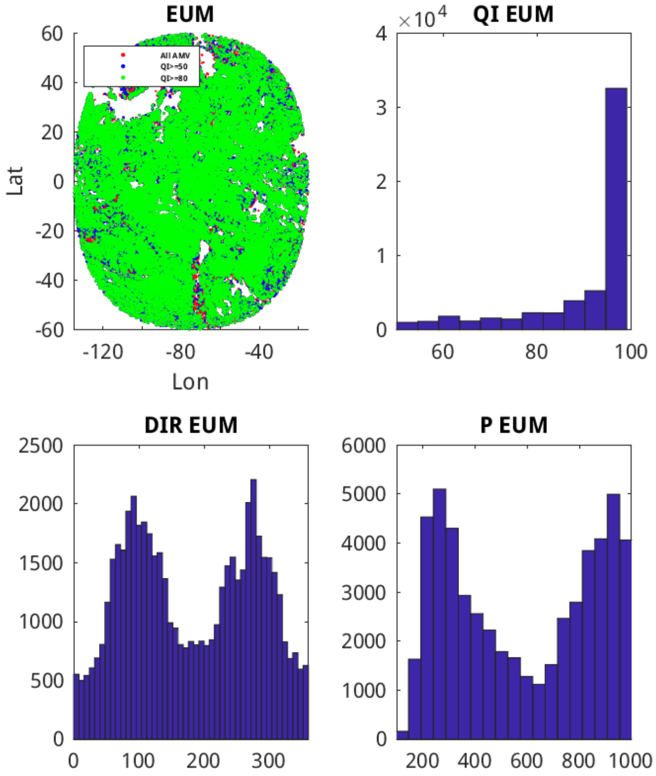

Figure 17-20: Experiment 2a EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

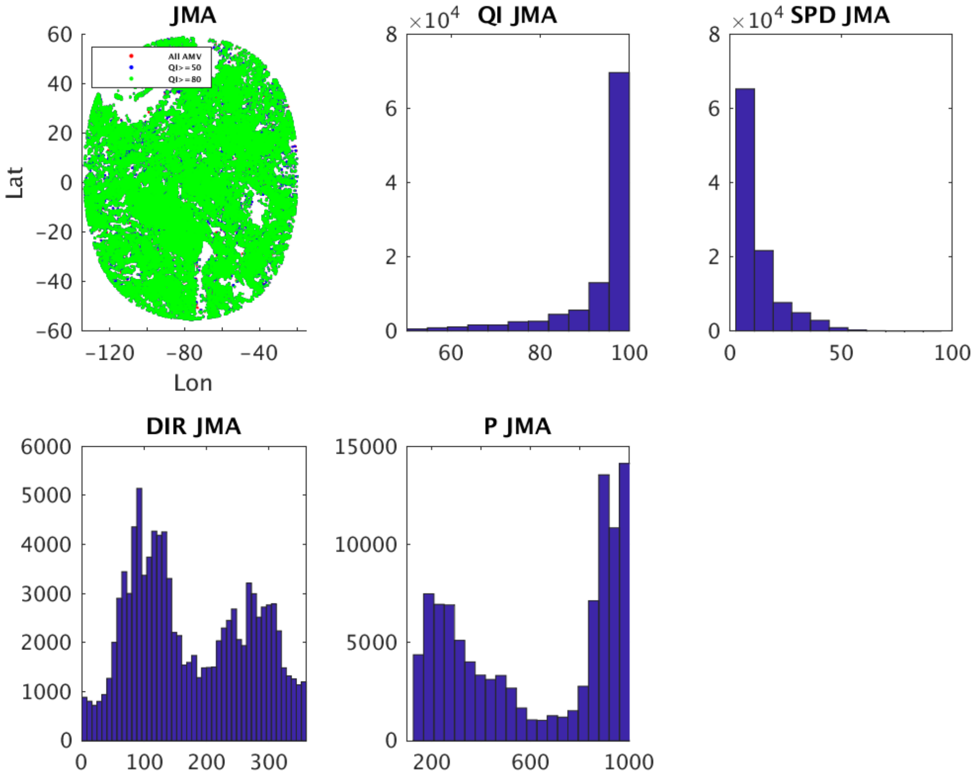

Figure 17-21: Experiment 2a JMA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

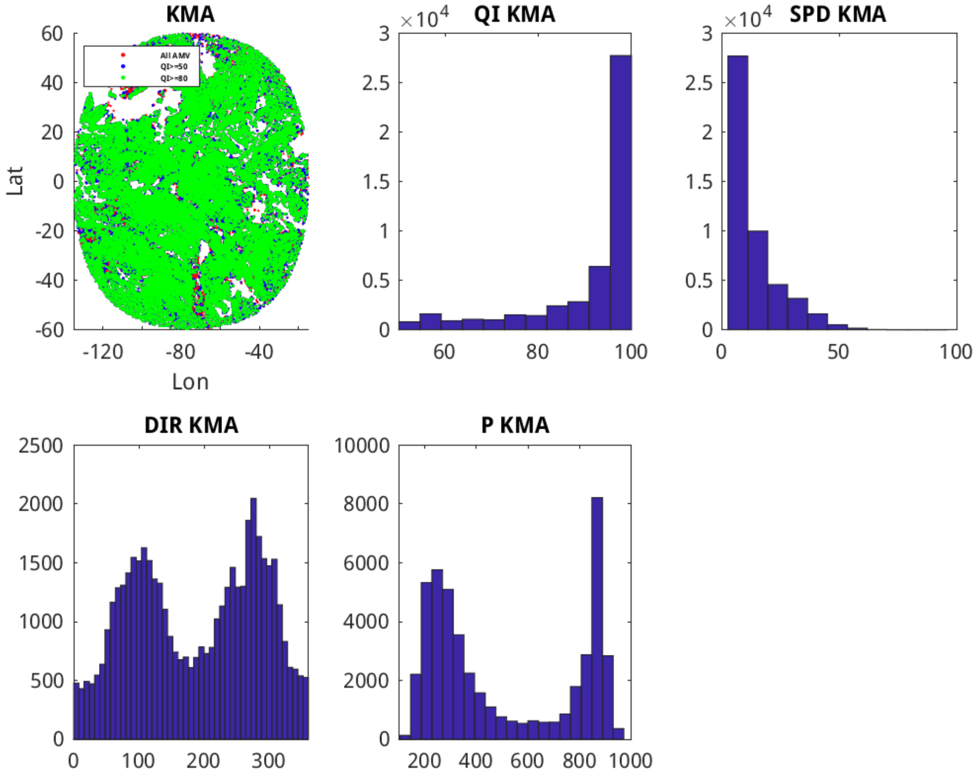

Figure 17-22: Experiment 2a KMA (CQI>=50) KMA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

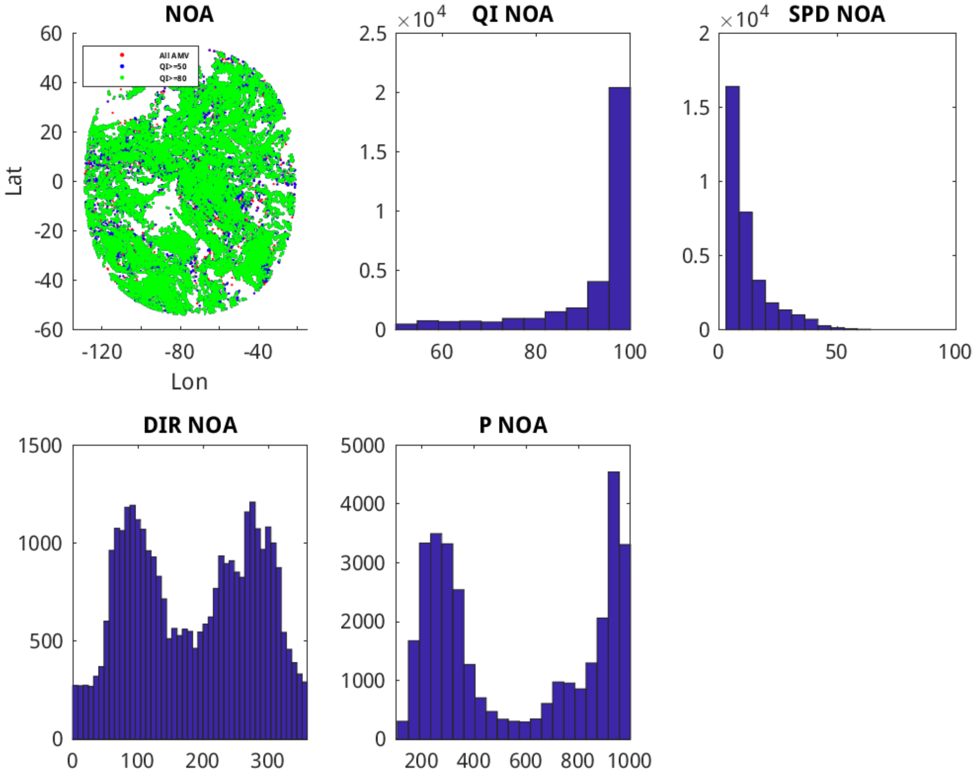

Figure 17-23: Experiment 2a NOA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

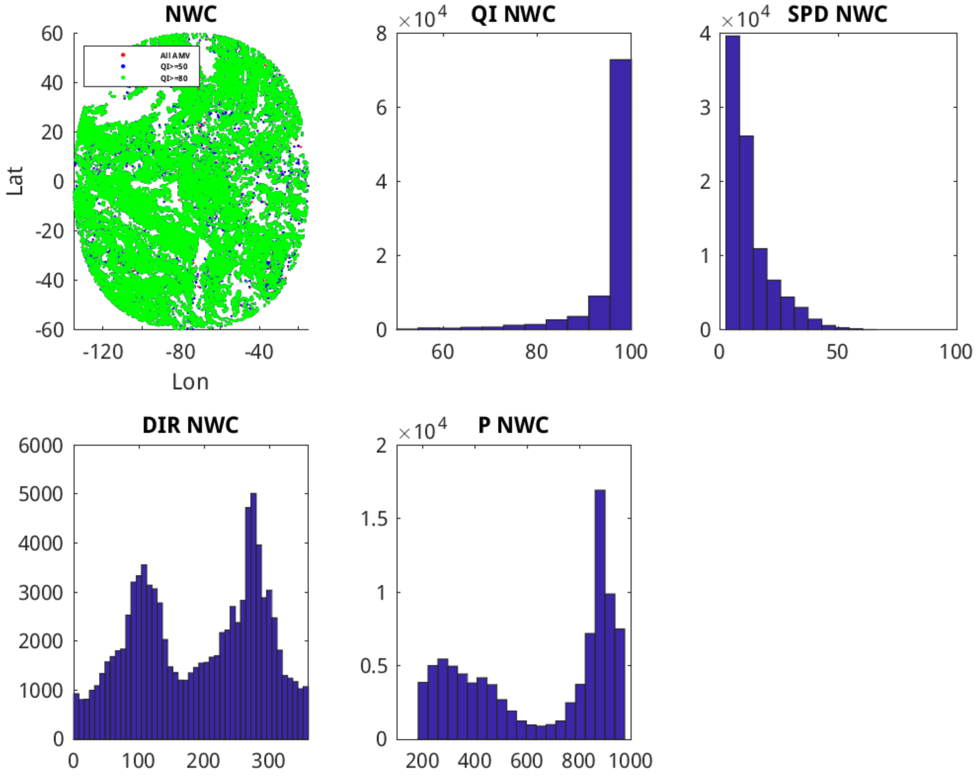

Figure 17-24: Experiment 2a NWC (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2b: QINF Parameter Distribution Histograms

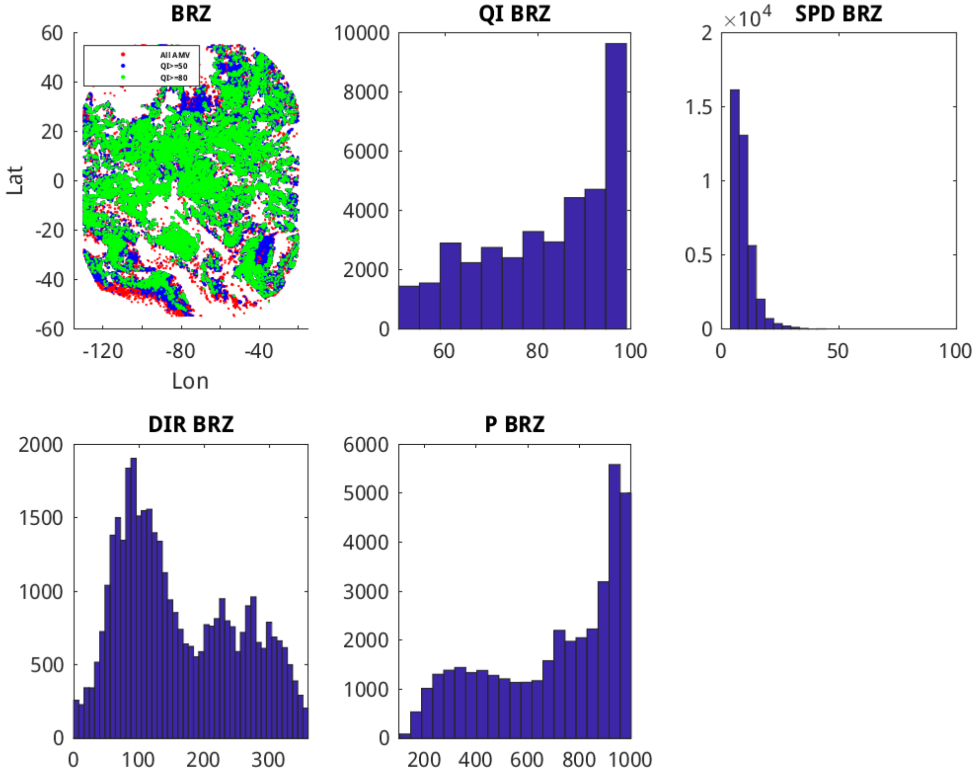

Figure 17-25: Experiment 2b BRZ (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

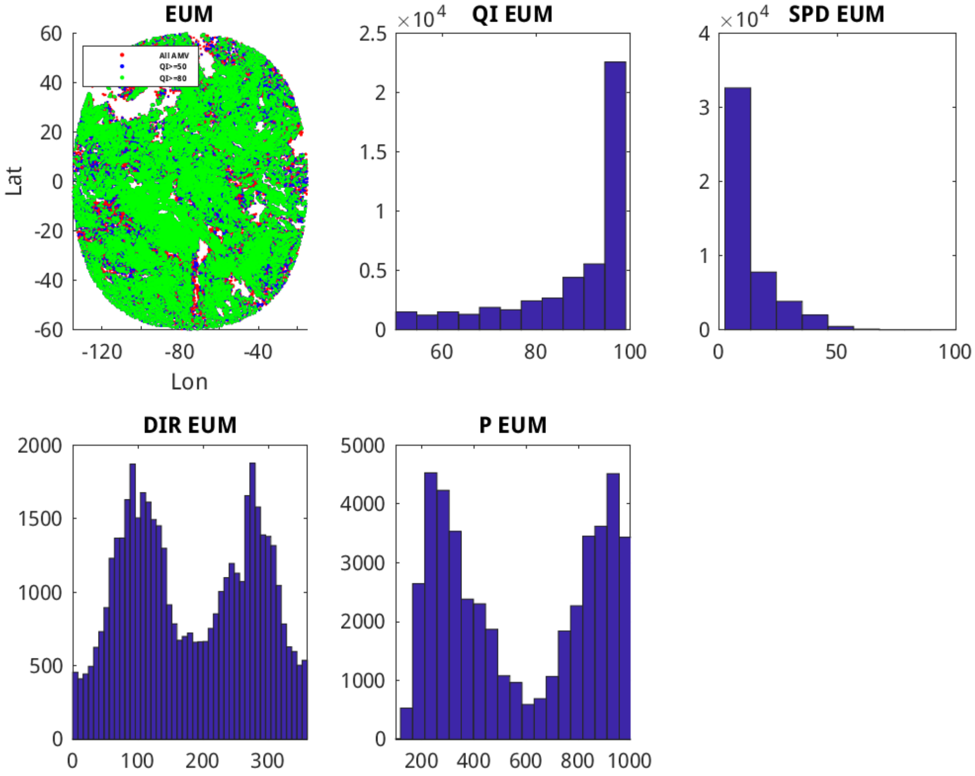

Figure 17-26: Experiment 2b EUM (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

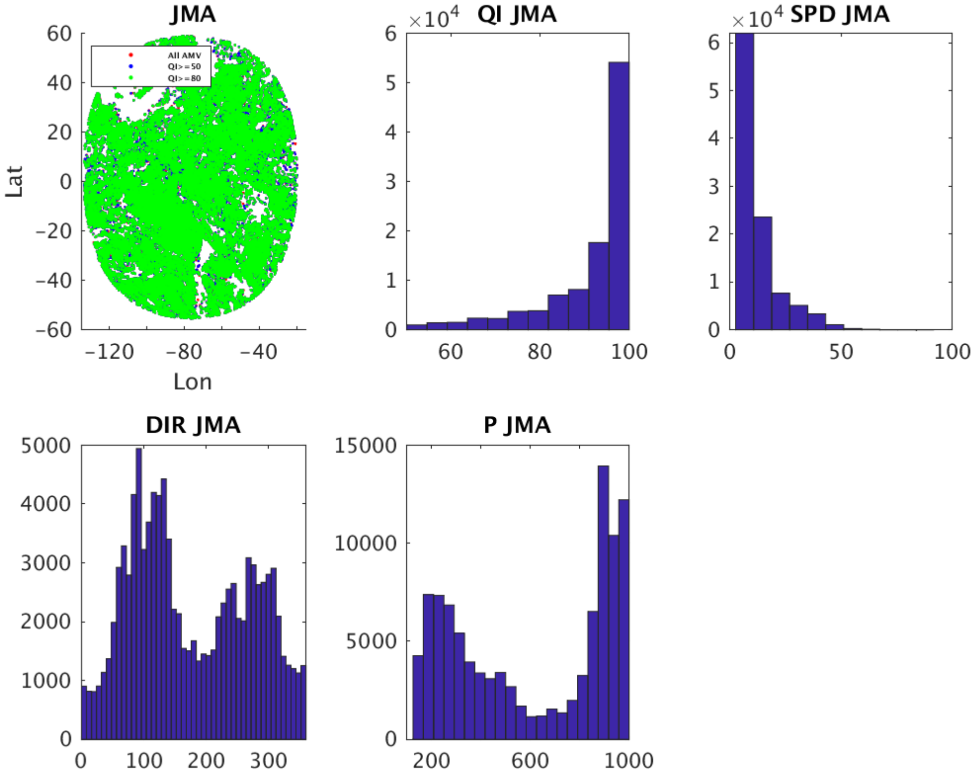

Figure 17-27: Experiment 2b JMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

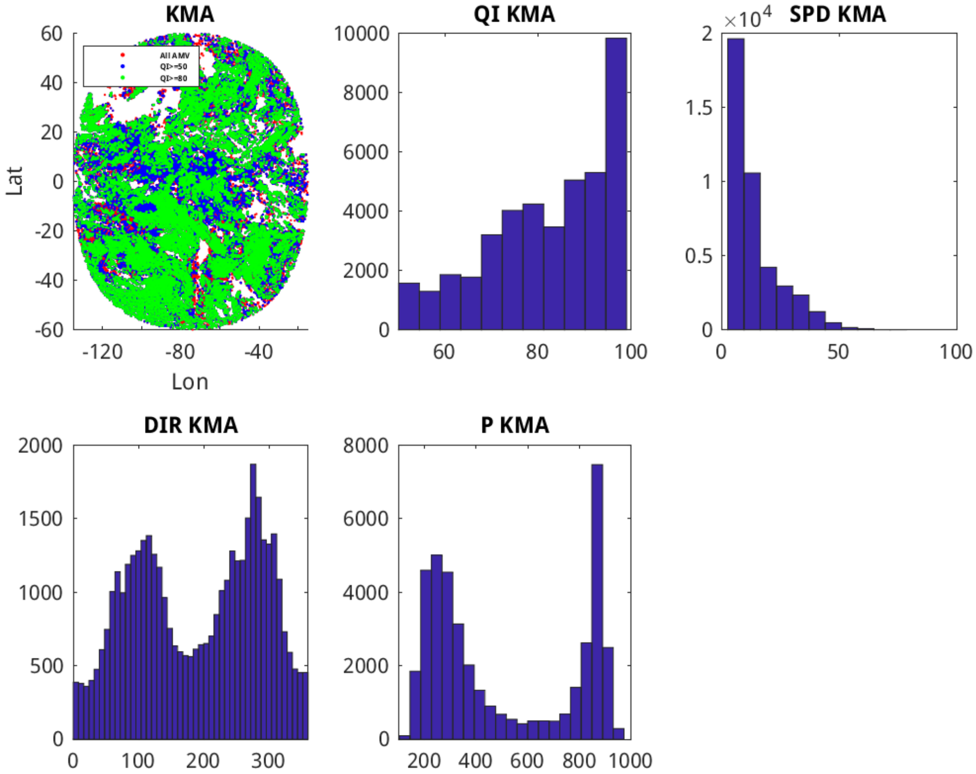

Figure 17-28: Experiment 2b KMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

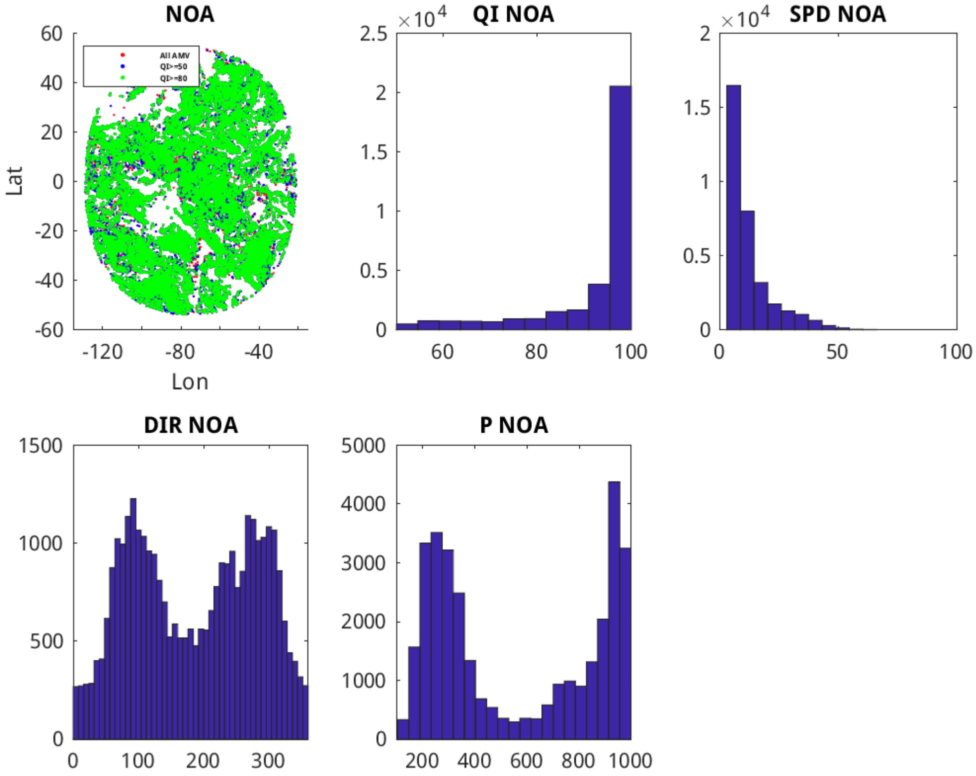

Figure 17-29: Experiment 2b NOA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

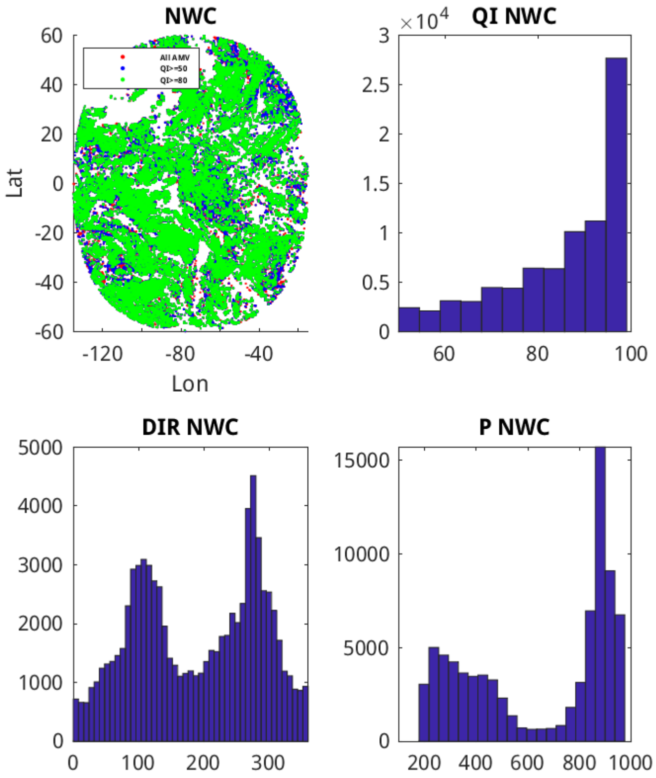

Figure 17-30: Experiment 2b NWC (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2b: CQI Parameter Distribution Histograms

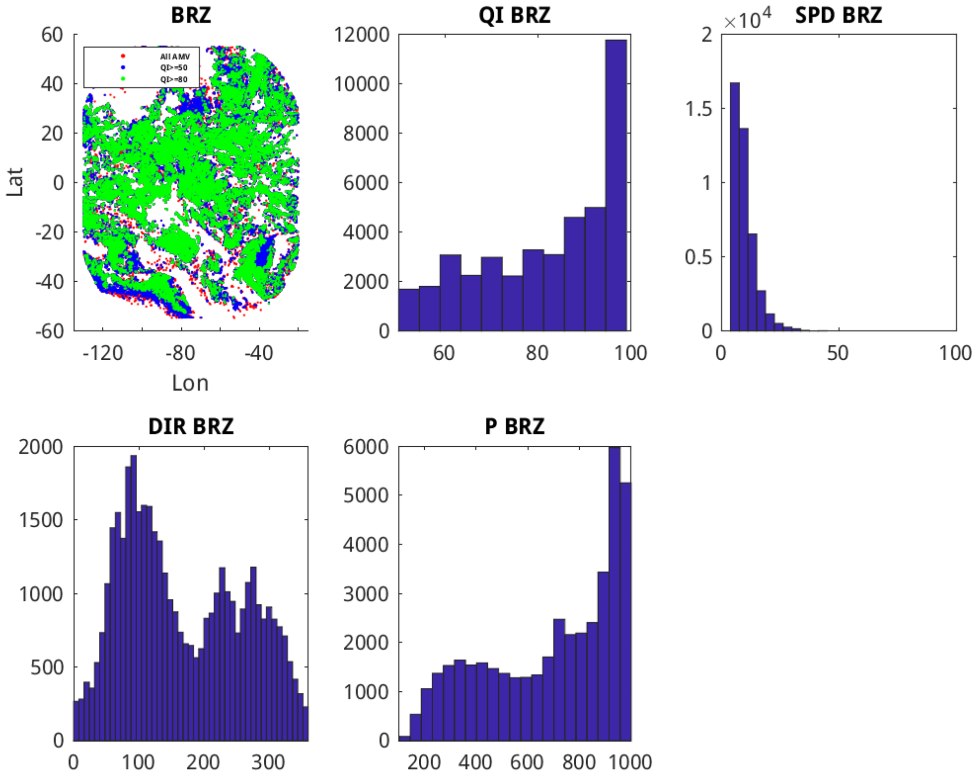

Figure 17-31: Experiment 2b BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

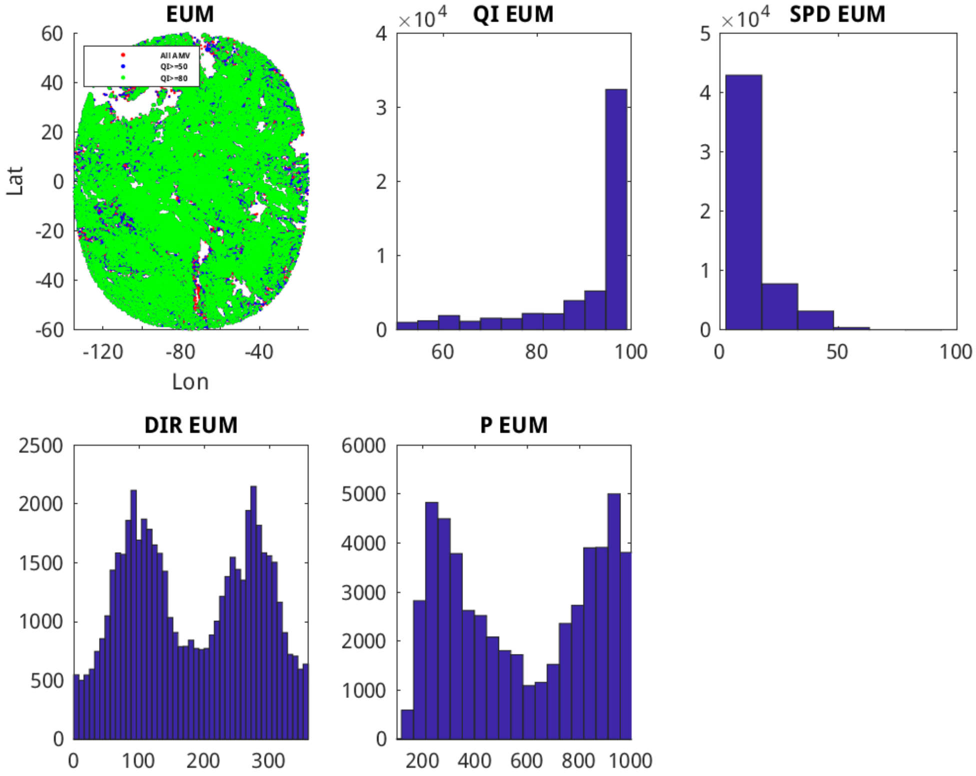

Figure 17-32: Experiment 2b EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

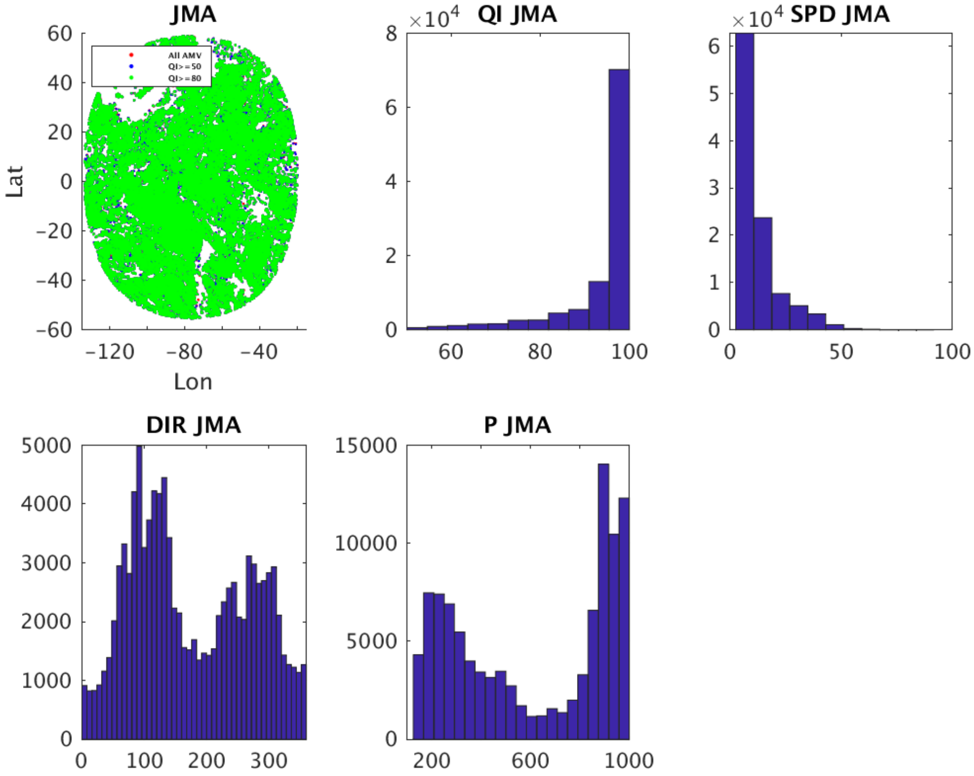

Figure 17-33: Experiment 2b JMA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

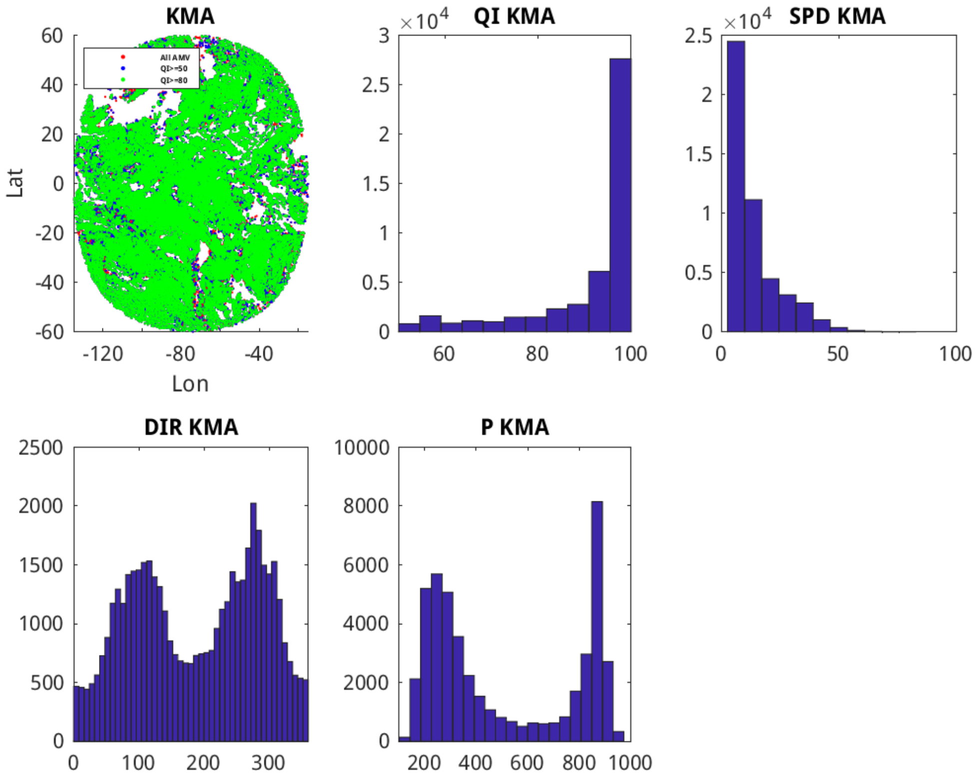

Figure 17-34: Experiment 2b KMA (CQI>=50) KMA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

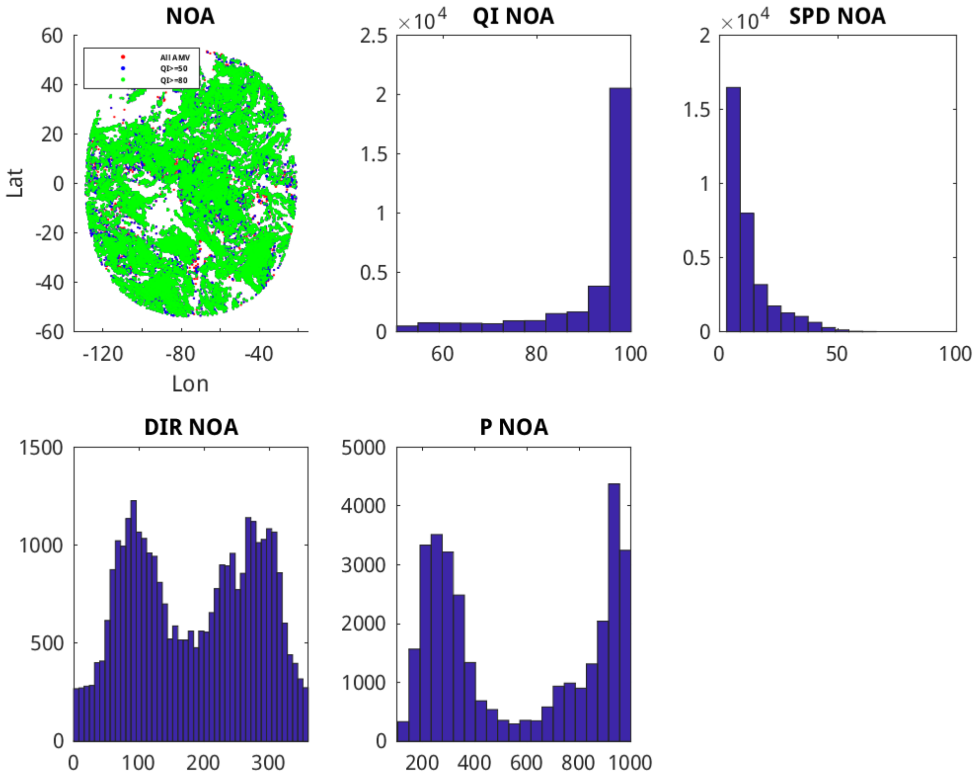

Figure 17-35: Experiment 2b NOA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

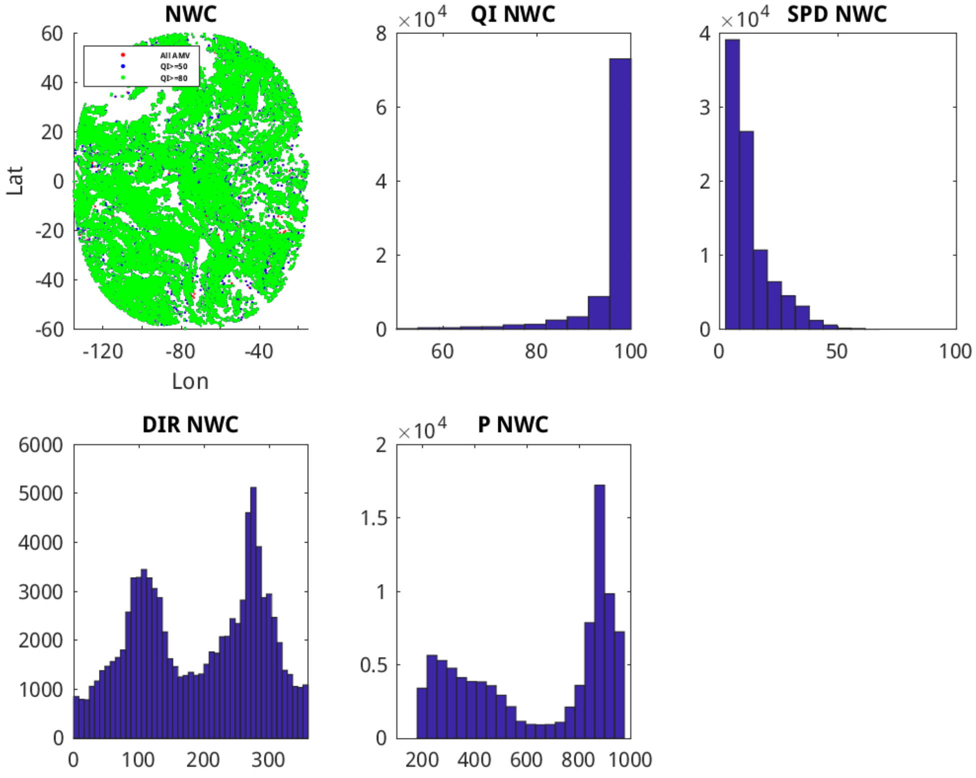

Figure 17-36: Experiment 2b NWC (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2c: QINF Parameter Distribution Histograms

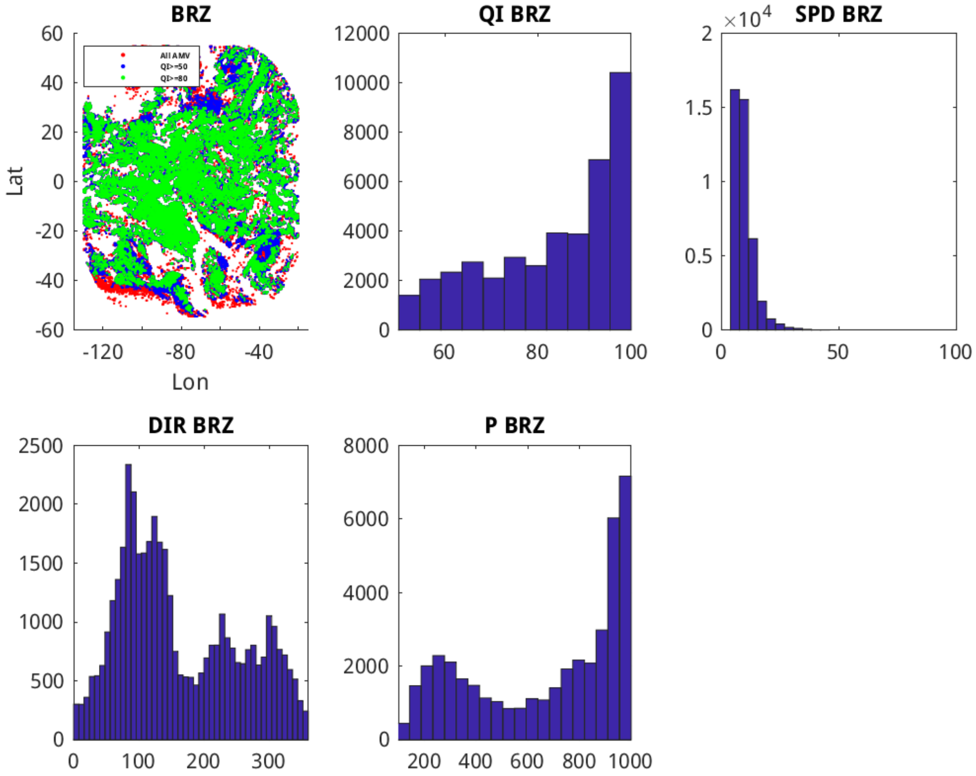

Figure 17-37: Experiment 2c BRZ (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

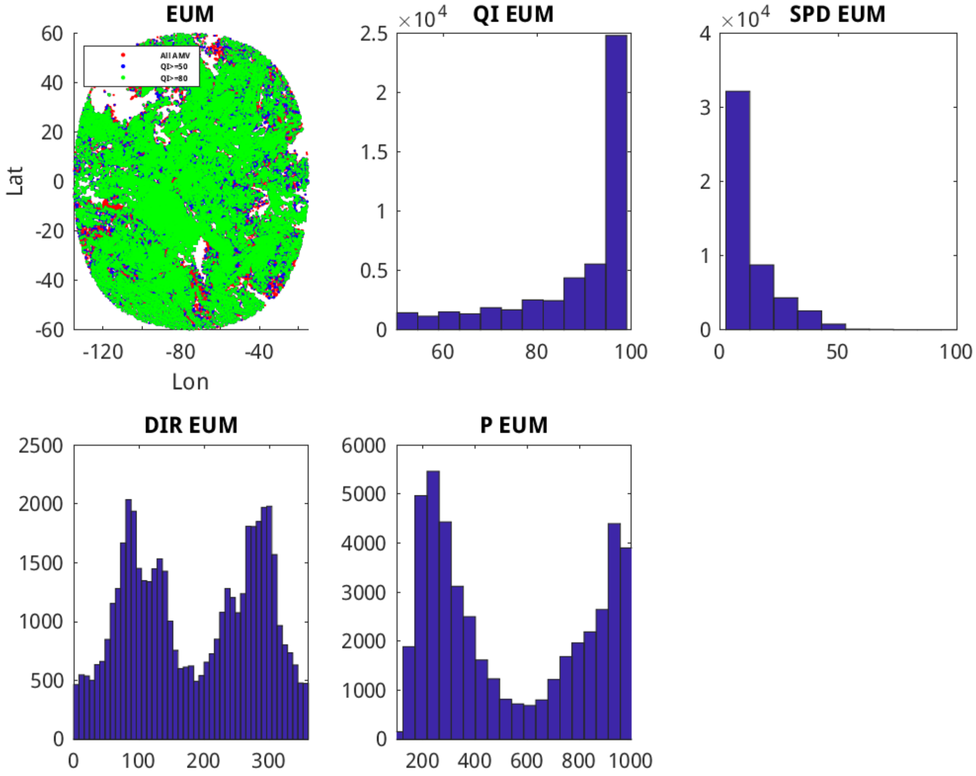

Figure 17-38: Experiment 2c EUM (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

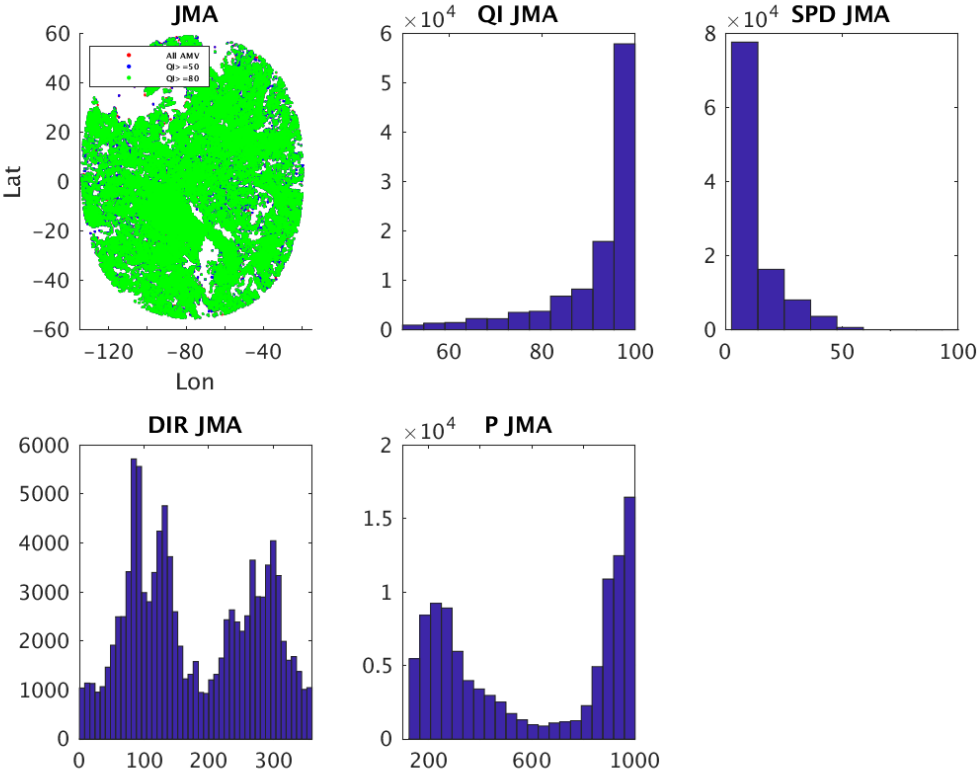

Figure 17-39: Experiment 2c JMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

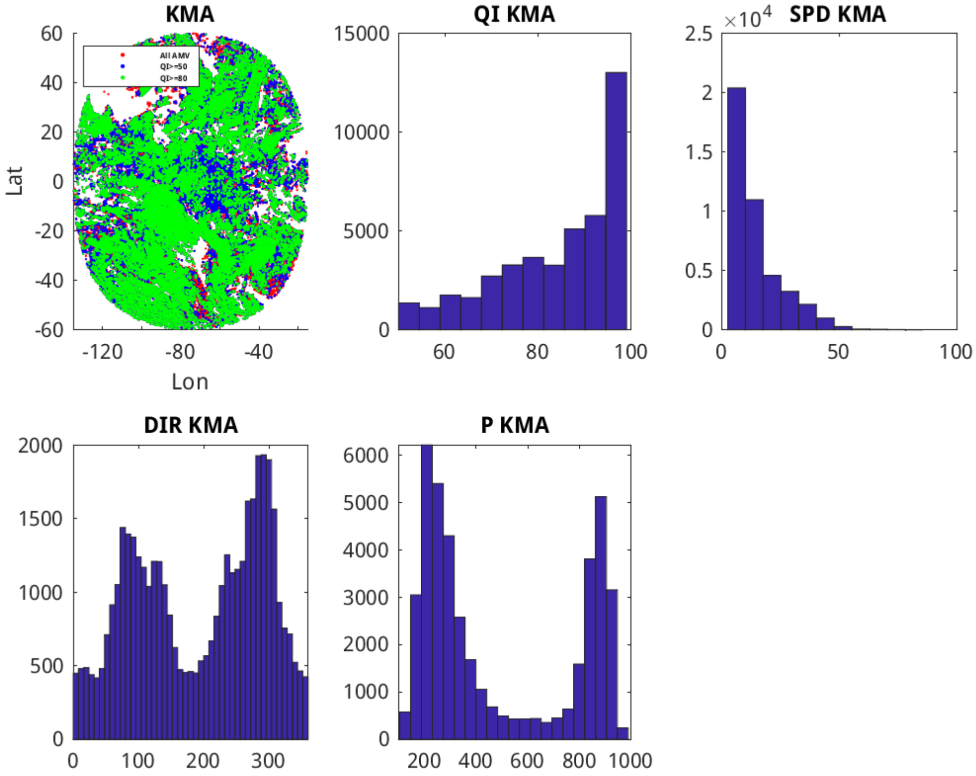

Figure 17-40: Experiment 2c KMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

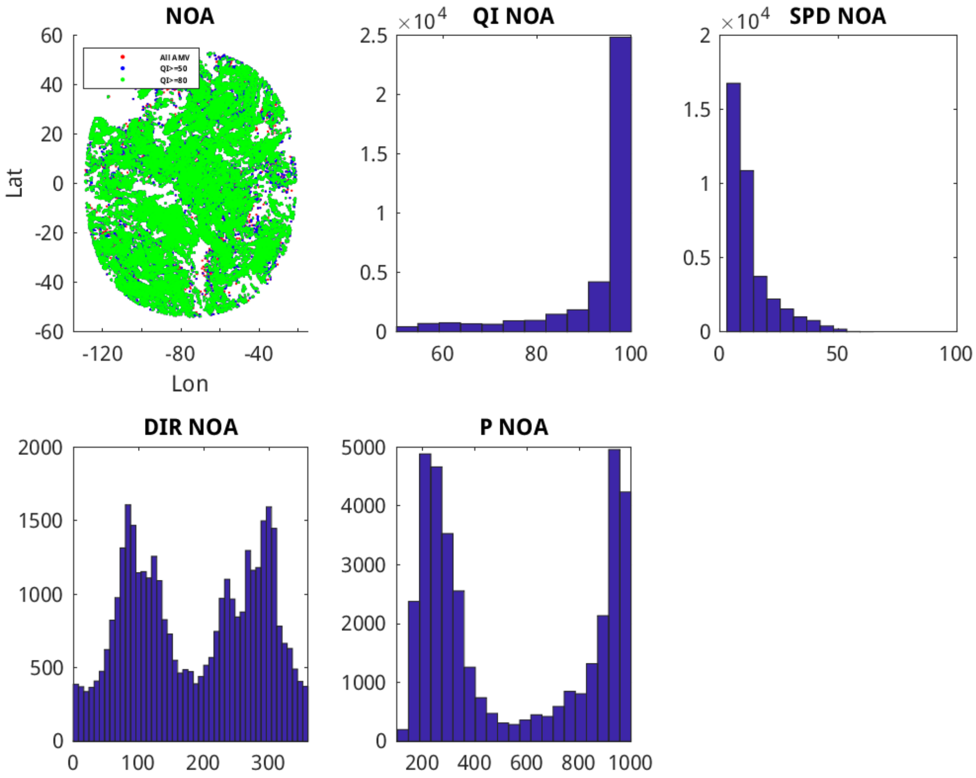

Figure 17-41: Experiment 2c NOA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

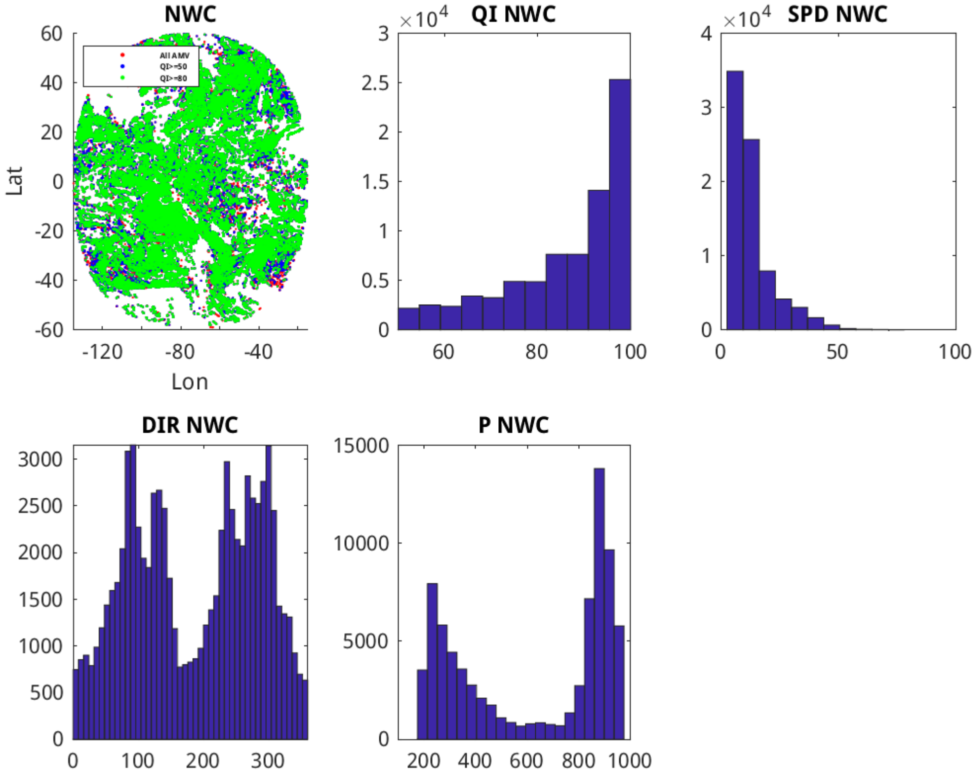

Figure 17-42: Experiment 2c NWC (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 2c: CQI Parameter Distribution Histograms

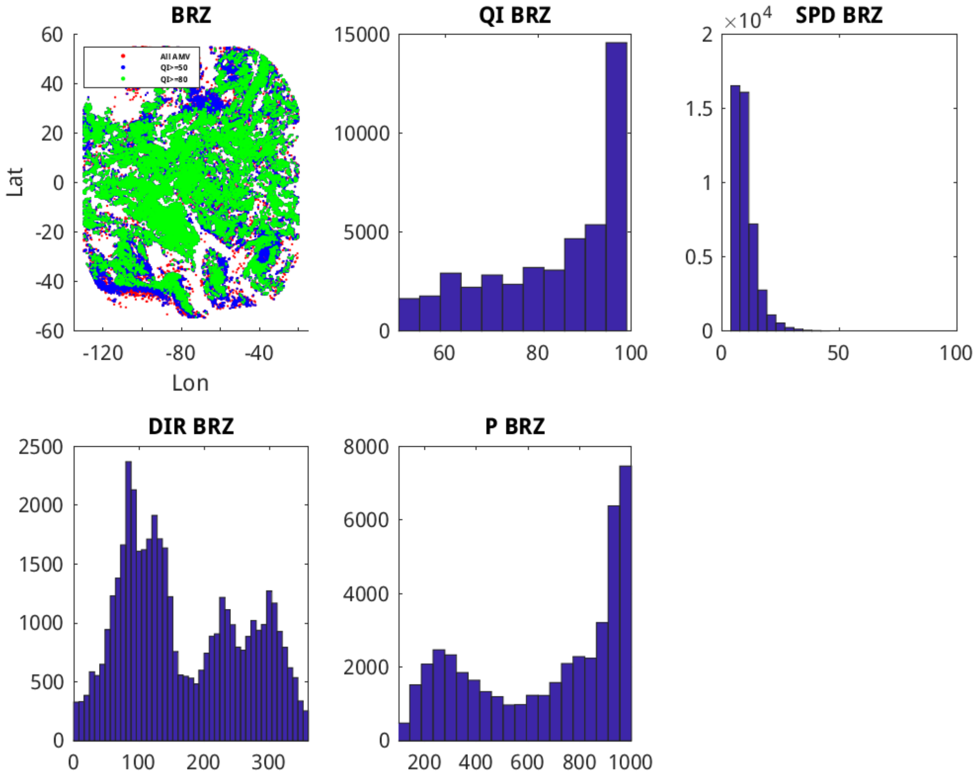

Figure 17-43: Experiment 2c BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

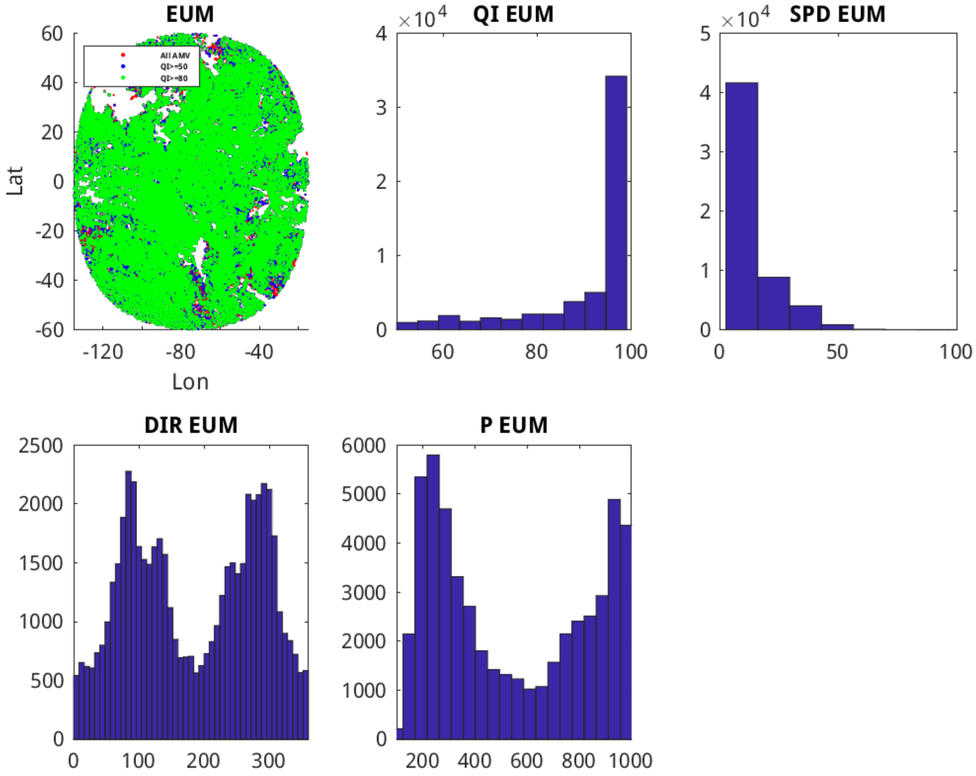

Figure 17-44: Experiment 2c EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

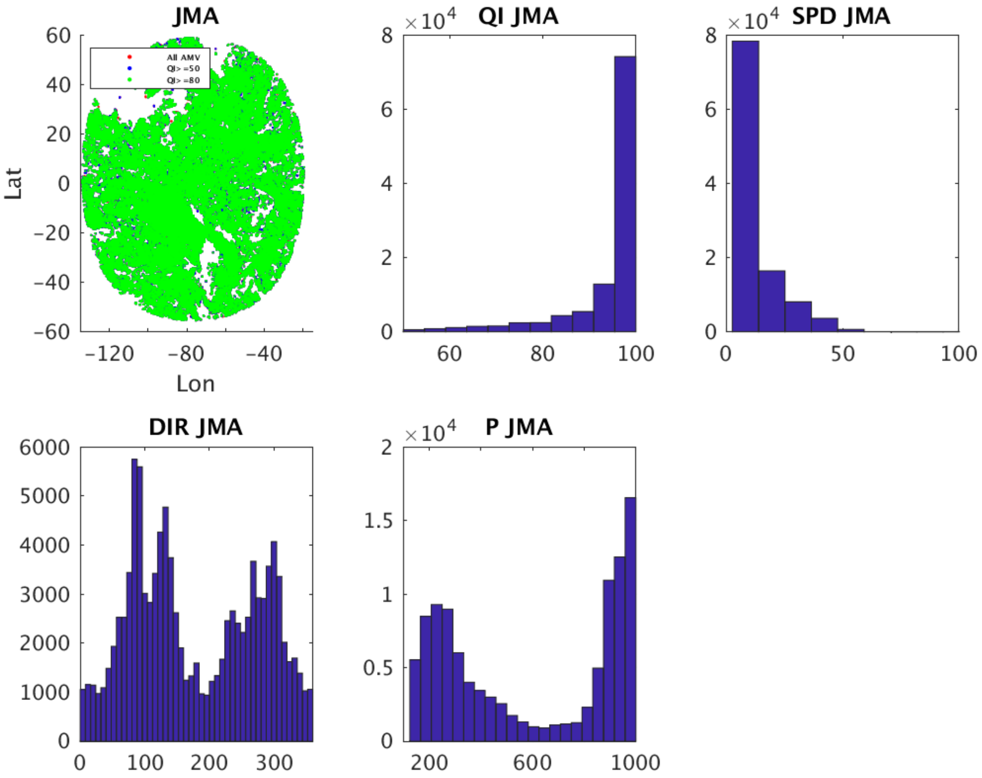

Figure 17-45: Experiment 2c JMA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

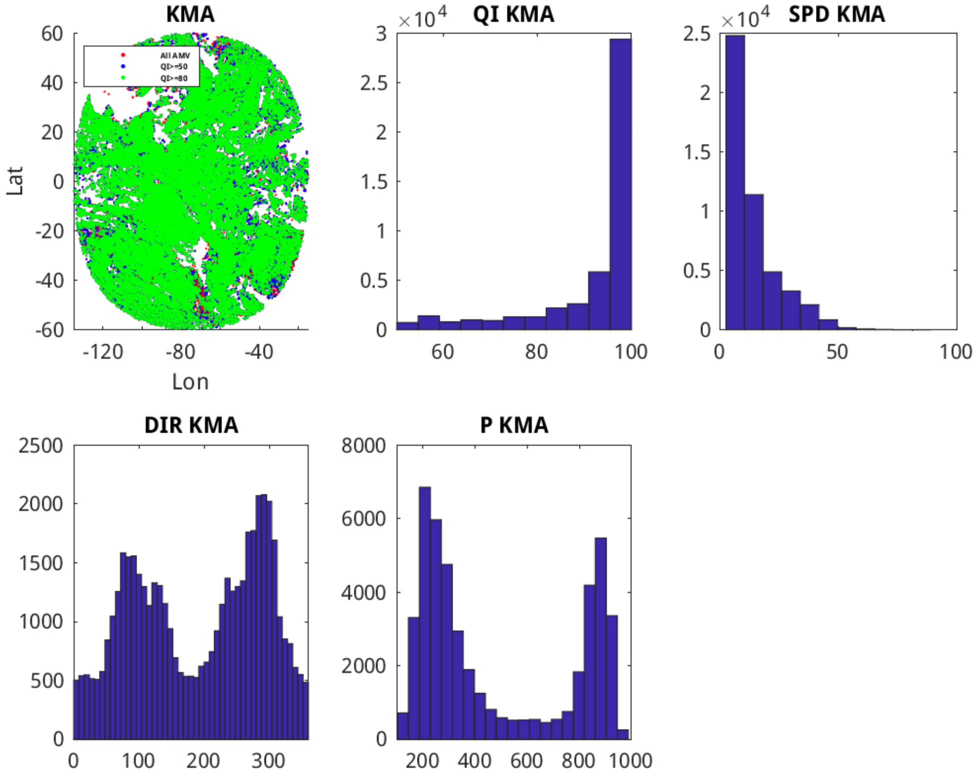

Figure 17-46: Experiment 2c KMA (CQI>=50) KMA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

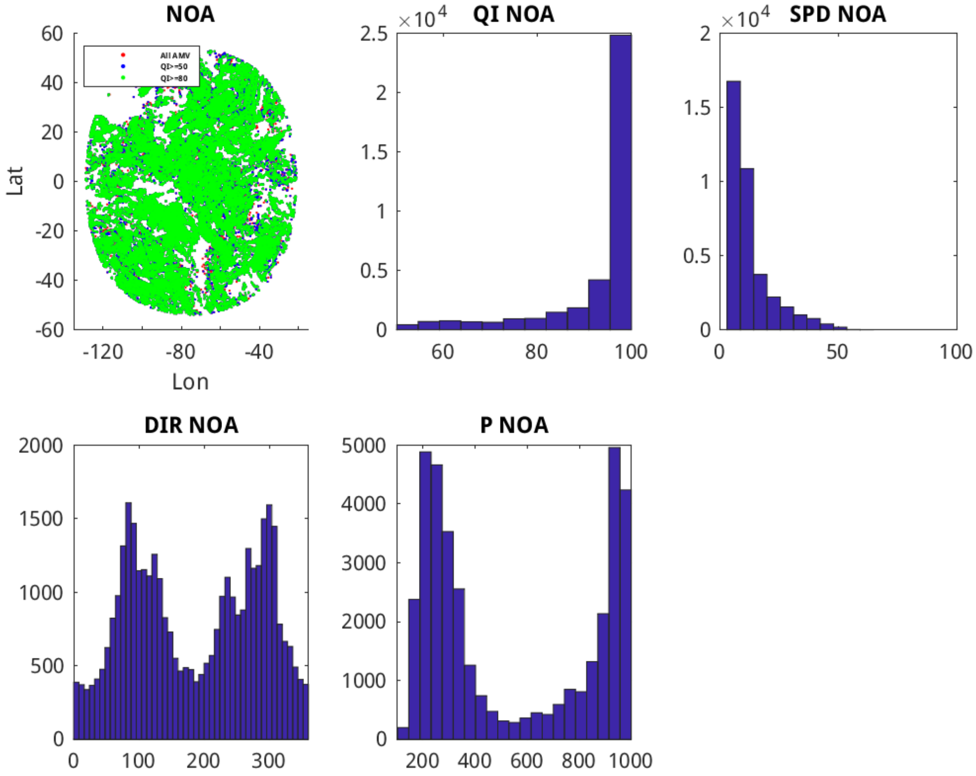

Figure 17-47: Experiment 2c NOA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

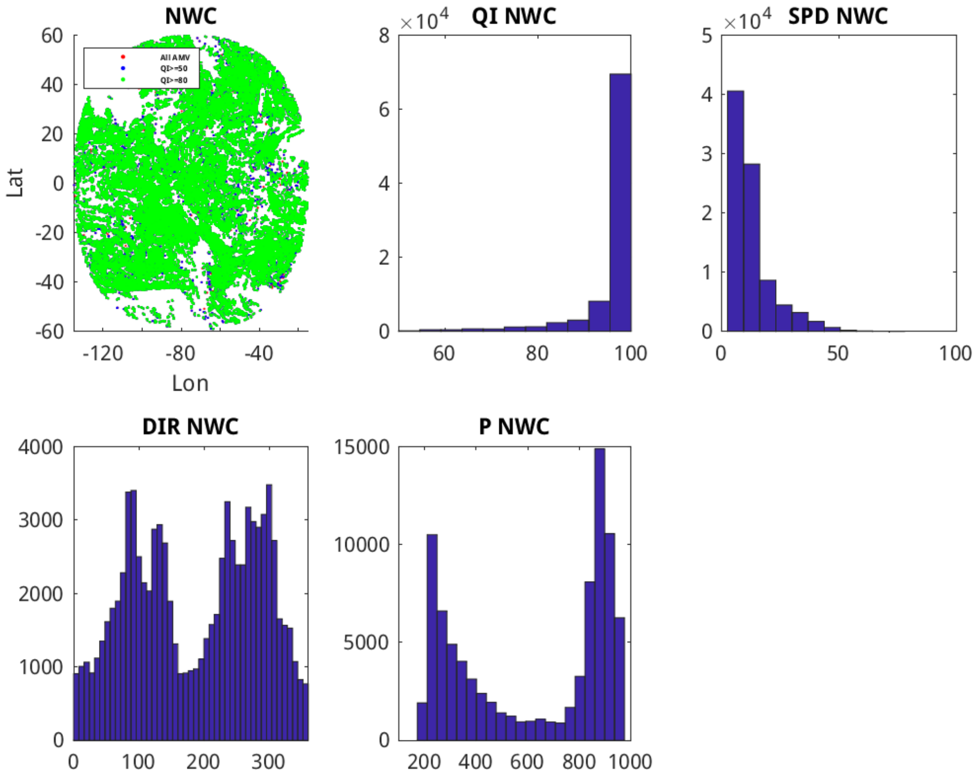

Figure 17-48: Experiment 2c NWC (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 3: QINF Parameter Distribution Histograms

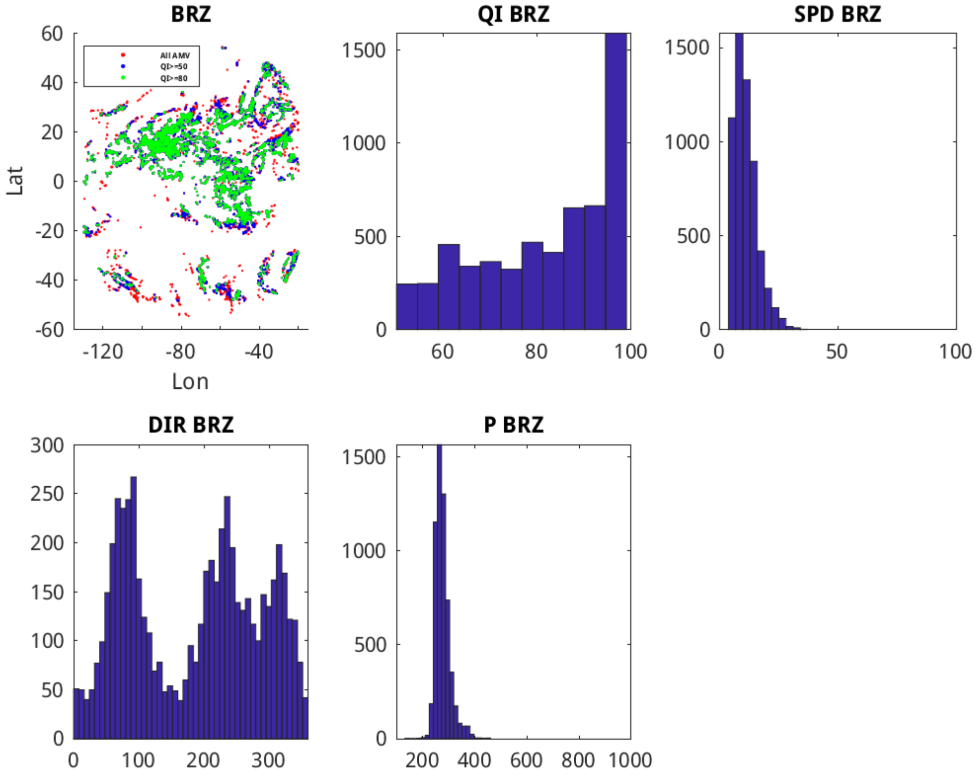

Figure 17-49: Experiment 3 BRZ (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

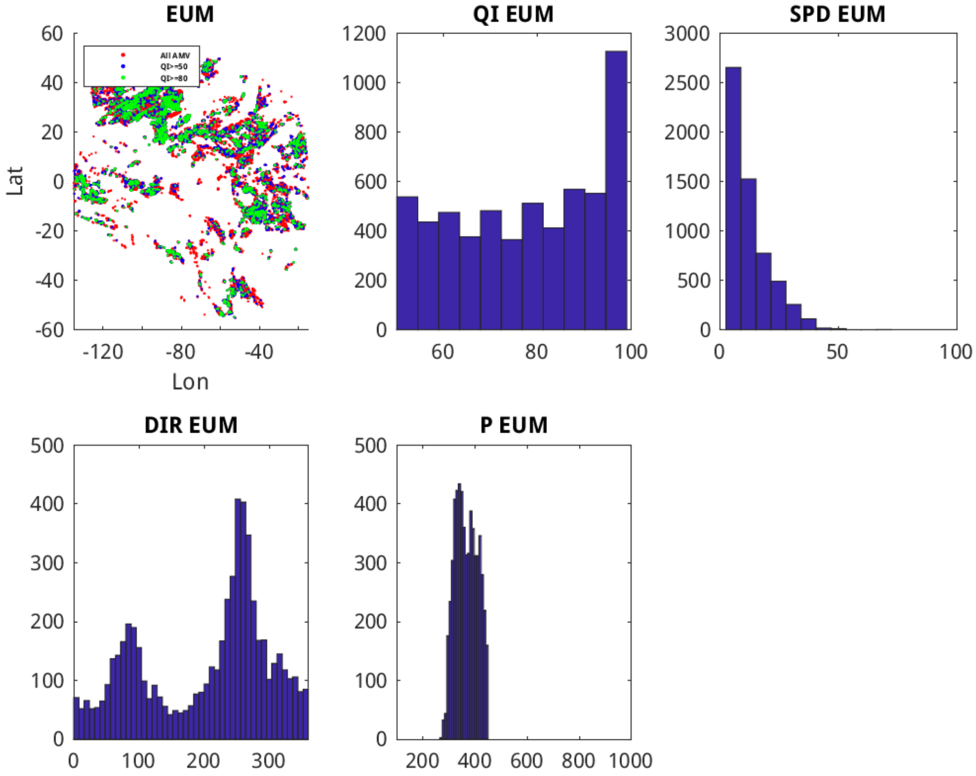

Figure 17-50: Experiment 3 EUM (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

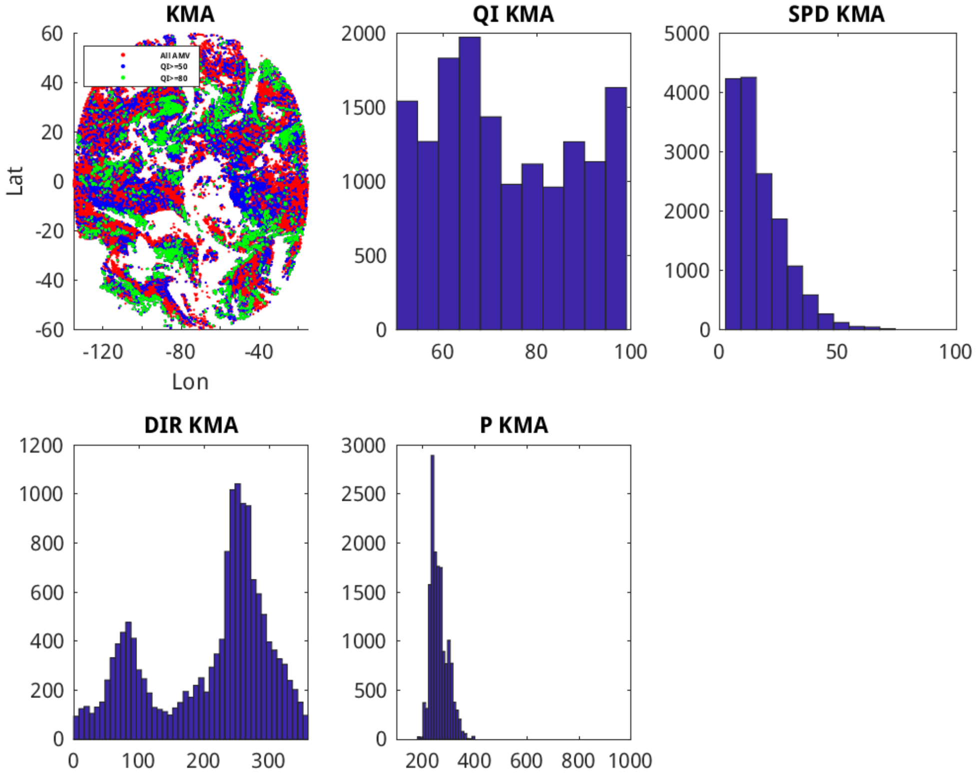

Figure 17-51: Experiment 3 KMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

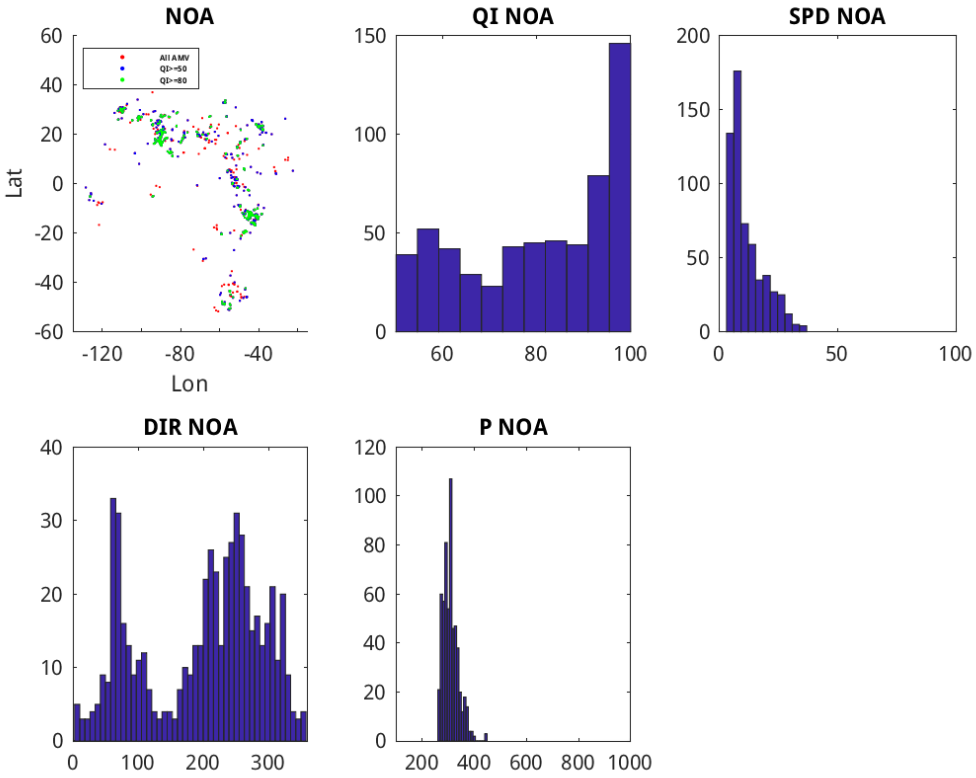

Figure 17-52: Experiment 3 NOA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

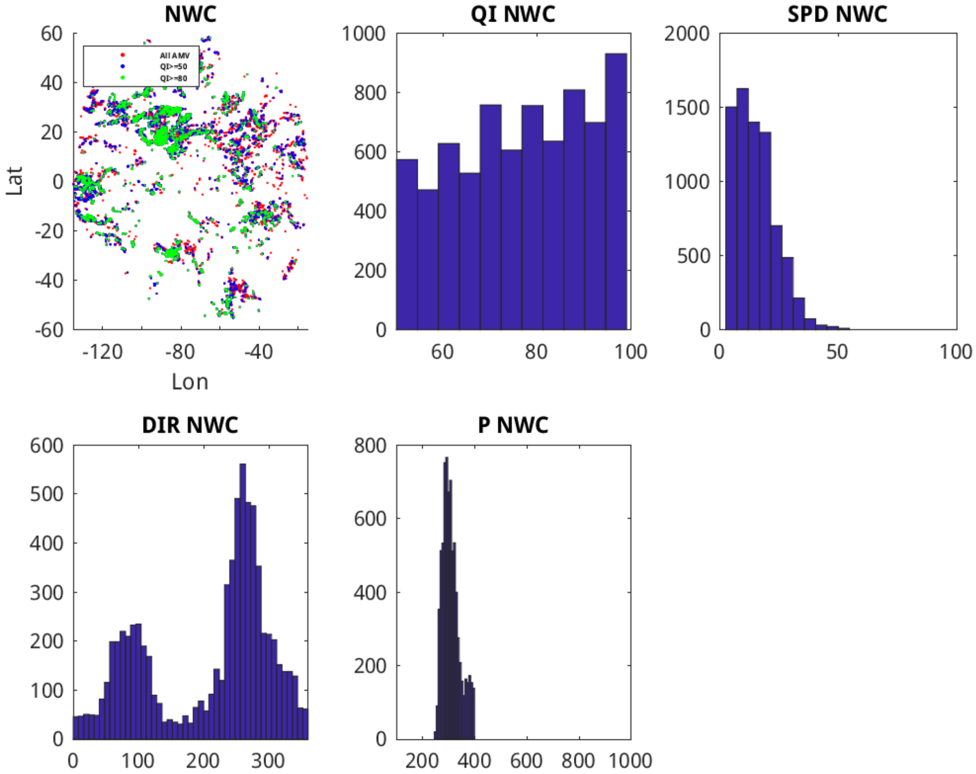

Figure 17-53: Experiment 3 NWC (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 3: CQI Parameter Distribution Histograms

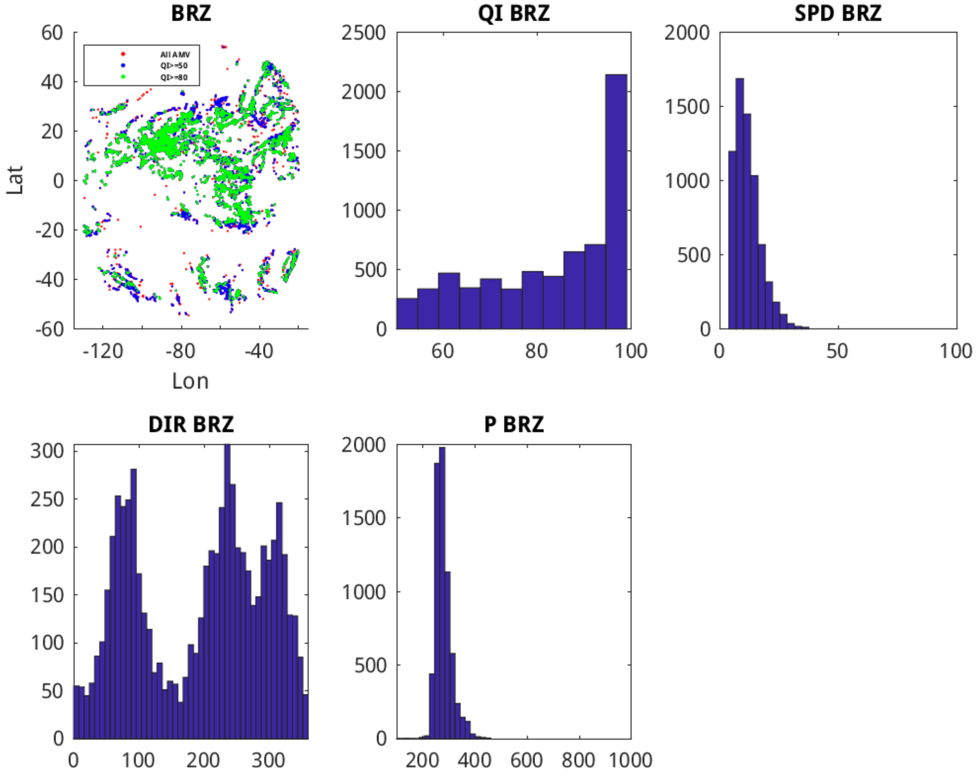

Figure 17-54: Experiment 3 BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

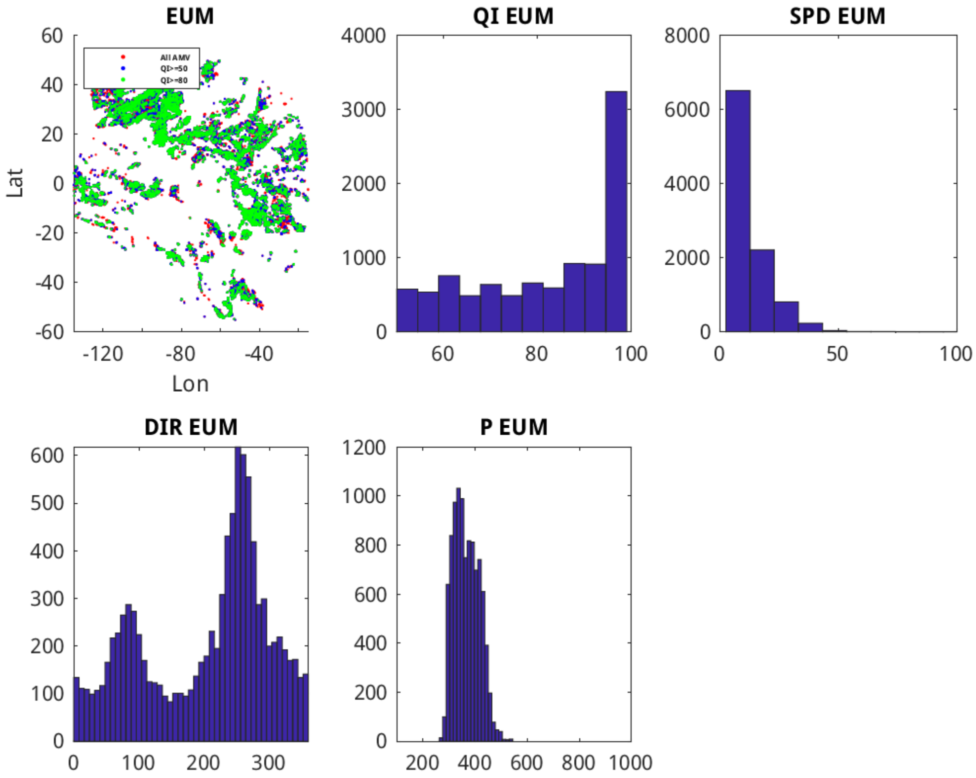

Figure 17-55: Experiment 3 EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

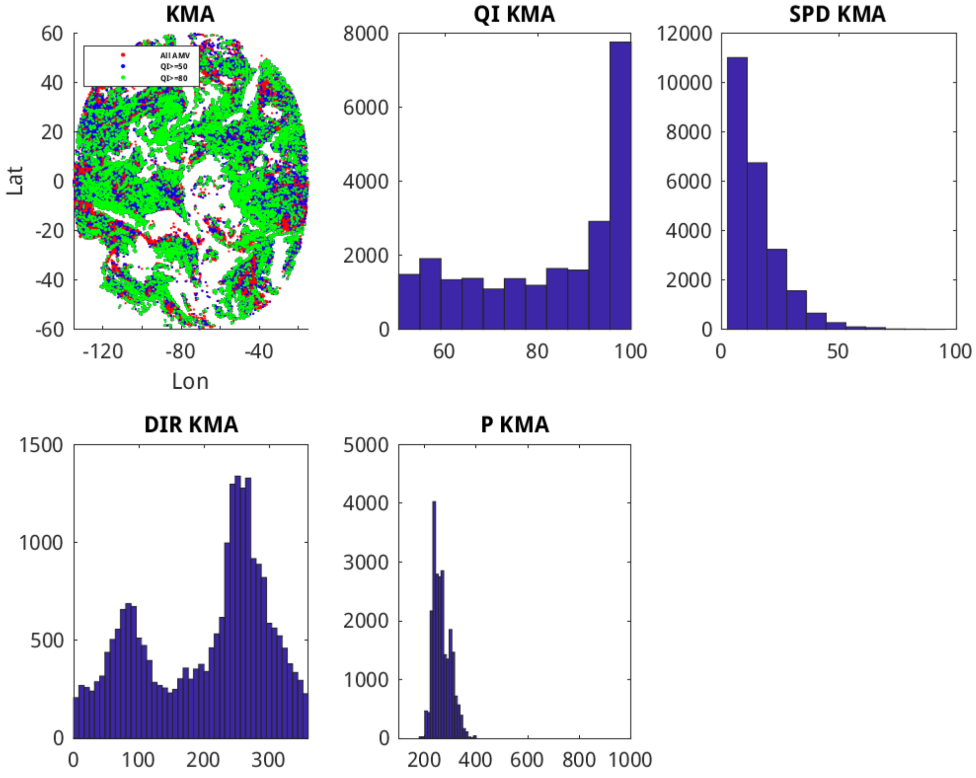

Figure 17-56: Experiment 3 KMA (CQI>=50) KMA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

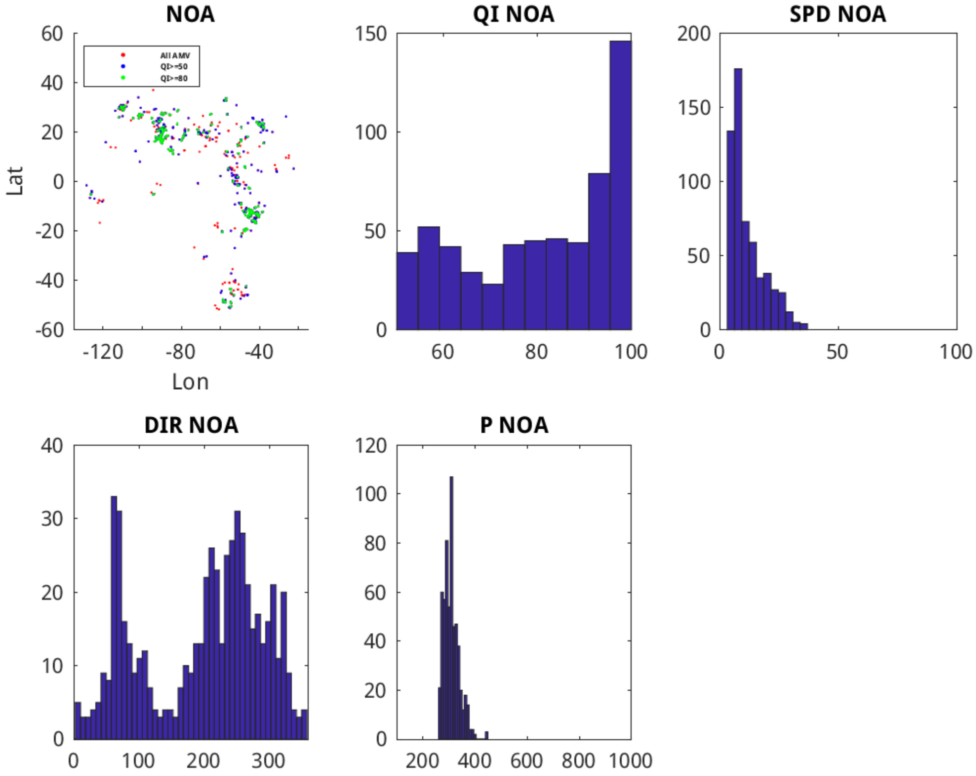

Figure 17-57: Experiment 3 NOA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

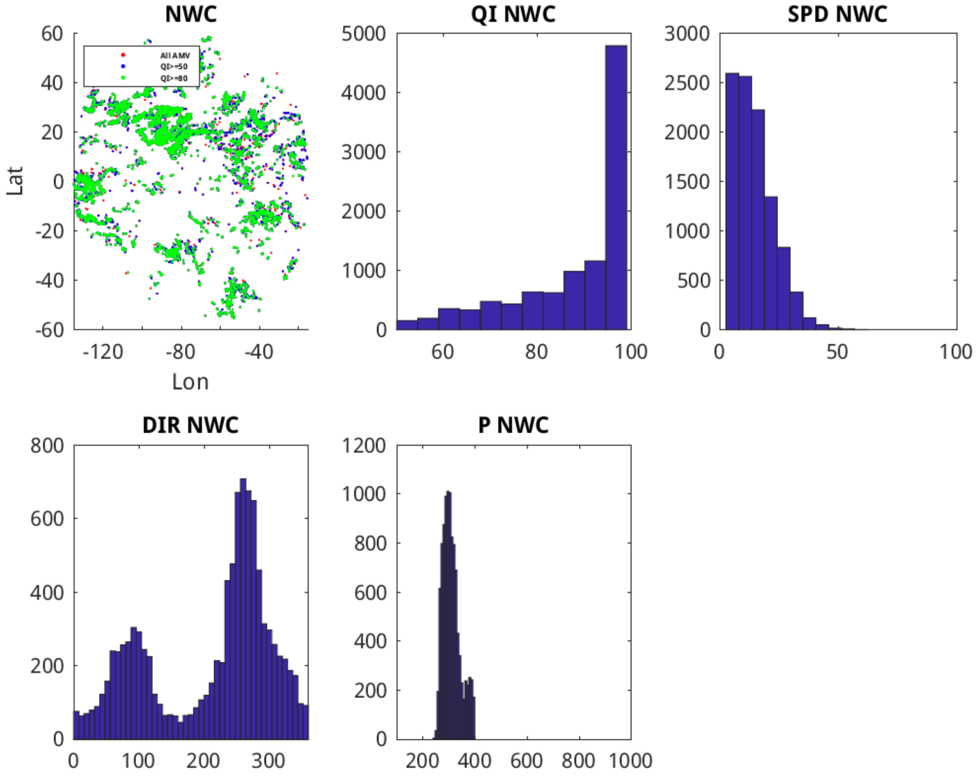

Figure 17-58: Experiment 3 NWC (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 4: QINF Parameter Distribution Histograms

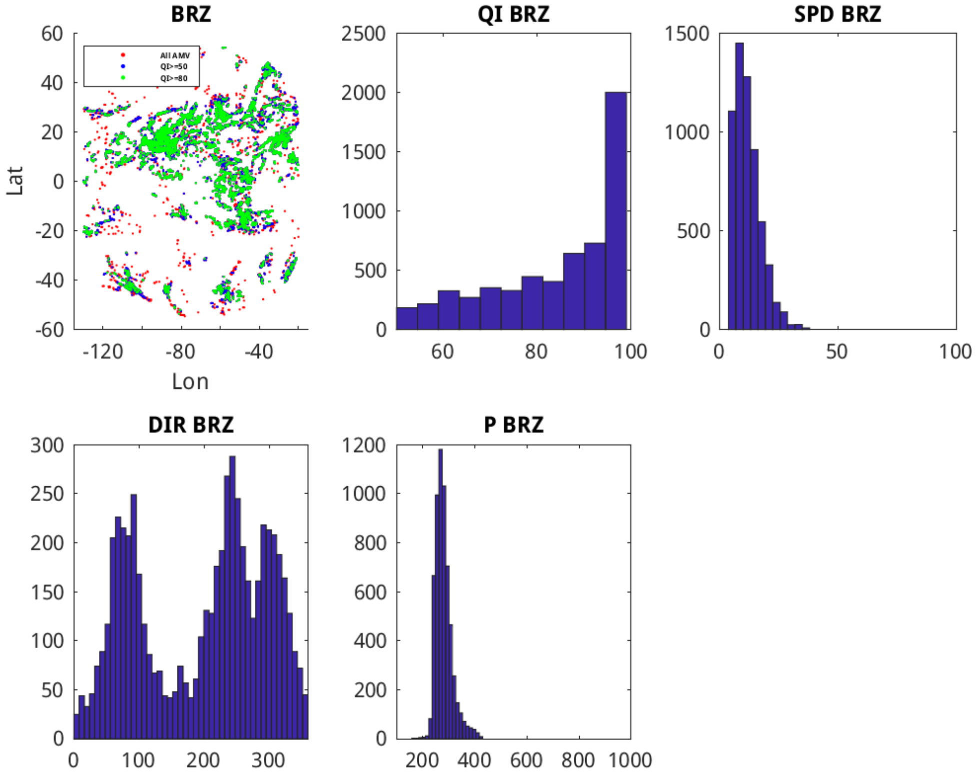

Figure 17-59: Experiment 4 BRZ (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

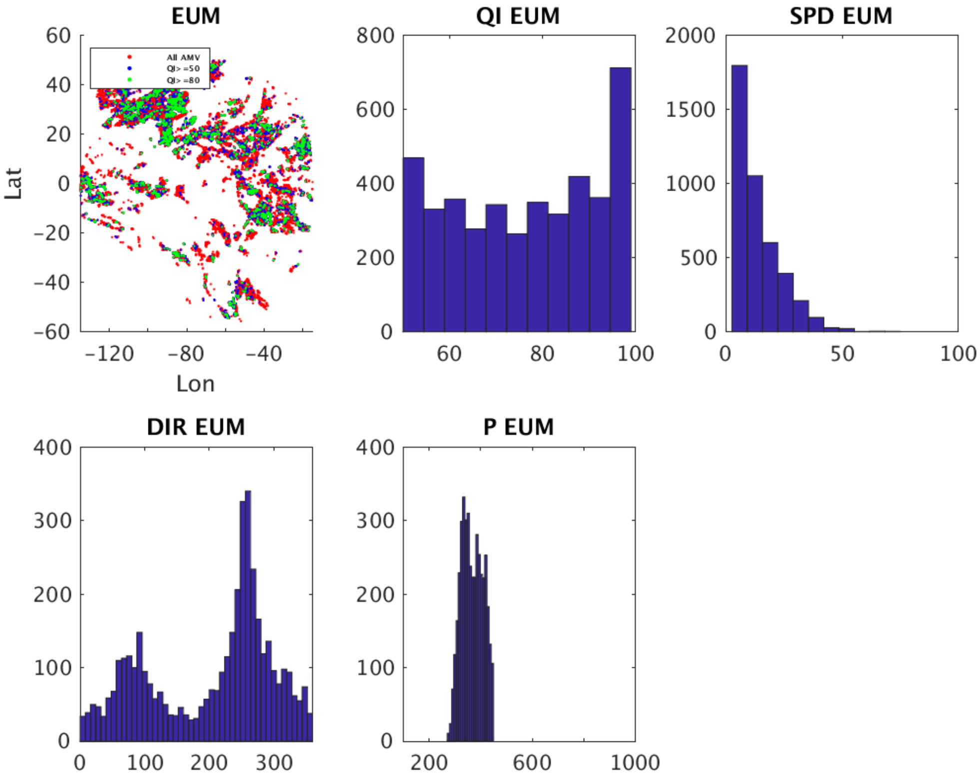

Figure 17-60: Experiment 4 EUM (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure

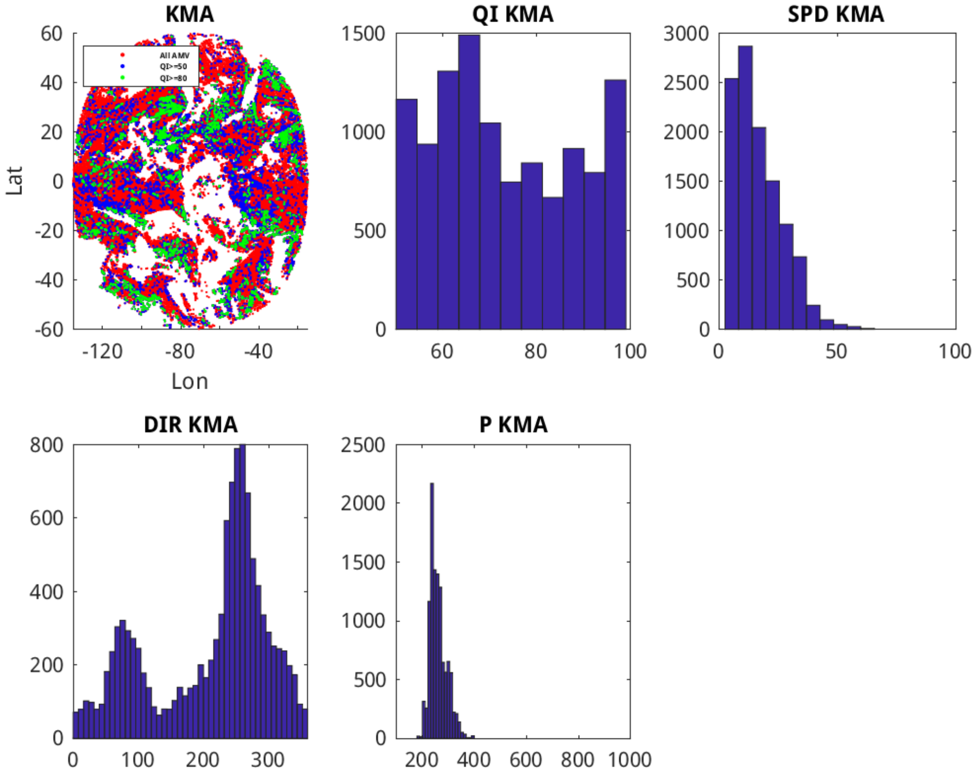

Figure 17-61: Experiment 4 KMA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

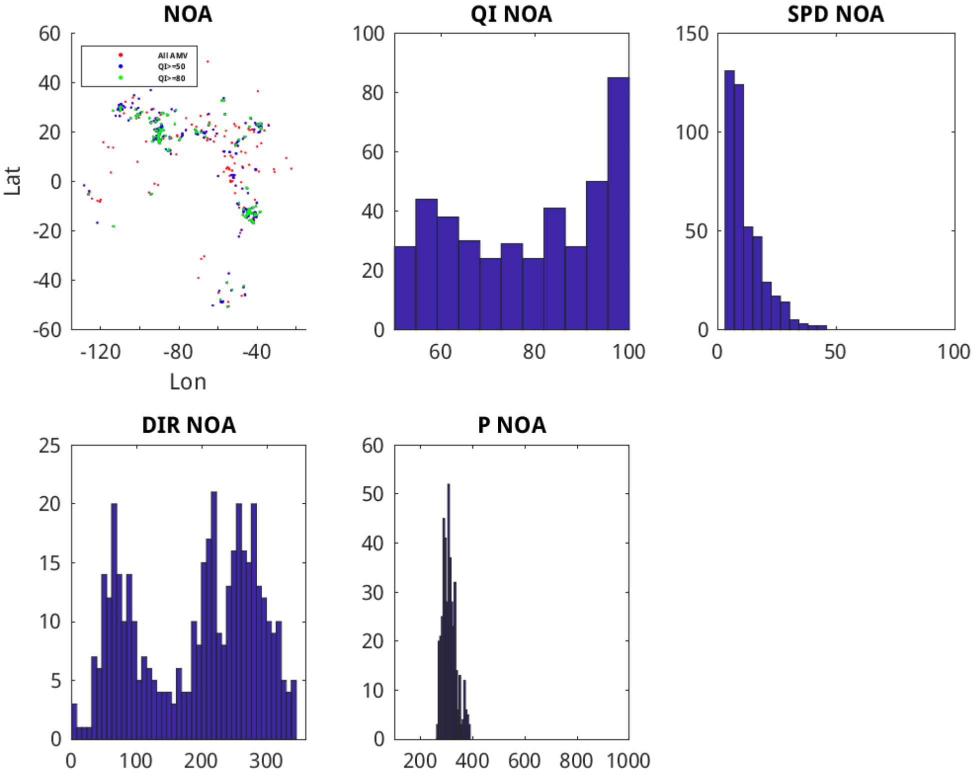

Figure 17-62: Experiment 4 NOA (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

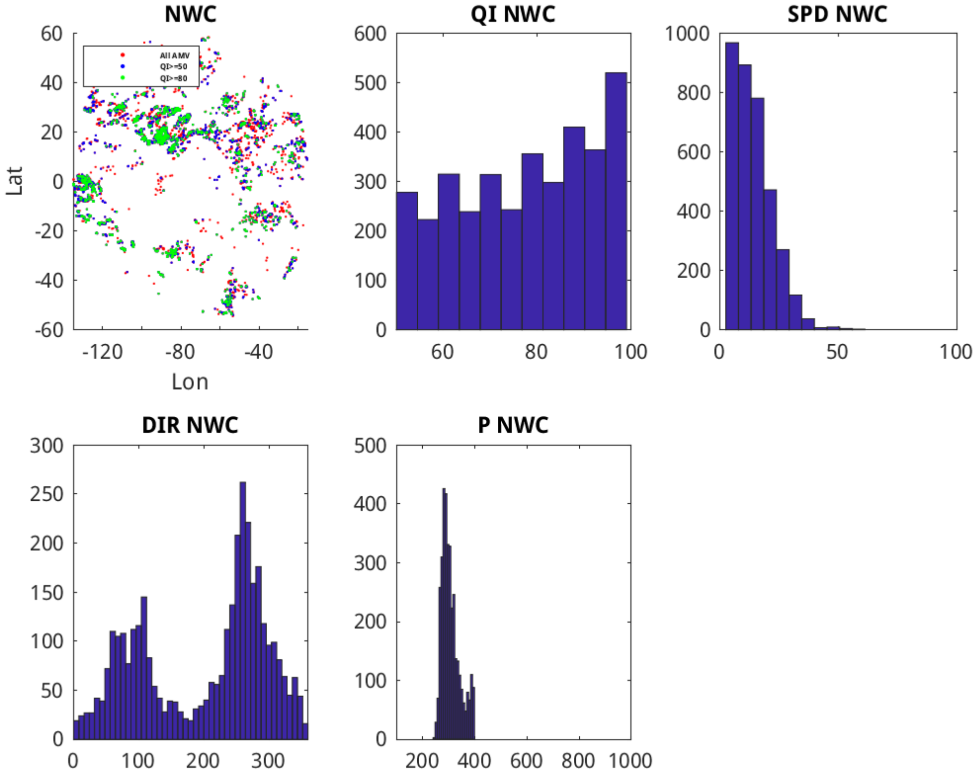

Figure 17-63: Experiment 4 NWC (QINF>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

Experiment 4: CQI Parameter Distribution Histograms

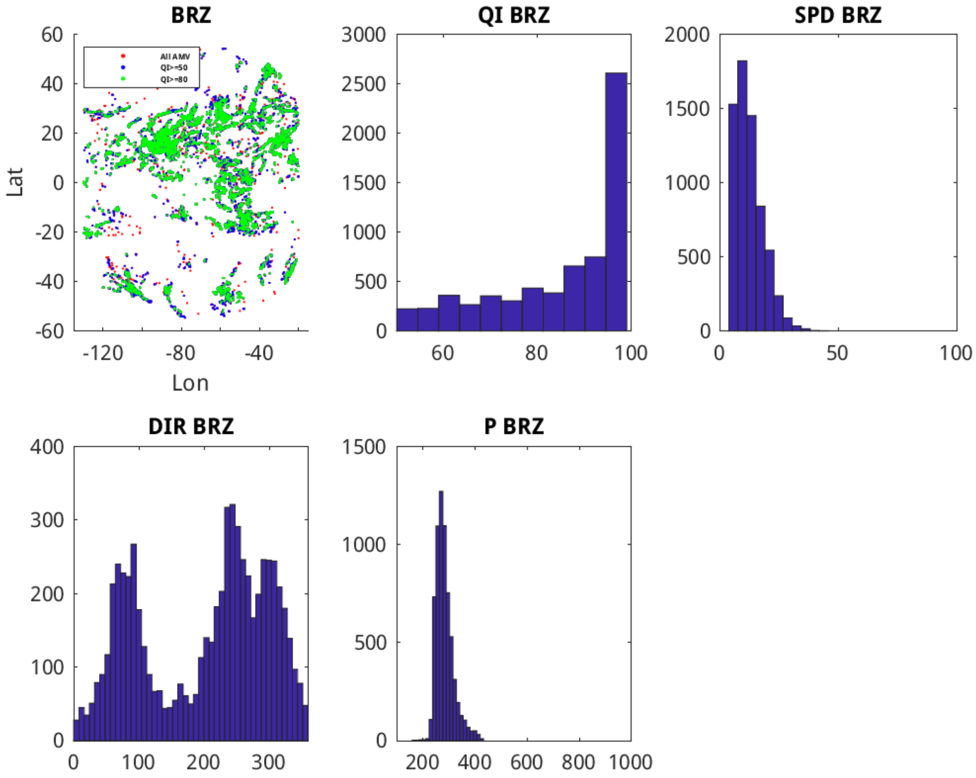

Figure 17-64: Experiment 4 BRZ (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

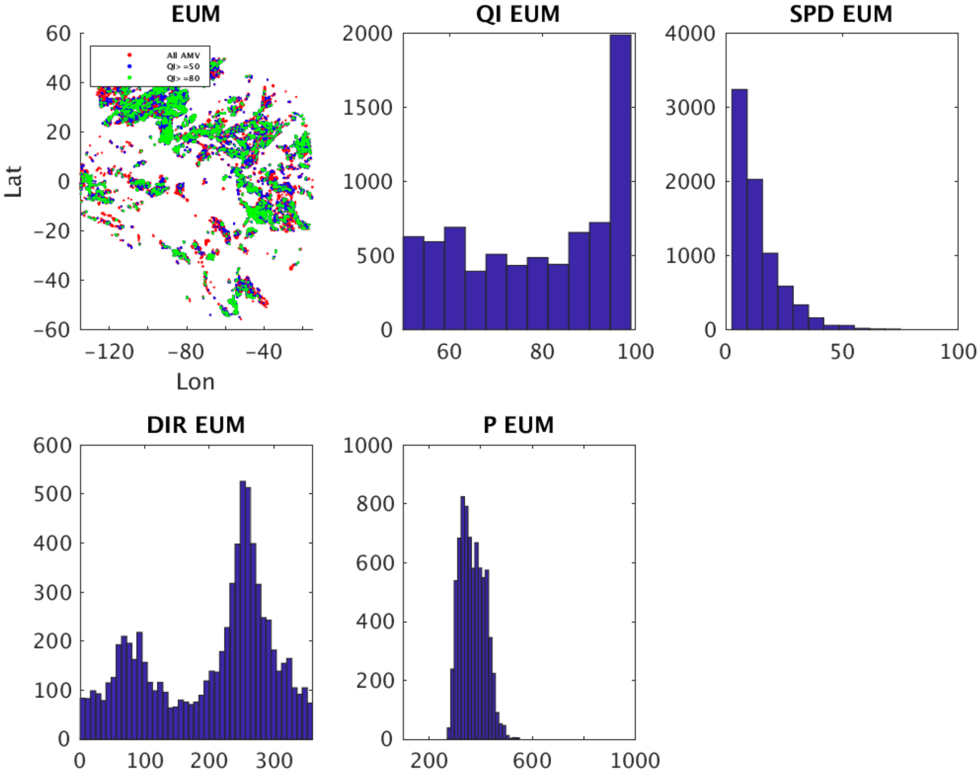

Figure 17-65: Experiment 4 EUM (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histo0grams of QI, wind speed, direction, and AMV pressure.

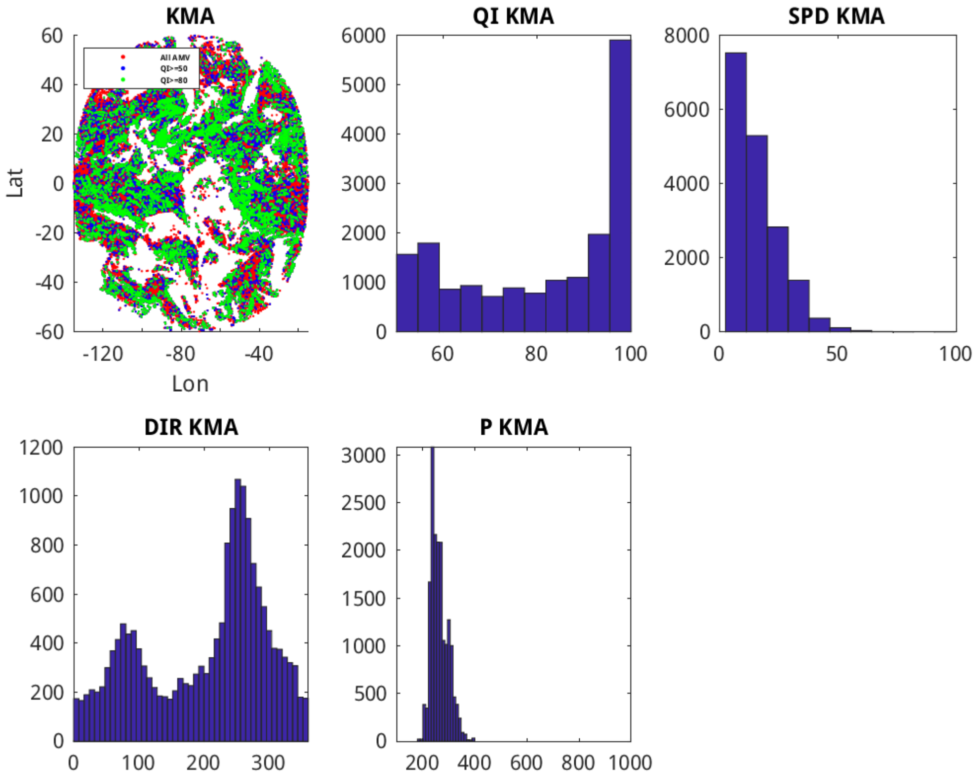

Figure 17-66: Experiment 4 KMA (CQI>=50) KMA parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

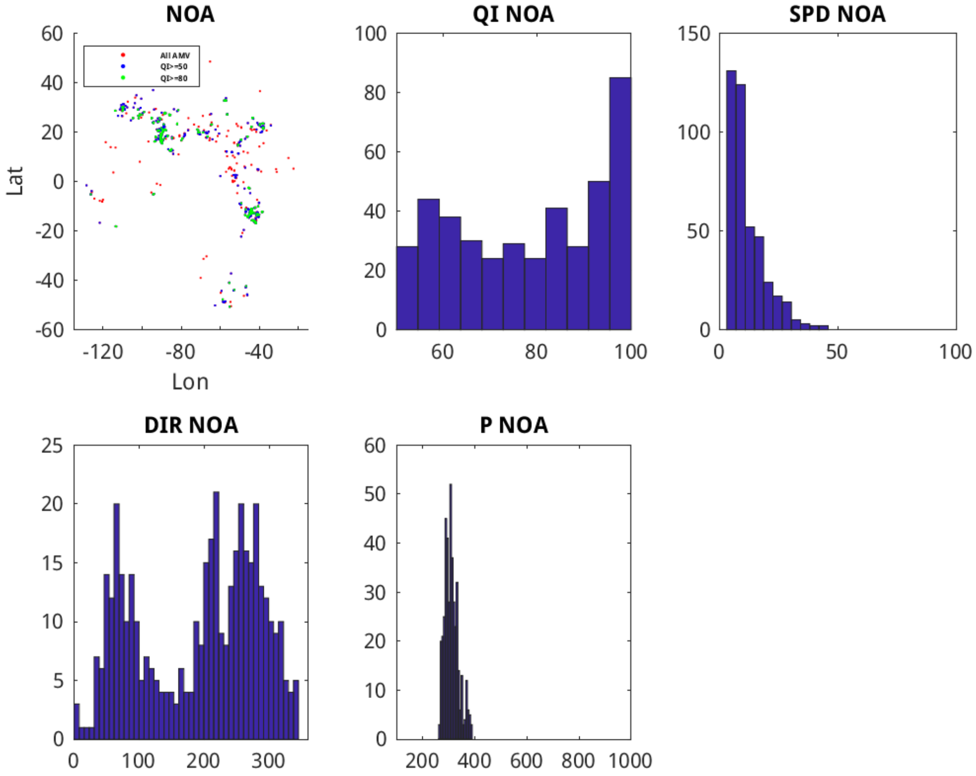

Figure 17-67: Experiment 4 NOA (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

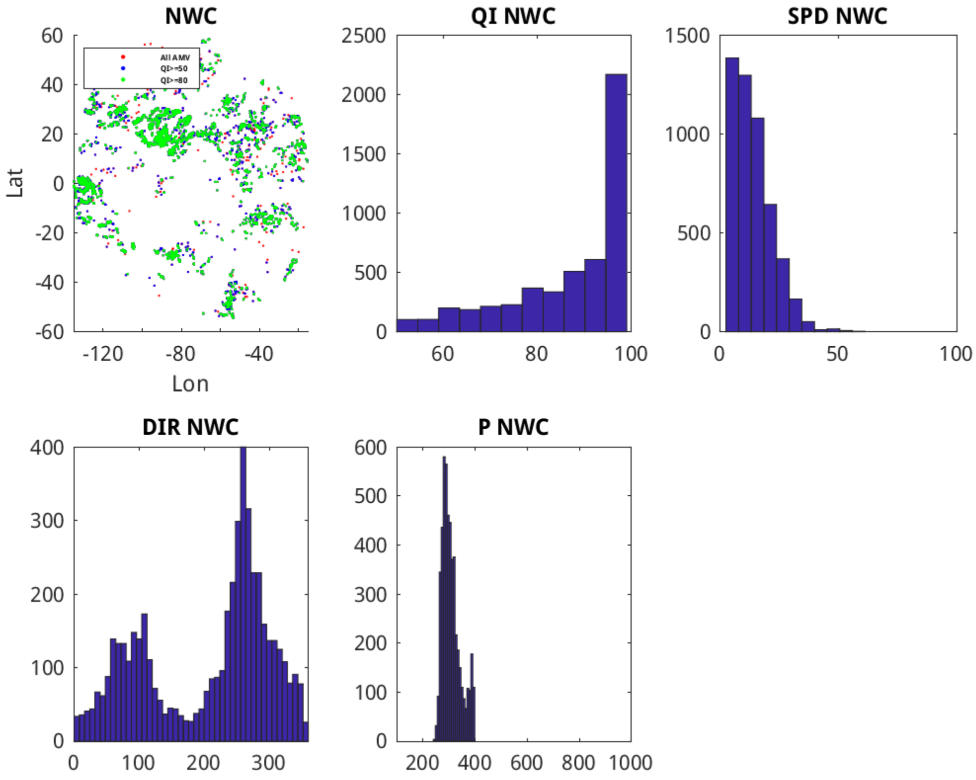

Figure 17-68: Experiment 4 NWC (CQI>=50) parameter distributions: latitude/longitude spatial distribution and histograms of QI, wind speed, direction, and AMV pressure.

18. Appendix B: Best Fit Speed and Vector Difference

a) Experiment 1 Best Fit speed difference

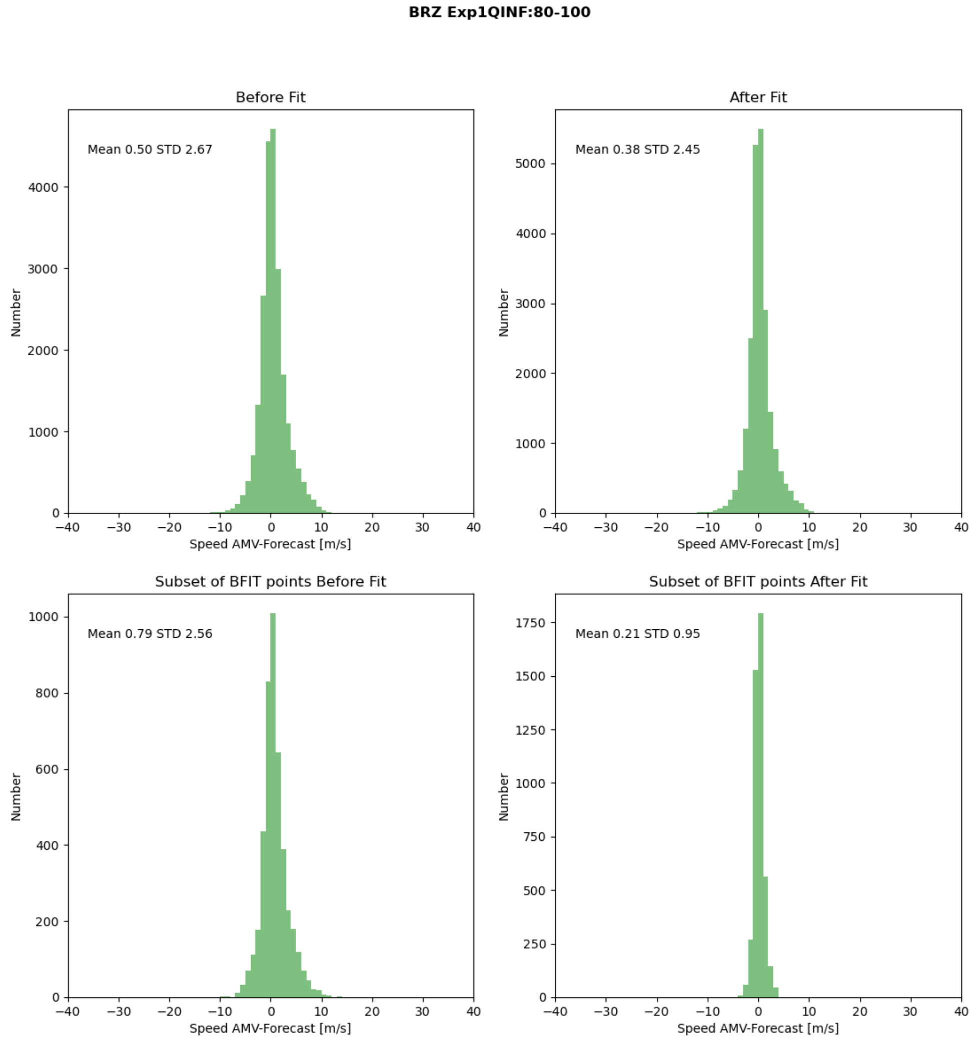

Figure 18-1: Experiment 1, BRZ (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

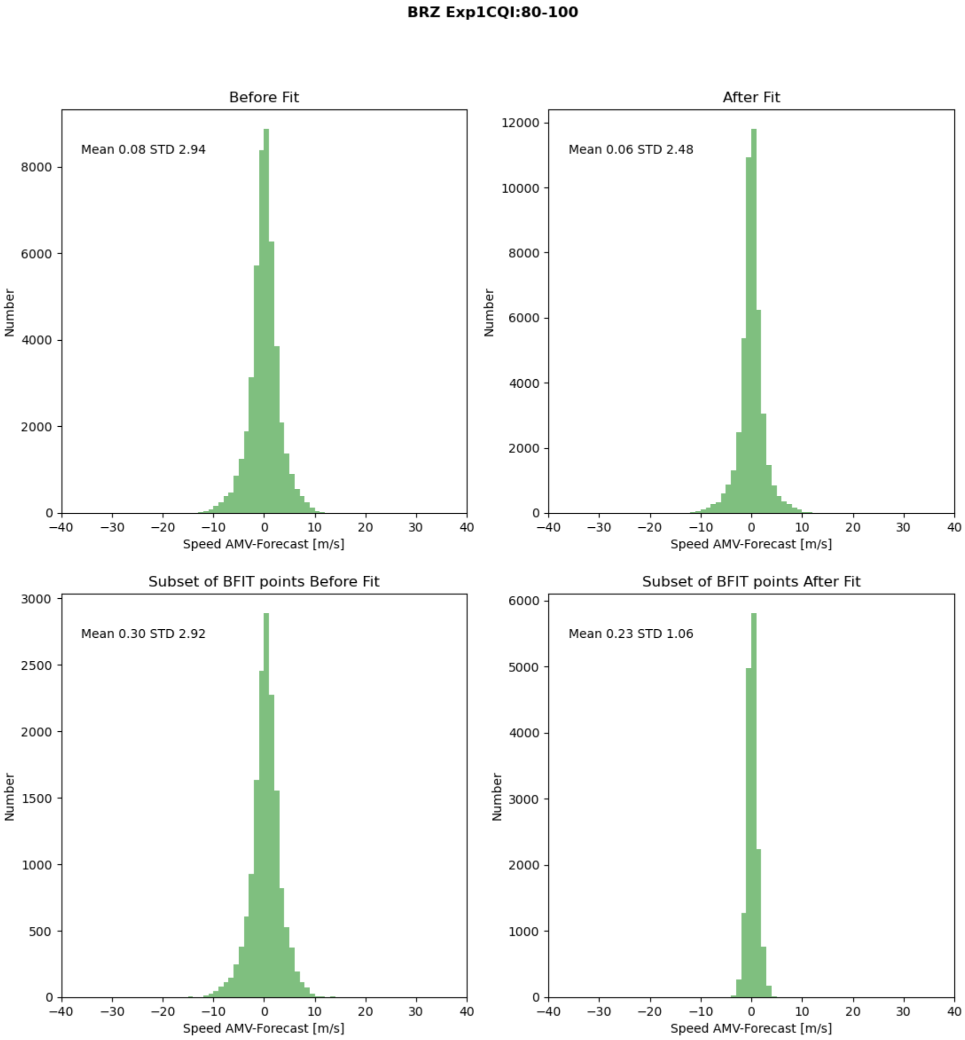

Figure 18-2: Experiment 1, BRZ (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

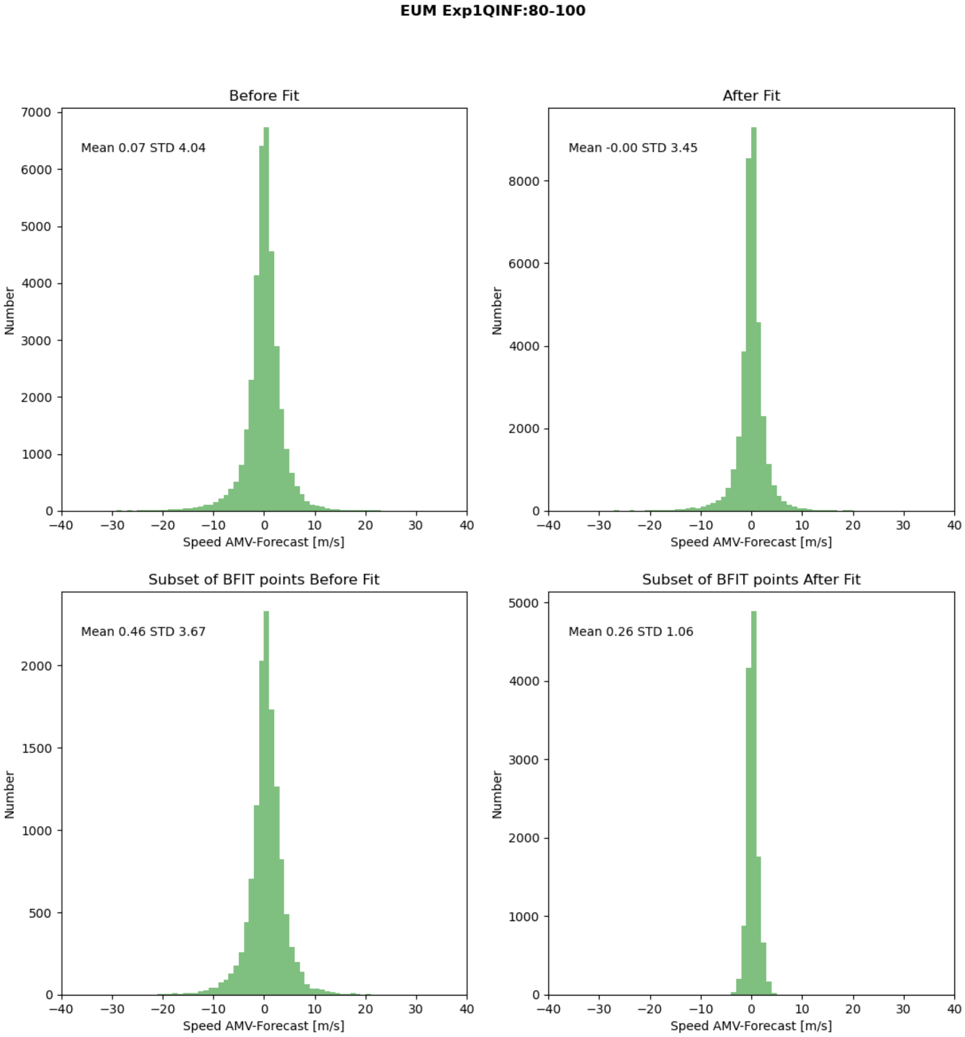

Figure 18-3: Experiment 1, EUM (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

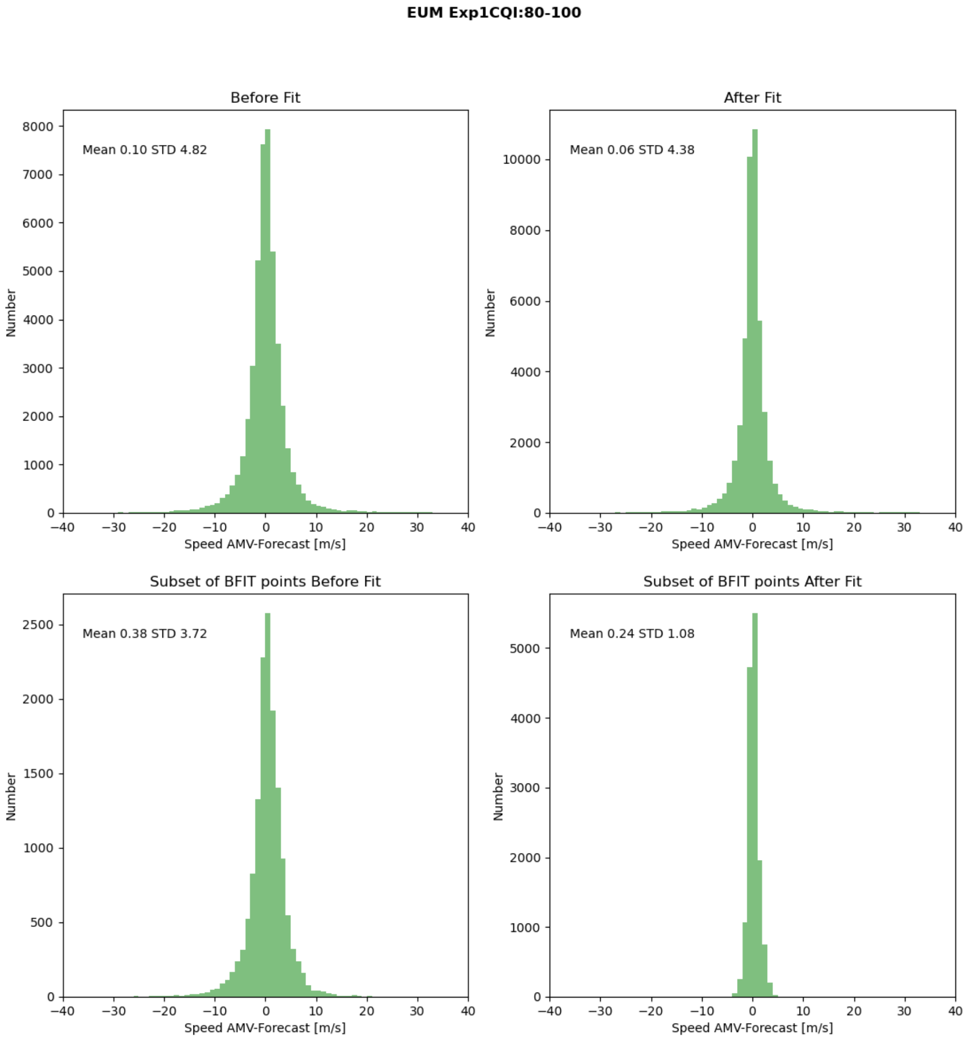

Figure 18-4: Experiment 1, EUM (CQI>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

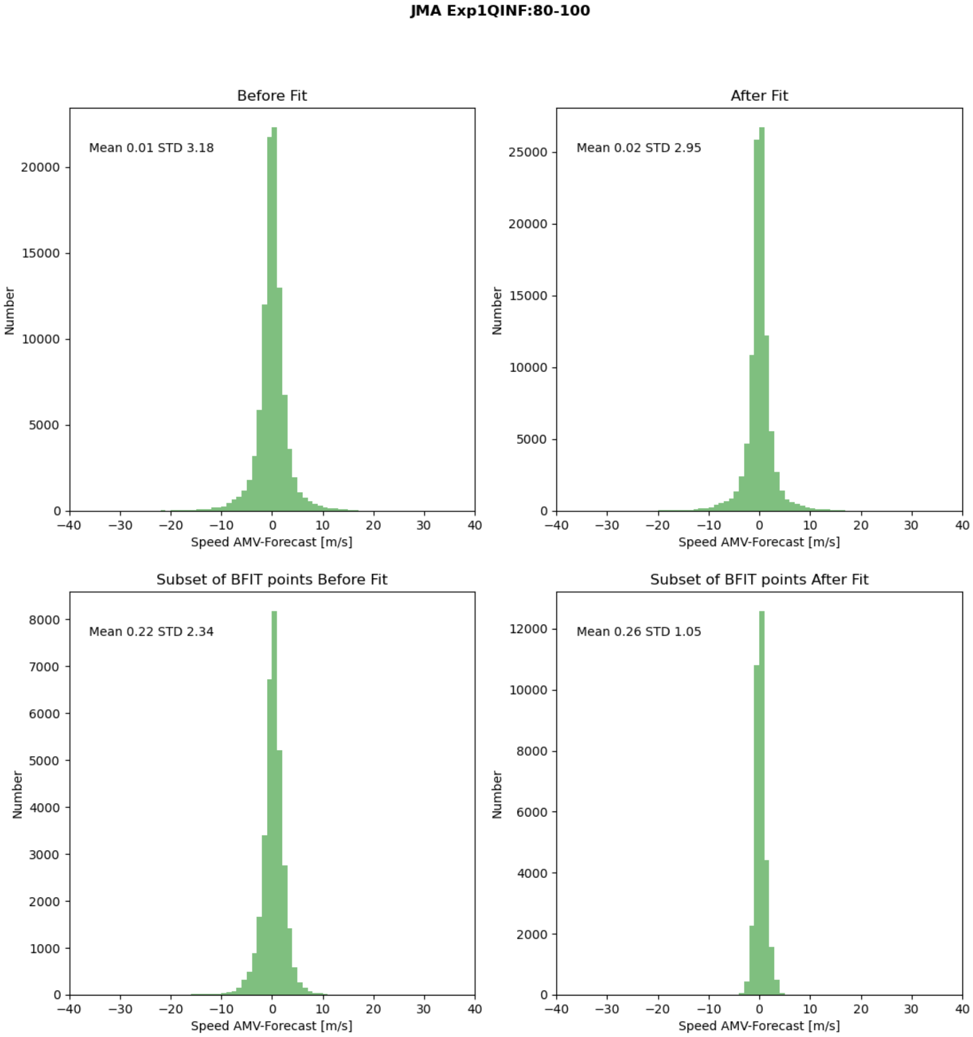

Figure 18-5: Experiment 1, JMA (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

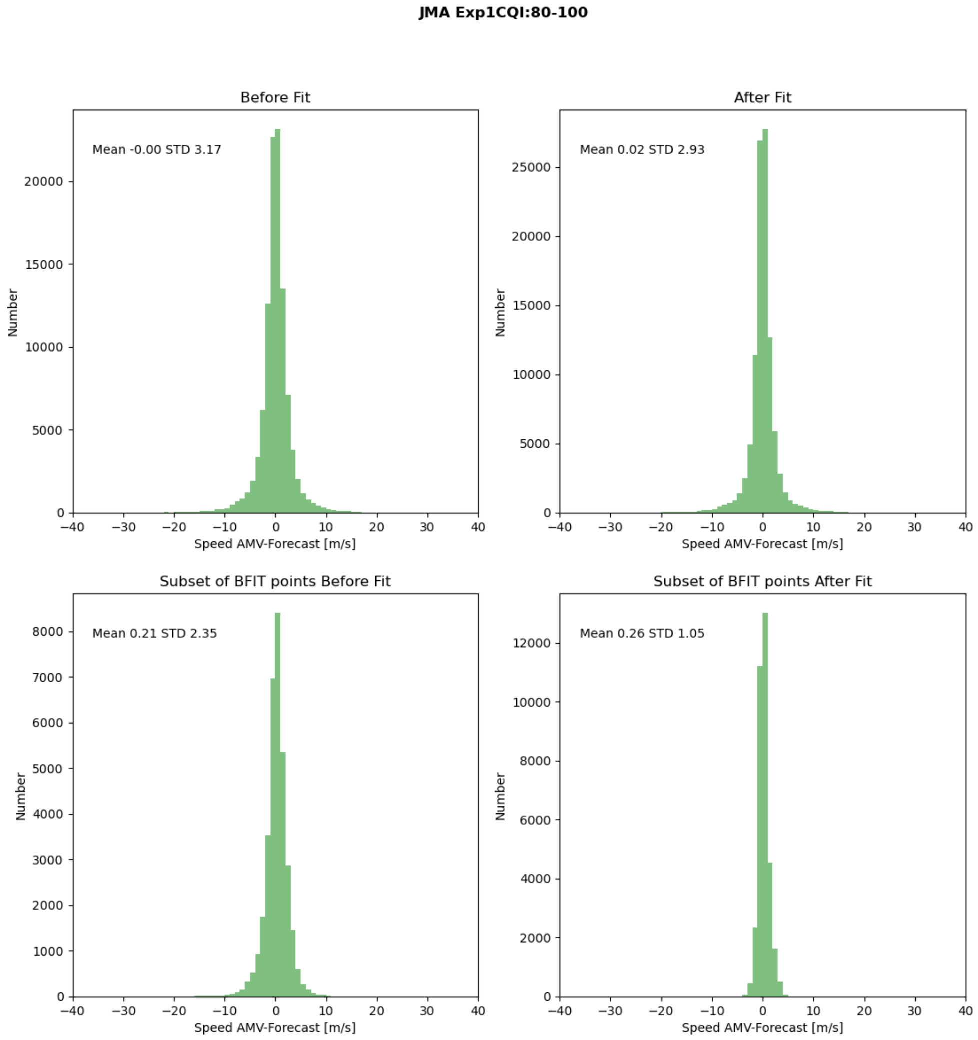

Figure 18-6: Experiment 1, JMA (CQI>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

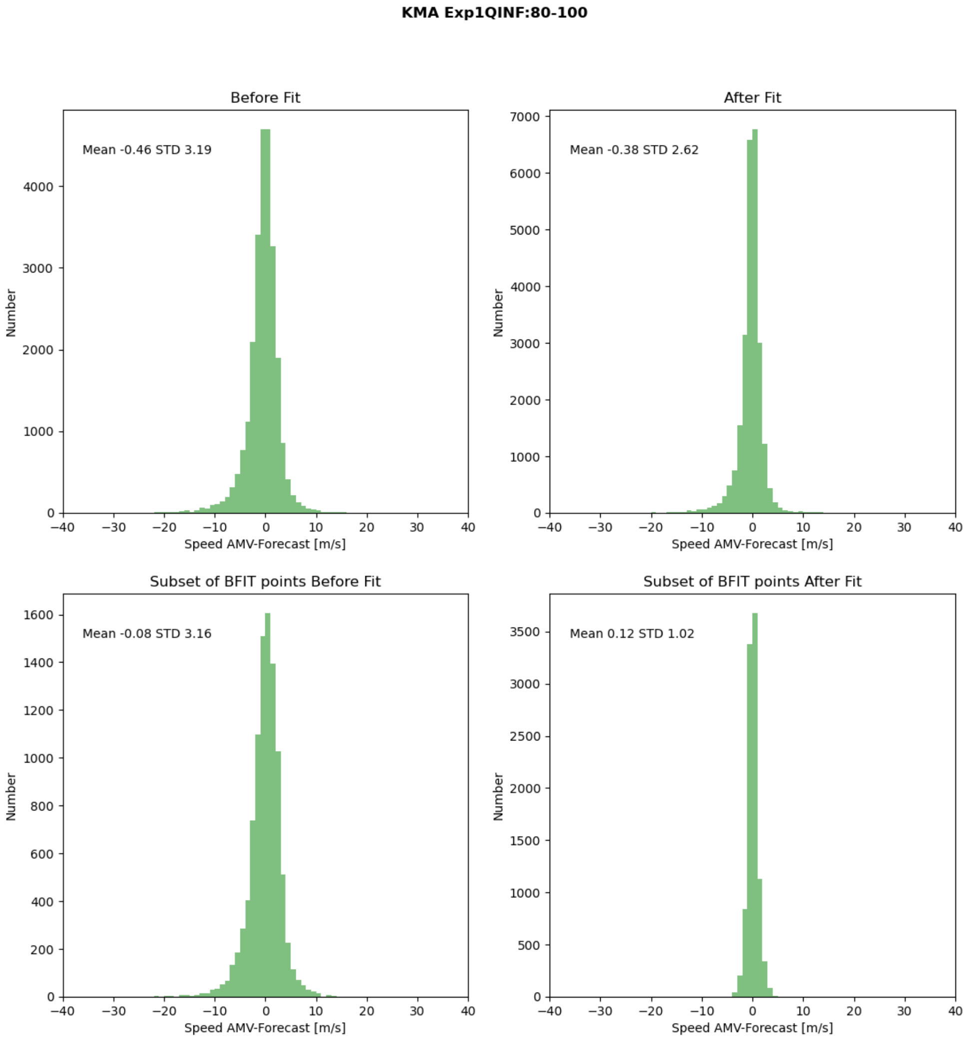

Figure 18-7: Experiment 1, KMA (QINF>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

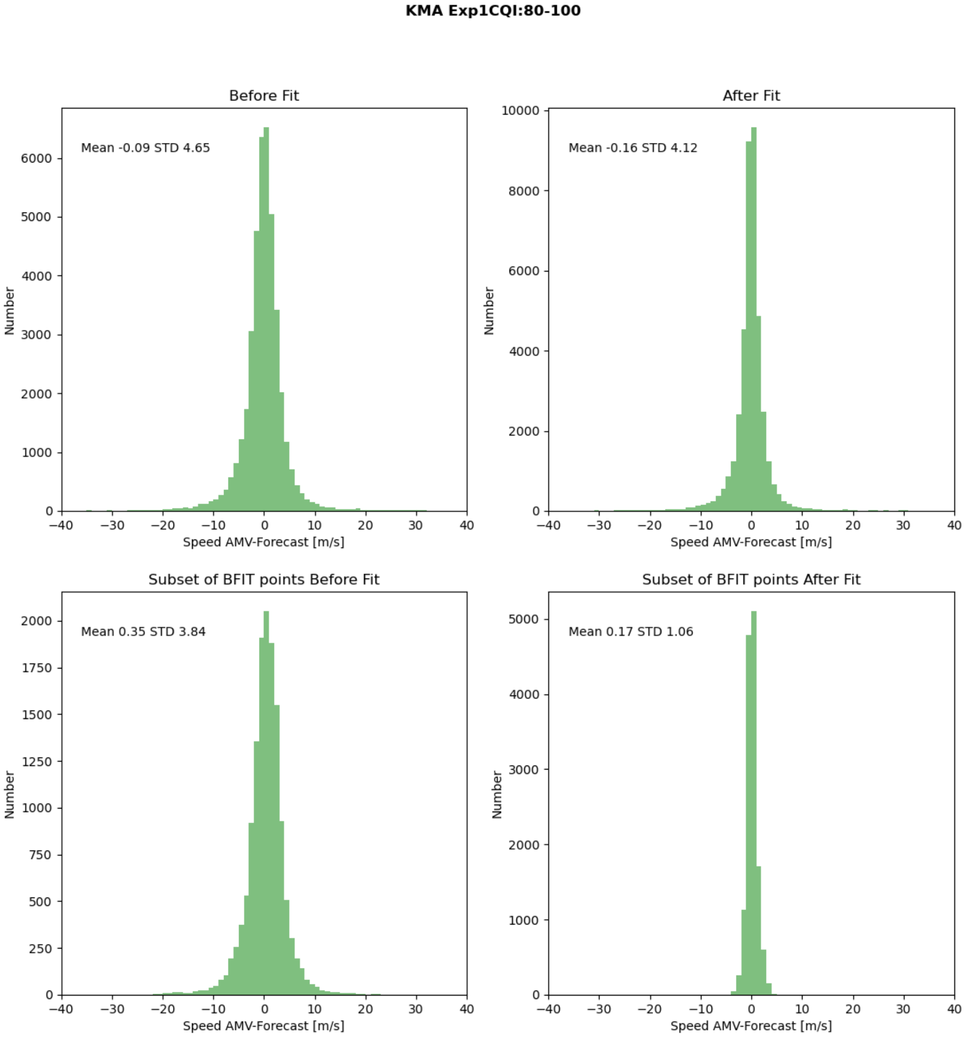

Figure 18-8: Experiment 1, KMA (CQI>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

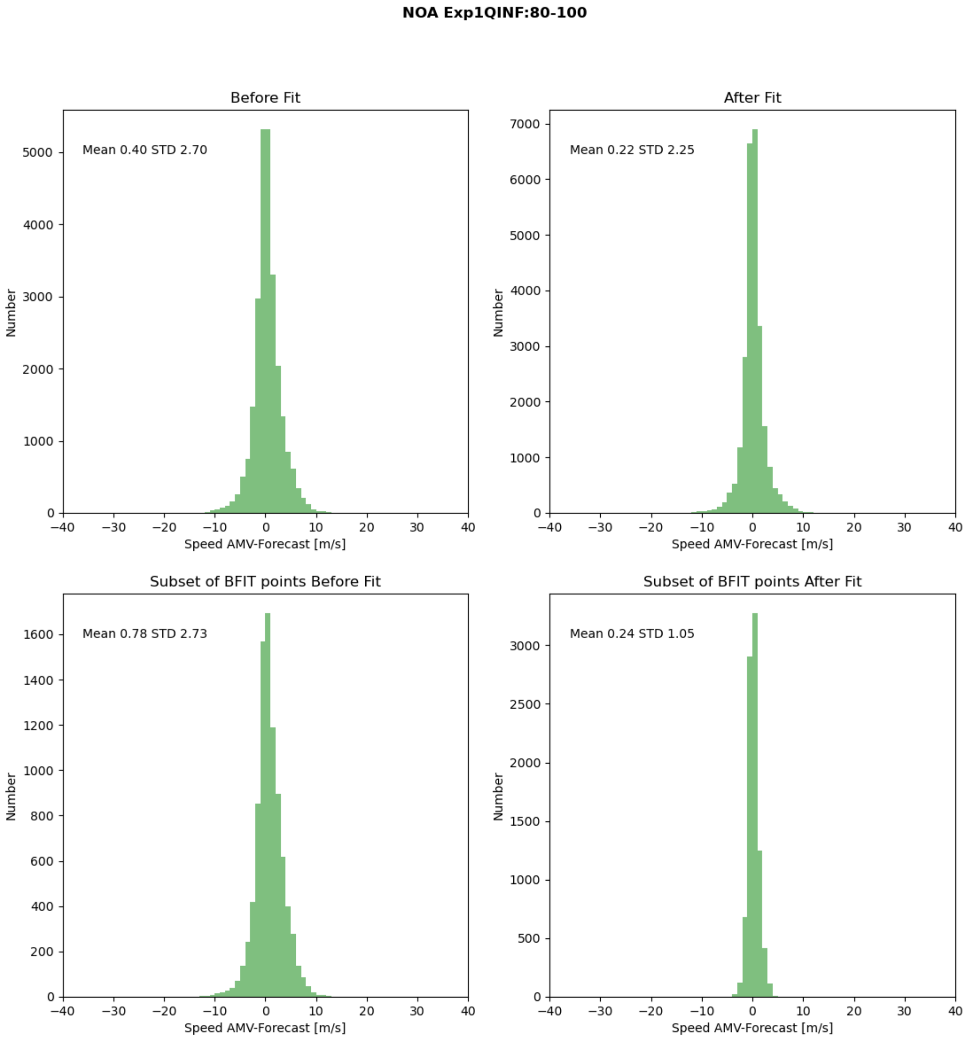

Figure 18-9: Experiment 1, NOA (QINF>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

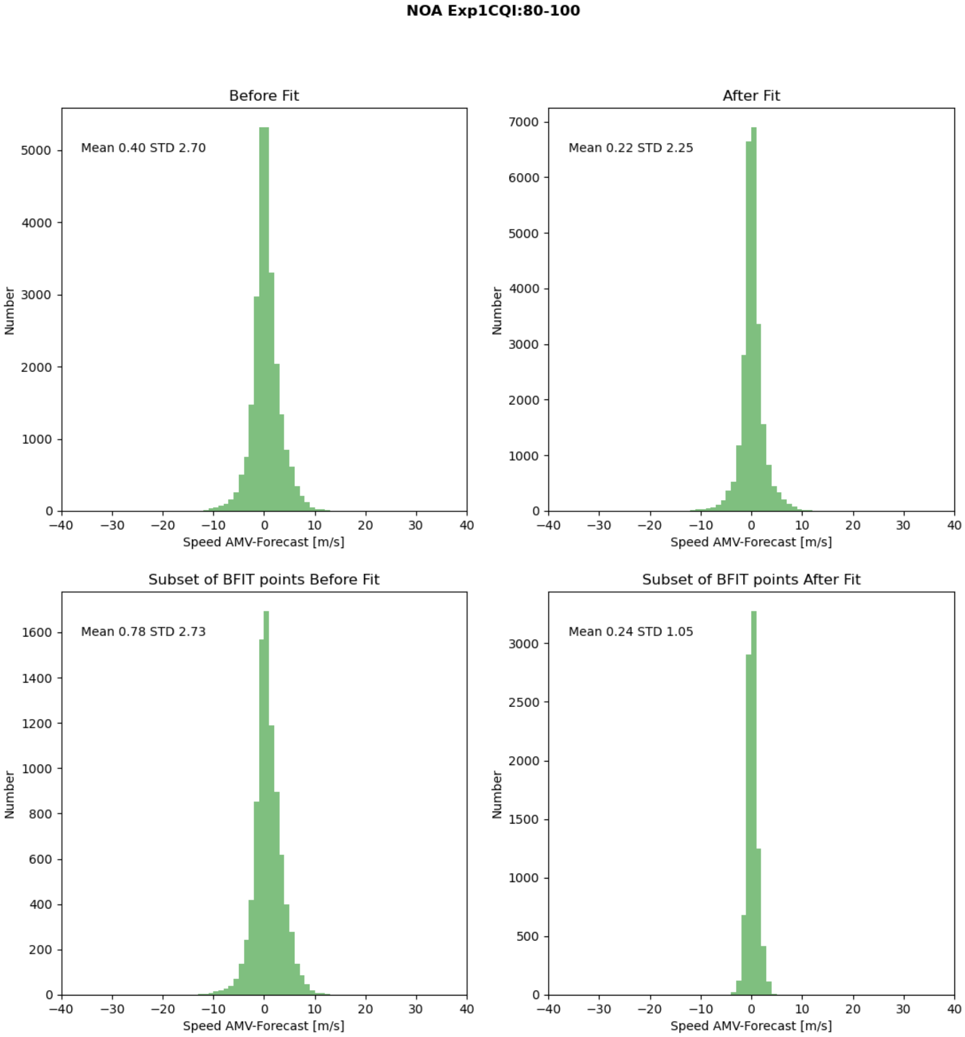

Figure 18-10: Experiment 1, NOA (CQI>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

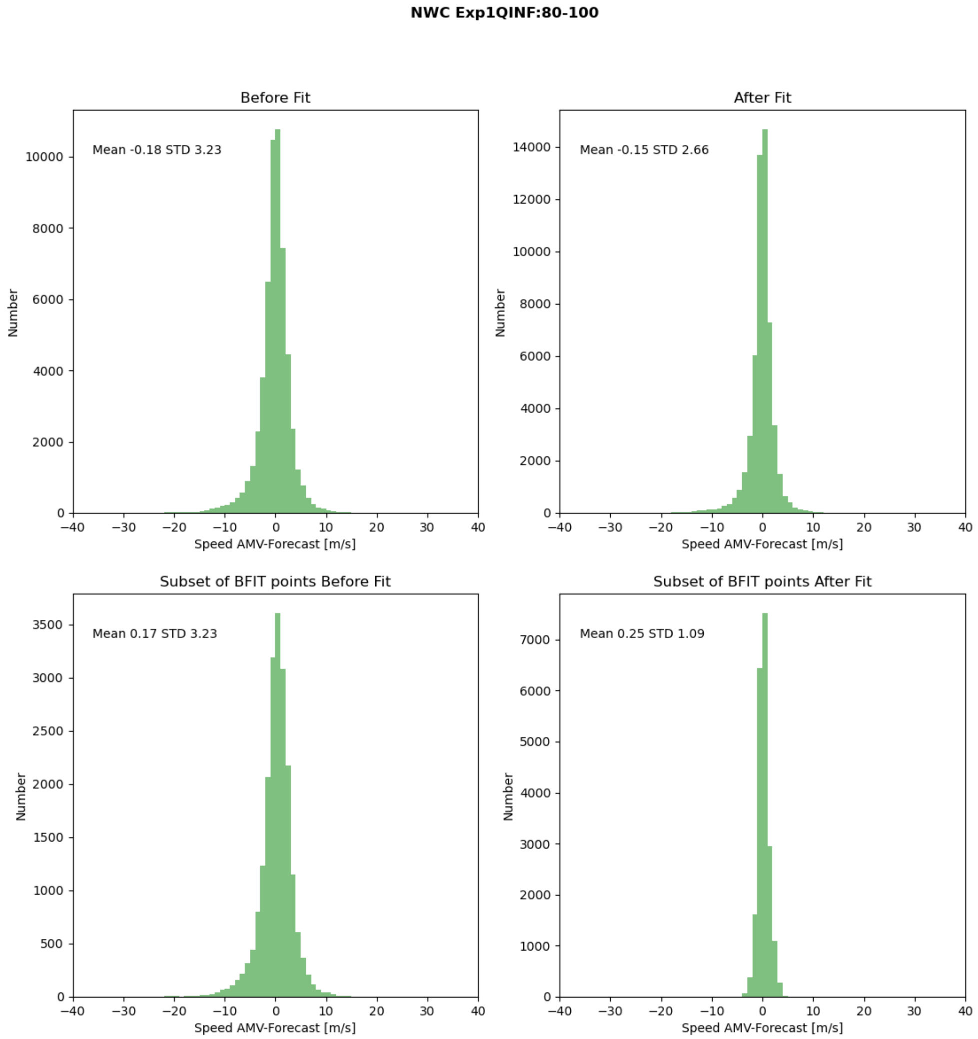

Figure 18-11: Experiment 1, NWC (QINF>= 80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

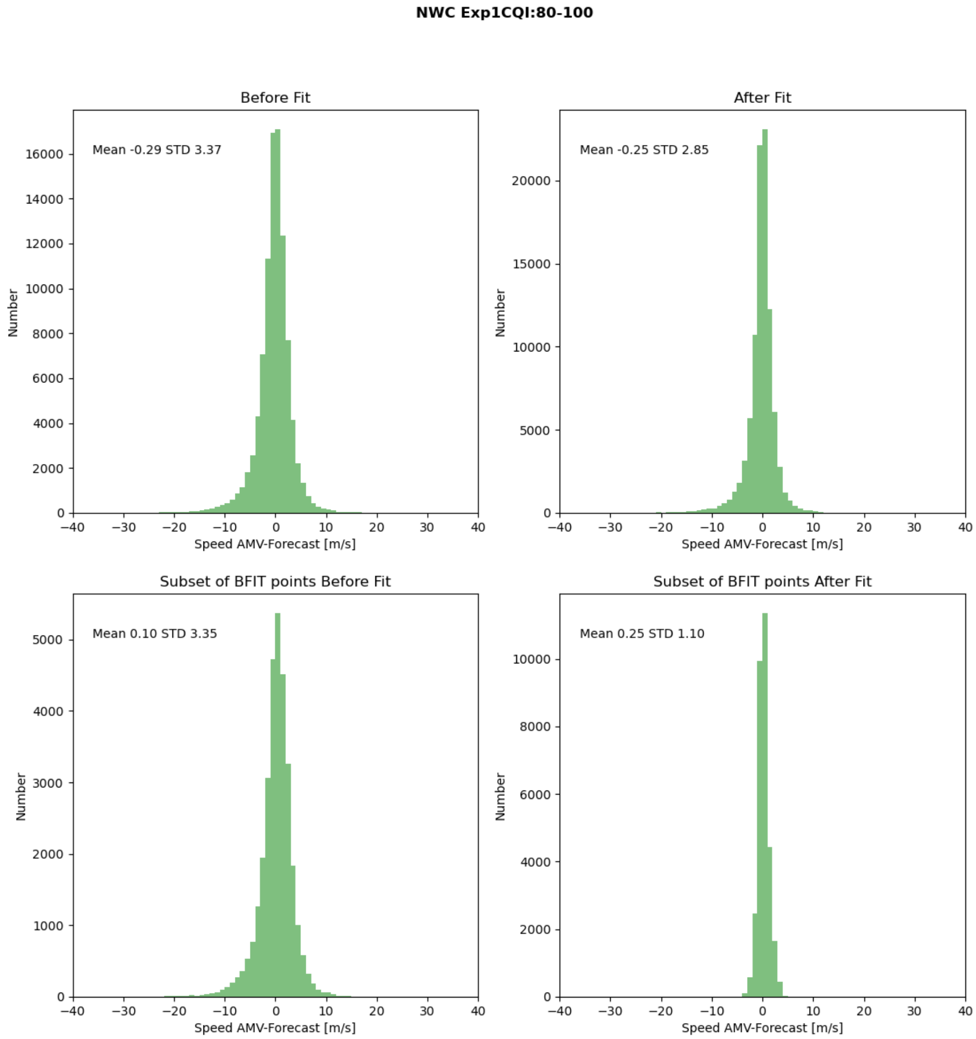

Figure 18-12: Experiment 1, NWC (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

b) Experiment 2b Best Fit speed difference

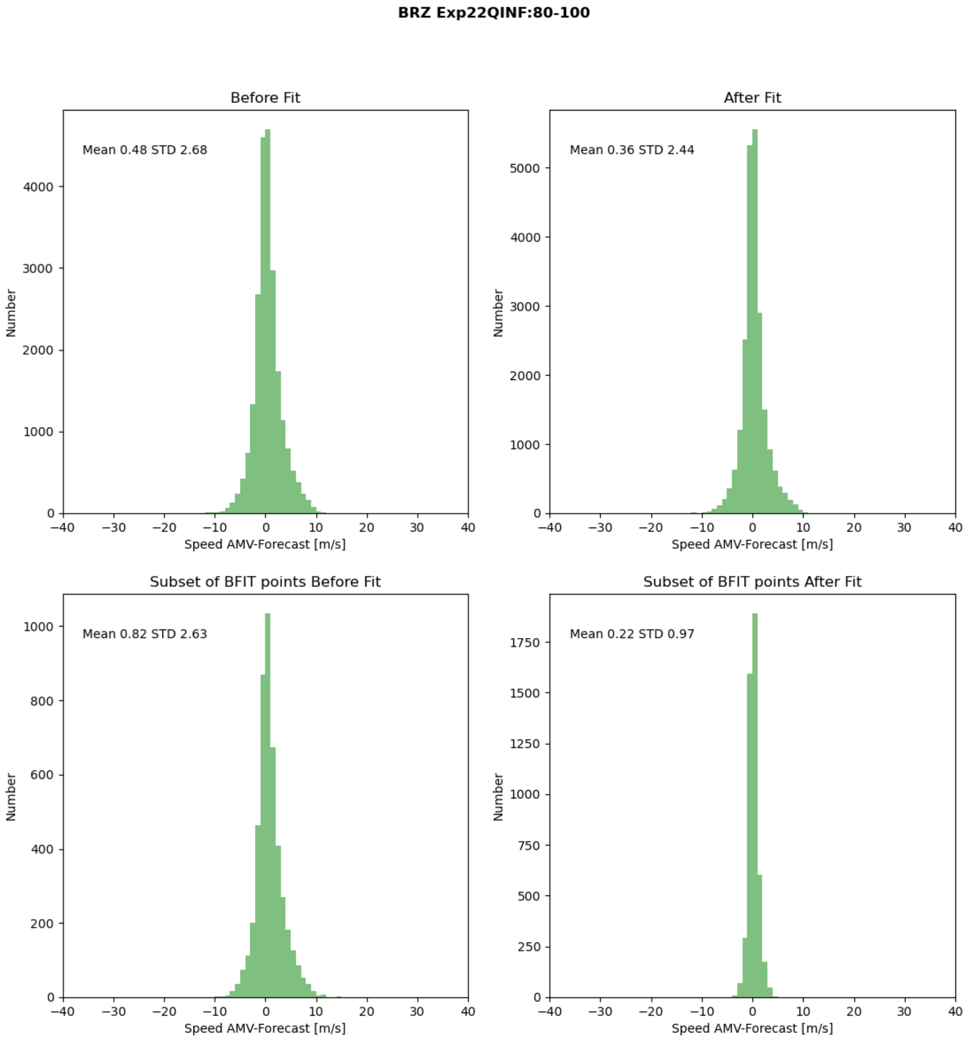

Figure 18-13: Experiment 2b, BRZ (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

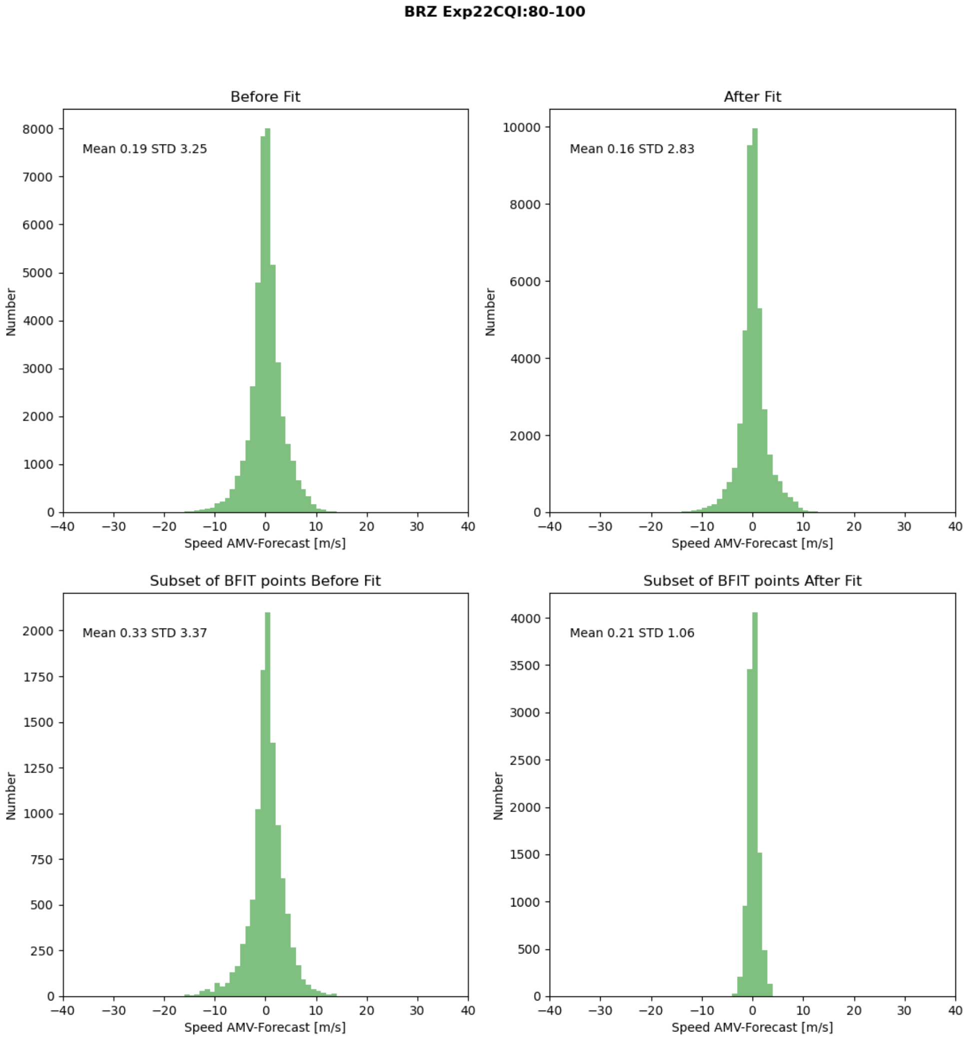

Figure 18-14: Experiment 2b, BRZ (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

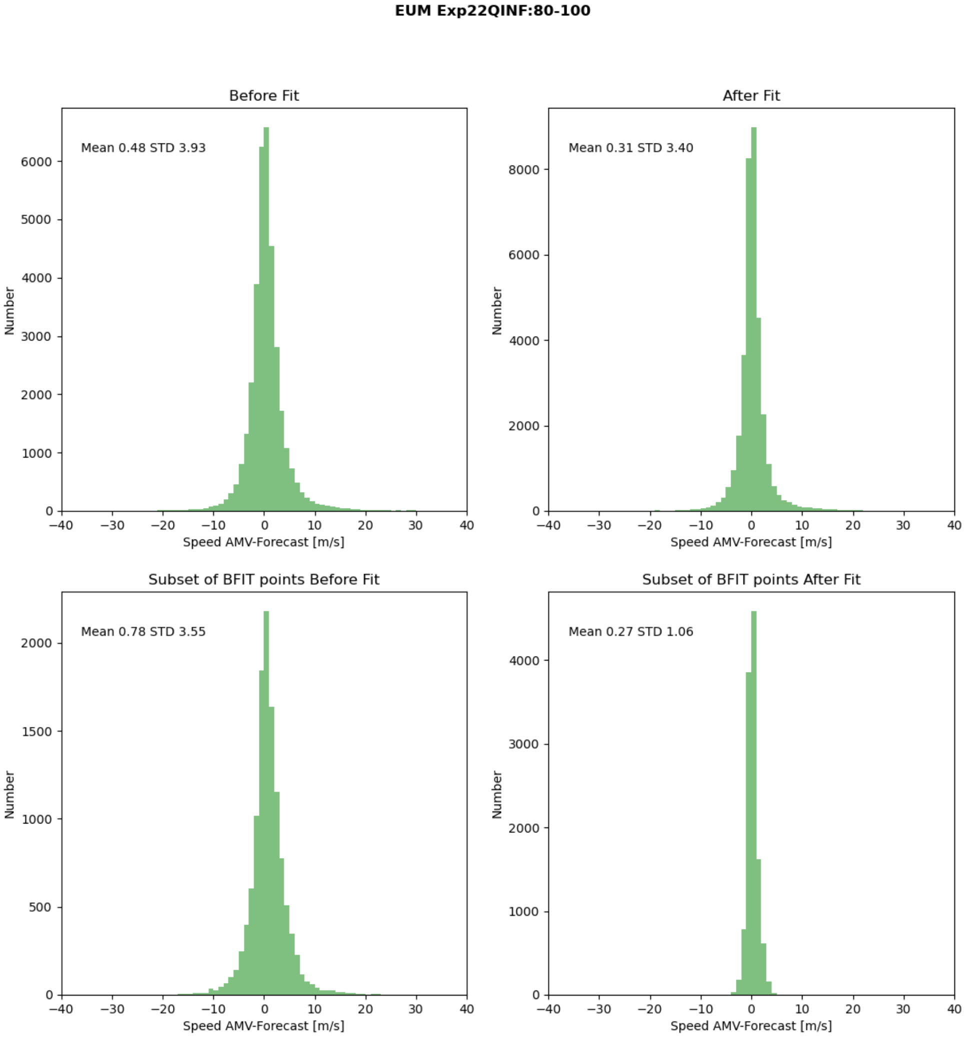

Figure 18-15: Experiment 2b, EUM (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

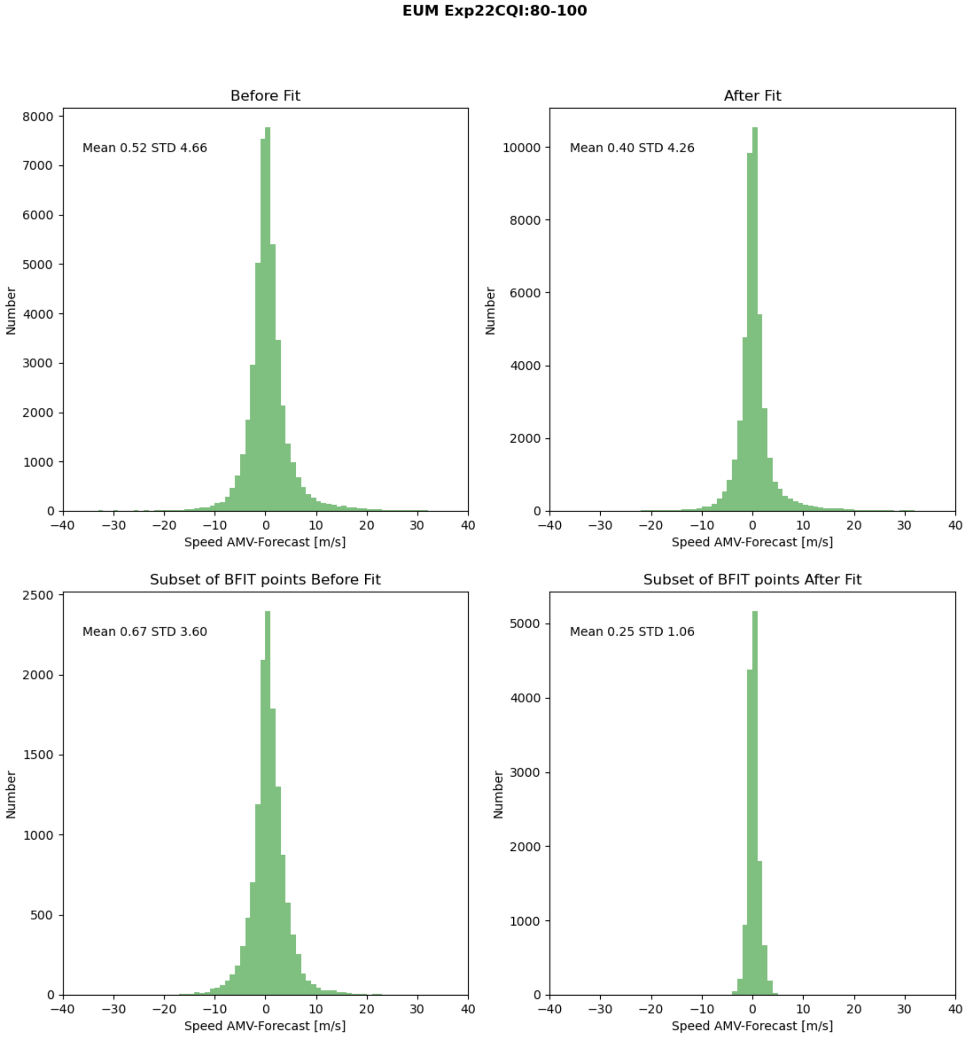

Figure 18-16: Experiment 2b, EUM (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

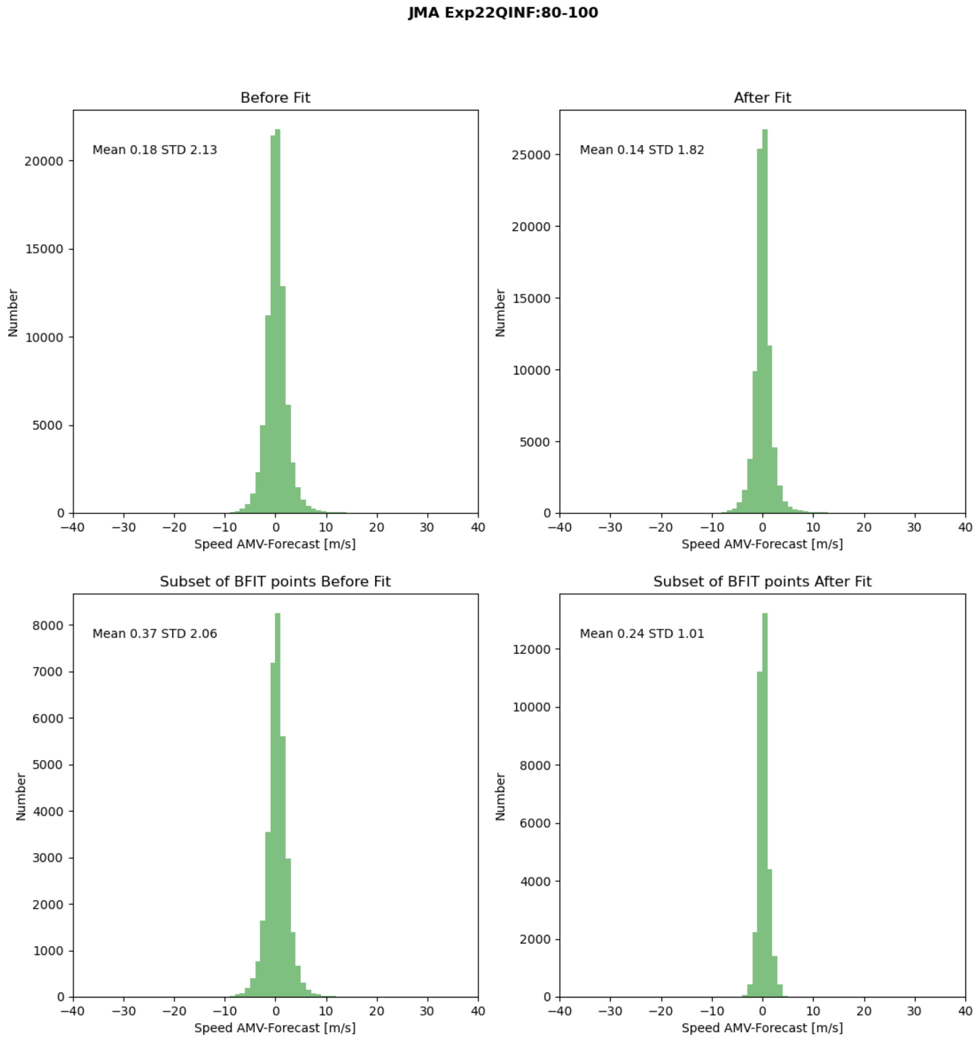

Figure 18-17: Experiment 2b, JMA (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

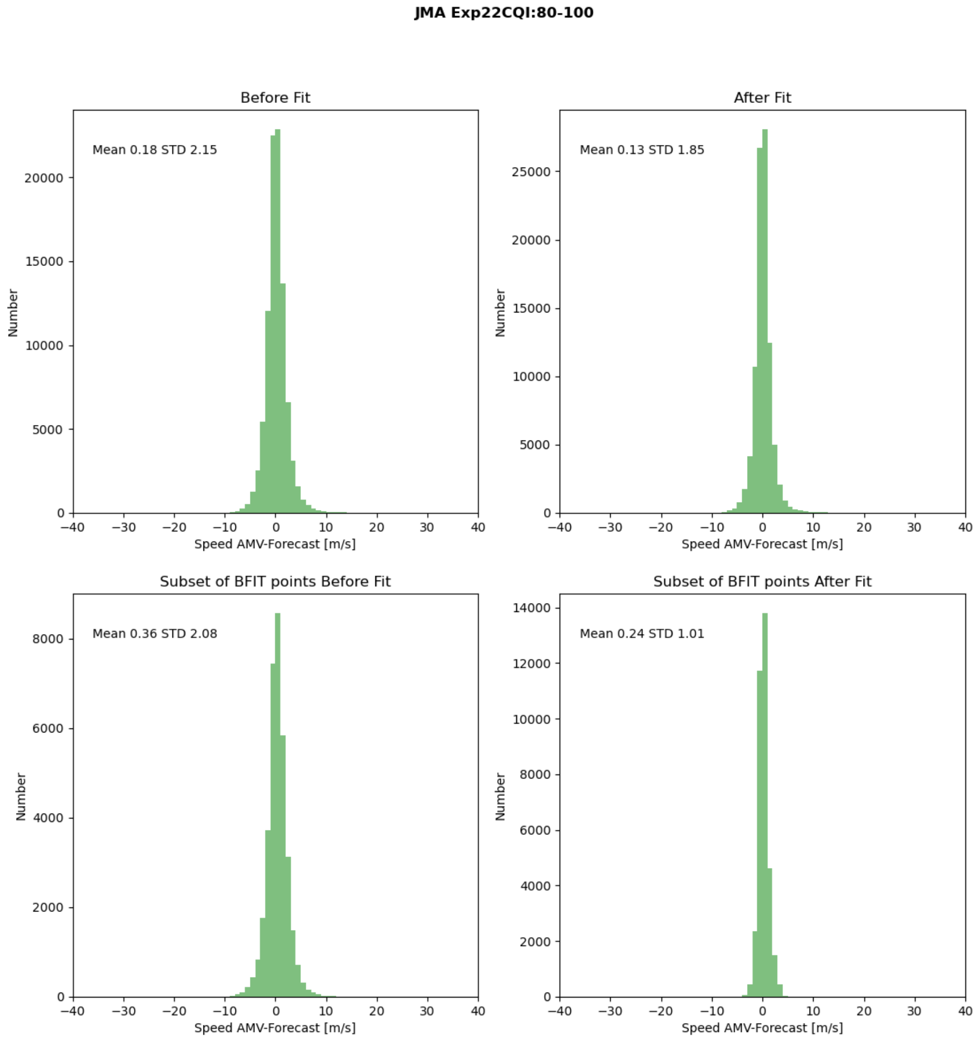

Figure 18-18: Experiment 2b, JMA (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

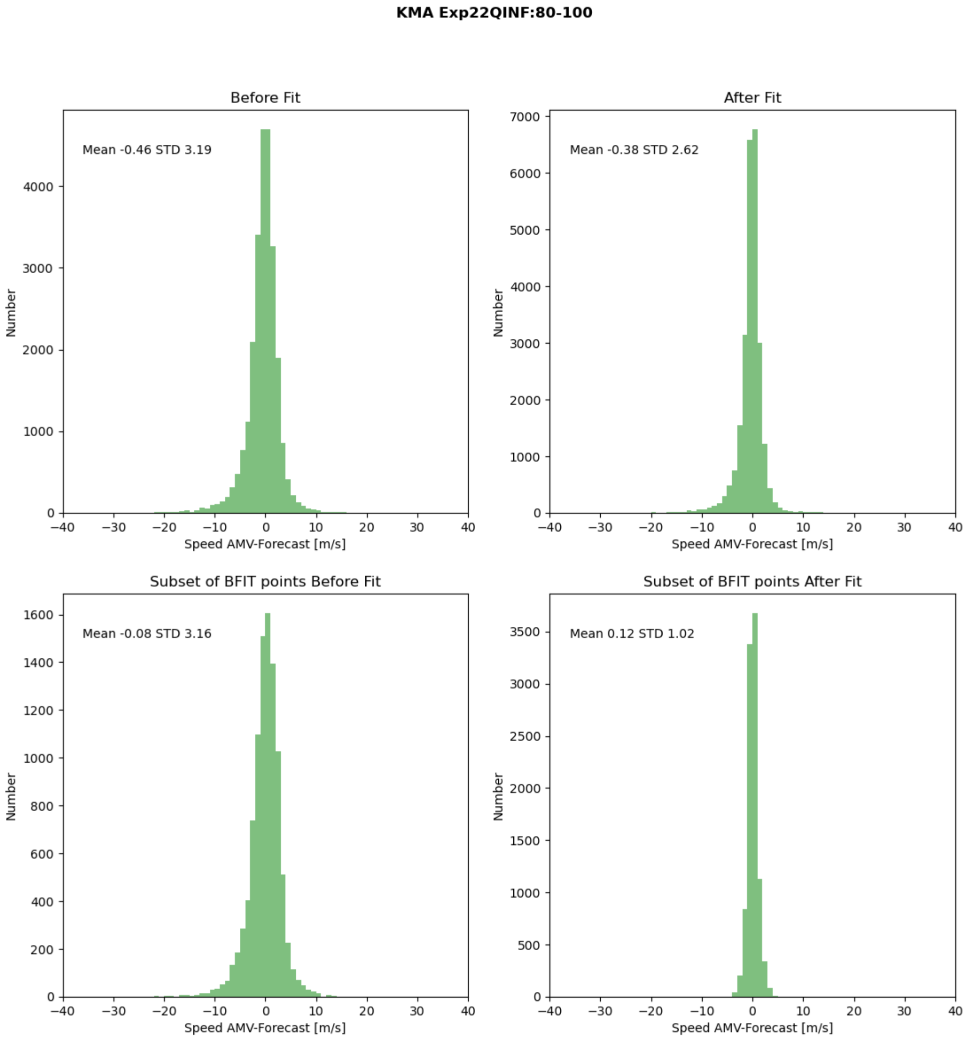

Figure 18-19: Experiment 2b, KMA (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

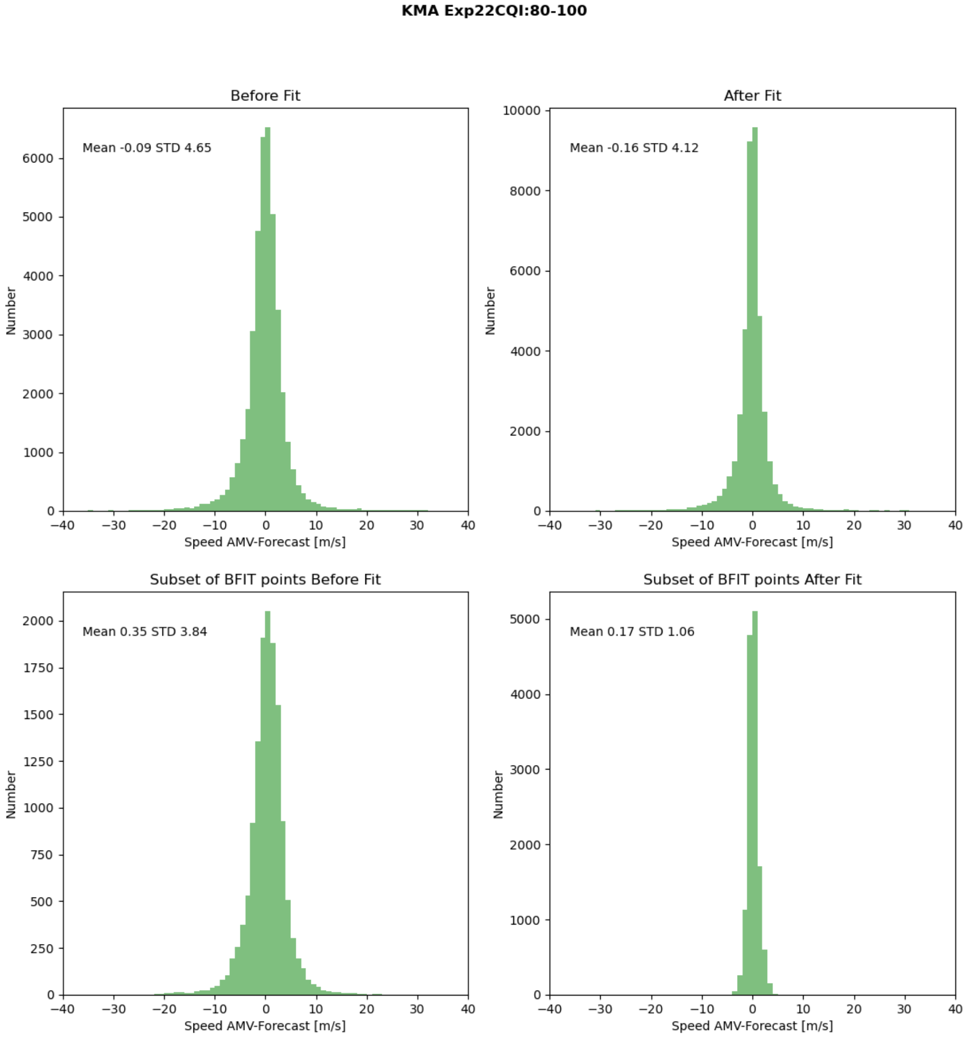

Figure 18-20: Experiment 2b, KMA (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

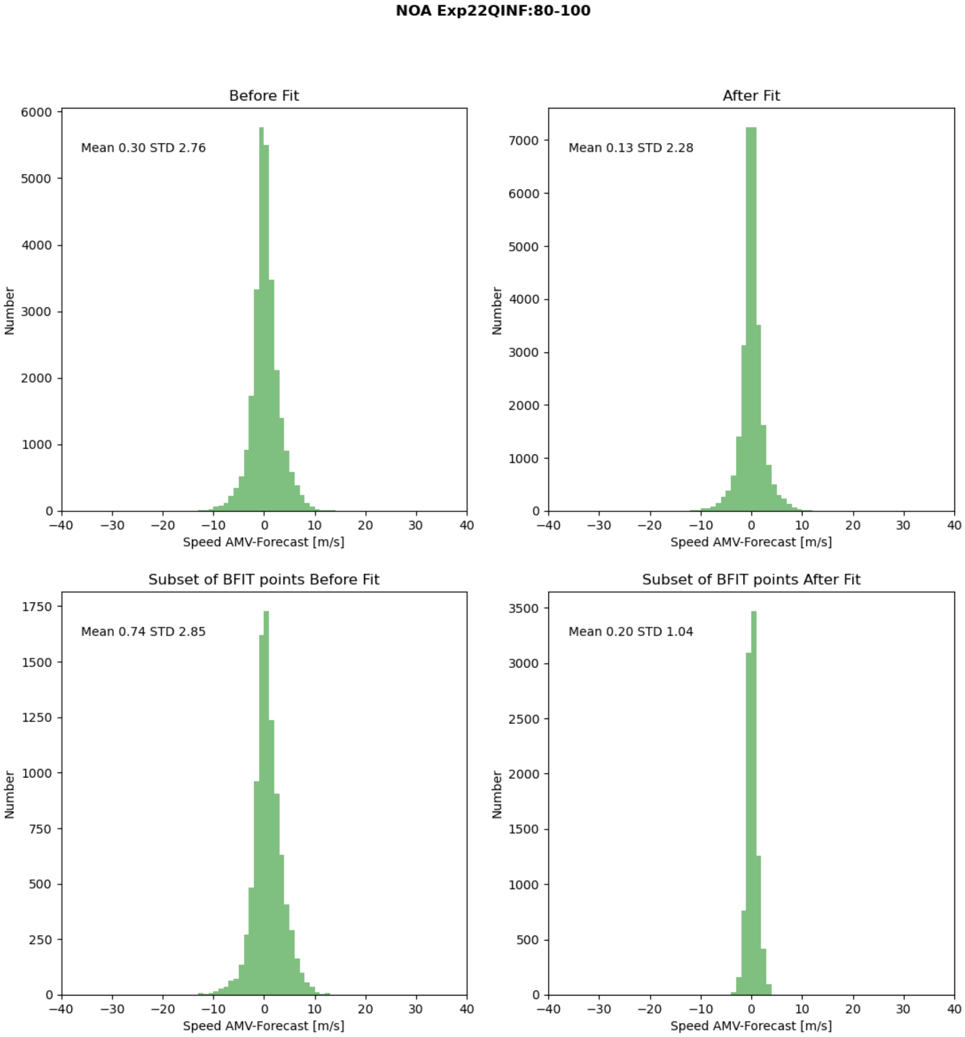

Figure 18-21: Experiment 2b, NOA (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

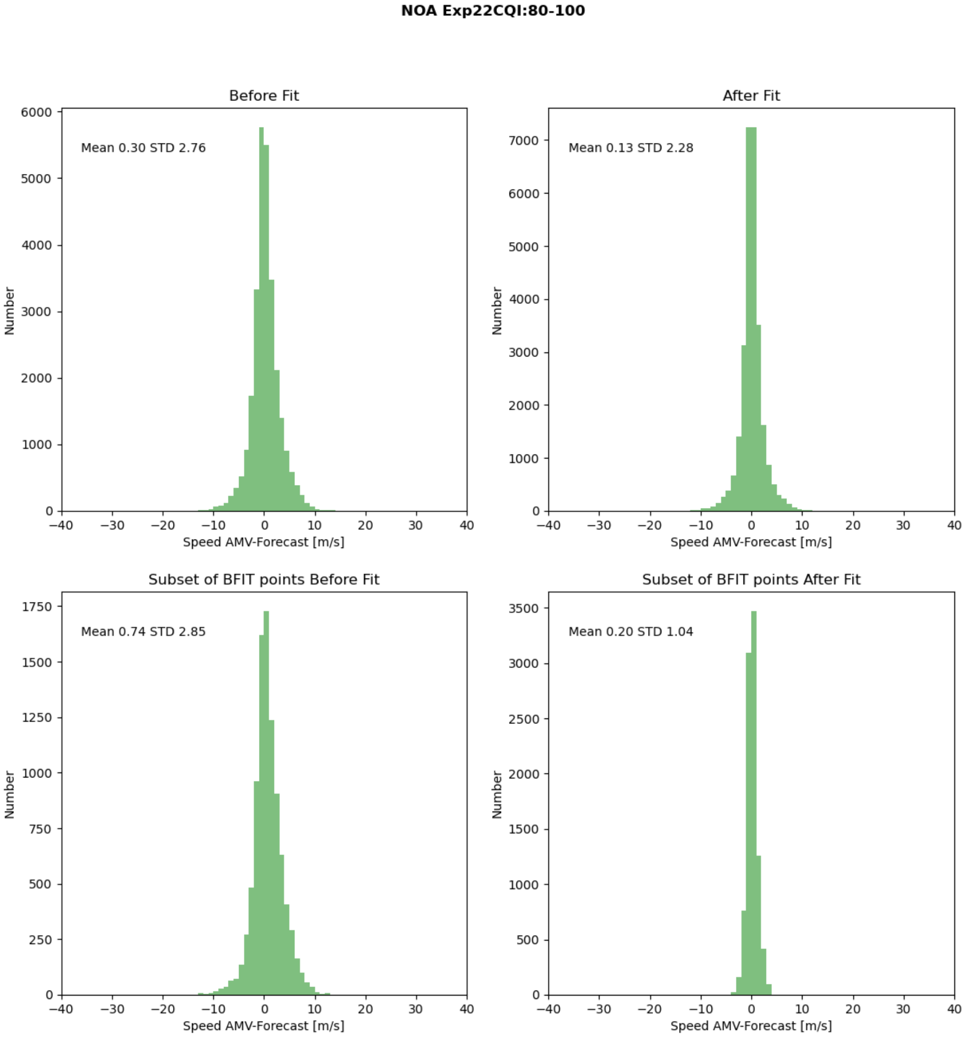

Figure 18-22: Experiment 2b, NOA (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

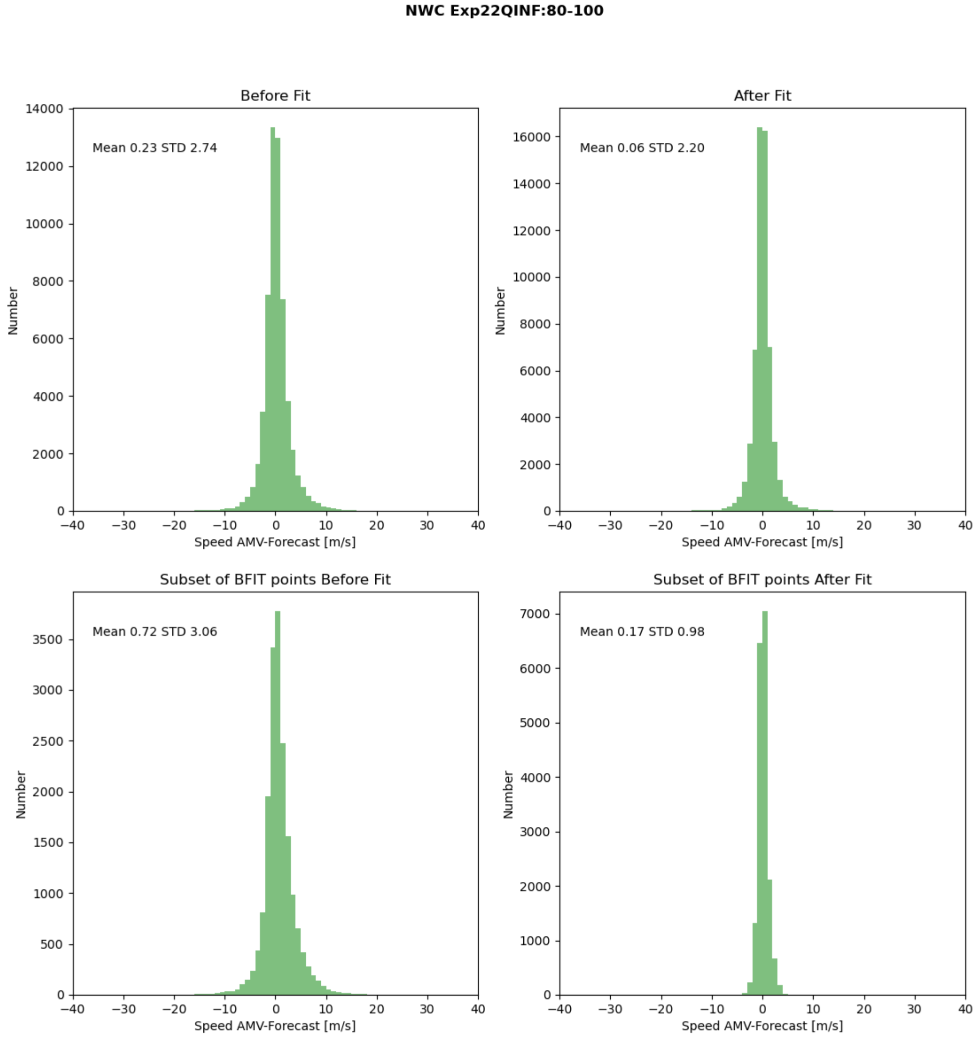

Figure 18-23: Experiment 2b, NWC (QINF>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

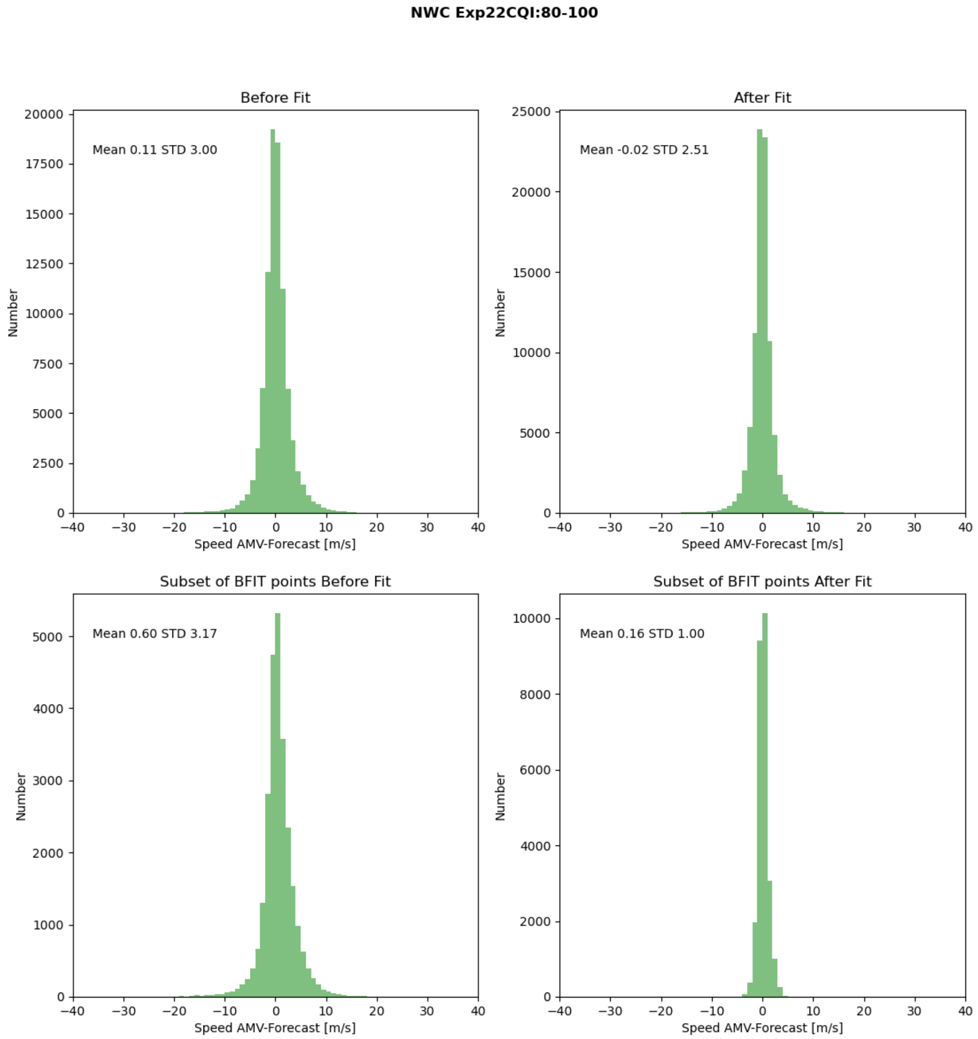

Figure 18-24: Experiment 2b, NWC (CQI>=80): AMV – background speed distribution of all AMVs (upper-left); AMV – background speed distribution of all AMVs, including those that are Best Fit adjusted. (upper-right); AMV – background speed distribution of Best Fit AMVs (lower-left); AMV – background speed distribution of Best Fit AMVs, after Best Fit adjustment (lower-right).

19. Appendix C: Shell and Driver Scripts Scripts

The following scripts are the main driver scripts that call Python and Matlab scripts.

testdriver.sh

```
unset DISPLAY

module unload matlab/r2021b
module load   matlab/r2018a

matlab –nosplash < Intercompdriver.m
```

Intercompdriver.m

```
%Winds_Bulk(1,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(1,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(1,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(1,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_1_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Bulk(21,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(21,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(21,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(21,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_21_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Bulk(22,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(22,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(22,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(22,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_22_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Bulk(23,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(23,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(23,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(23,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_23_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Bulk(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_3_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Bulk(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',50)
%Winds_Bulk(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',80)
%Winds_Bulk(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',50)
%Winds_Bulk(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',80)
%status=system('mv  Exp_4_* /home/daves/intercomparison2021/analysis/output/.')

%Winds_Match_EUM(1,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM(1,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

%Winds_Match_EUM(1,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM(1,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM(21,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM(21,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

%Winds_Match_EUM(21,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM(21,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM(22,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM(22,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

%Winds_Match_EUM(22,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM(22,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM(23,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM(23,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)
```

```
%Winds_Match_EUM(23,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM(23,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

%Winds_Match_EUM_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
%Winds_Match_EUM_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

%Winds_Match_EUM_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
%Winds_Match_EUM_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

Winds_Match_NWCref_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
Winds_Match_NWCref_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

Winds_Match_NWCref_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
Winds_Match_NWCref_noJMA(3,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

Winds_Match_NWCref_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,50)
Winds_Match_NWCref_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','QINF',55,80)

Winds_Match_NWCref_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,50)
Winds_Match_NWCref_noJMA(4,'/home/daves/intercomparison2021/analysis/amv/','CQI',55,80)

exit
```

runit_noplot

```
#!/bin/bash

# USAGE: ./runit_noplot {PRS_RANGE}
# ./runit_noplot L (low range)
# ./runit_noplot   (default to all range)

# LOW (L) PRS: 700 to 1020
# MID (M) PRS: 401 to 699
# HIGH (H) PRS: 100 to 400
# DEFAULT (A) PRS: 100 to 1000

if [ "$1" == "L" ]; then
   PRS_MIN=700
   PRS_MAX=1000
elif [ "$1" == "M" ]; then
   PRS_MIN=400
   PRS_MAX=699
elif [ "$1" == "H" ]; then
   PRS_MIN=100
   PRS_MAX=400
else
   PRS_MIN=100
   PRS_MAX=1000
fi

QC_MIN=80
```

```
QC_MAX=100
PRS_RANGE=$1
main_script=test_noplot.py

################ EXP 1 ################
BRZ_FILE=/home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
EUM_FILE=/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test
11.txt
JMA_FILE=/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt
KMA_FILE=/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc
NOA_FILE=/home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
NWC_FILE=/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt

exp_num=1
QC_TYPE=CQI
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}_${PRS_RANGE}.txt

#### EXP 1 CQI 80-100 ####
./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file}
./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file}


QC_TYPE=QINF
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}_${PRS_RANGE}.txt

#### EXP 1 QINF 80-100 ####
./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file}
./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file}


################ EXP 22 ################
BRZ_FILE=/home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
EUM_FILE=/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test
22.txt
JMA_FILE=/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt
KMA_FILE=/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc
NOA_FILE=/home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT
NWC_FILE=/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt
```

```
exp_num=22
QC_TYPE=CQI
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}_${PRS_RANGE}.txt

#### EXP 22 CQI 80-100 ####
./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file} &
./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file}
./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file} &
./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file}

QC_TYPE=QINF
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}_${PRS_RANGE}.txt

#### EXP 1 QINF 80-100 ####
./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file} &
./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file}
./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file} &
./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${PRS_MIN}
${PRS_MAX} ${stats_file} &
./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX}
${PRS_MIN} ${PRS_MAX} ${stats_file}
```

runit_plotting

```
#!/bin/bash

# Script for running test_amv.py for experiments and variable qi values

# USAGE ./runit_plotting {QC_MIN} {QC_MAX}
# ./runit_plotting 80 100
# ./runit_plotting 50 100

QC_MIN=$1
QC_MAX=$2
main_script=test_amv.py

if [ -z "$1" ] || [ -z "$2" ]; then
   echo "Usage: ./runit_plotting <qc_min> <qc_max>"
   exit 1
fi

################ EXP 1 ################
BRZ_FILE=/home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
EUM_FILE=/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
JMA_FILE=/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt
KMA_FILE=/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc
NOA_FILE=/home/daves/intercomparison2021/NOAA/ASCII_AMV-4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
NWC_FILE=/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt


QC_TYPE=CQI
exp_num=1
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 1 CQI ####
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}

QC_TYPE=QINF
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 1 QINF ####
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
```

```
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp1' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}


################ EXP 21 ################
BRZ_FILE=/home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2a_final.txt
EUM_FILE=/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt
JMA_FILE=/home/daves/intercomparison2021/JMA/JMA_test21_1130.txt
KMA_FILE=/home/daves/intercomparison2021/KMA/KMA_test21_goes16_abi_ch14_amv_201910201130.asc
NOA_FILE=/home/daves/intercomparison2021/NOAA/ASCII_AMV-4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT
NWC_FILE=/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST21.txt

QC_TYPE=CQI
exp_num=21
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 21 CQI ####
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}

QC_TYPE=QINF
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 21 QINF ####
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp21' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}


################ EXP 22 ################
BRZ_FILE=/home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
EUM_FILE=/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
JMA_FILE=/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt
KMA_FILE=/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc
NOA_FILE=/home/daves/intercomparison2021/NOAA/ASCII_AMV-4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT
NWC_FILE=/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt

QC_TYPE=CQI
exp_num=22
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 22 CQI ####
```

```
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}

QC_TYPE=QINF
stats_file=amv_vd_stats_exp${exp_num}.${QC_TYPE}_${QC_MIN}-${QC_MAX}.txt

#### EXP 22 QINF ####
#./${main_script} ${BRZ_FILE} BRZexp${exp_num} 'BRZ Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${EUM_FILE} EUMexp${exp_num} 'EUM Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${JMA_FILE} JMAexp${exp_num} 'JMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${KMA_FILE} KMAexp${exp_num} 'KMA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NOA_FILE} NOAexp${exp_num} 'NOA Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
#./${main_script} ${NWC_FILE} NWCexp${exp_num} 'NWC Exp22' ${QC_TYPE} ${QC_MIN} ${QC_MAX} ${stats_file}
```

doit_ exp1

```
#!/bin/bash

path=$1
exp=$2
mdir=/home/rdworak/Intercomp/mfiles/
echo $path/$exp > inputfile
/opt/matlab/2014b/bin/matlab -nosplash < ${mdir}raobdiff_exp1_norm.m
exit
```

runit_exp1

```
#./doit /data/rdworak/Intercomp/exp21 BRZCPTECfin_121_csv.csv
#./doit /data/rdworak/Intercomp/exp21 EUM321_csv.csv
#./doit /data/rdworak/Intercomp/exp21 JMA421_csv.csv
#./doit /data/rdworak/Intercomp/exp21 KMA521NI_csv.csv
#./doit /data/rdworak/Intercomp/exp21 NOA621_csv.csv
#./doit /data/rdworak/Intercomp/exp21 NWC721_csv.csv

#./doit /data/rdworak/Intercomp/exp22 BRZCPTECfin_122_csv.csv
#./doit /data/rdworak/Intercomp/exp22 EUM322_csv.csv
#./doit /data/rdworak/Intercomp/exp22 JMA422_csv.csv
#./doit /data/rdworak/Intercomp/exp22 KMA522NI_csv.csv
#./doit /data/rdworak/Intercomp/exp22 NOA622_csv.csv
#./doit /data/rdworak/Intercomp/exp22 NWC722_csv.csv

#./doit /home/daves/intercomparison2021/NOAA ASCII_AMV-4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT
#./doit /home/daves/intercomparison2021/EUM AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt
#./doit /home/daves/intercomparison2021/BRZ 4th_AMVIC_INPE_Test_2a_final.txt
#./doit /home/daves/intercomparison2021/JMA JMA_test21_1130.txt
#./doit /home/daves/intercomparison2021/KMA KMA_test21_goes16_abi_ch14_amv_201910201130.asc
#./doit /home/daves/intercomparison2021/NWC INTERCOMP2021_NWCSAFTEST21.txt

./doit_exp1 /home/daves/intercomparison2021/NOAA ASCII_AMV-4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
./doit_exp1 /home/daves/intercomparison2021/EUM AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
./doit_exp1 /home/daves/intercomparison2021/BRZ 4th_AMVIC_INPE_Test_1_final.txt
./doit_exp1 /home/daves/intercomparison2021/JMA JMA_test11_1200.txt
./doit_exp1 /home/daves/intercomparison2021/KMA KMA_test11_goes16_abi_ch14_amv_201910201200.asc
./doit_exp1 /home/daves/intercomparison2021/NWC INTERCOMP2021_NWCSAFTEST11.txt

#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NOA ASCII_AMV-4thInt_TEST2.GOES16.2019293.1900.CH_14.FD.CT
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/EUM AMVIntm_Chan14_20191020190000Z_GOES_ASCII_Test23.txt
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/BRZ 4th_AMVIC_INPE_Test_2c_final
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/JMA JMA_test23_1900.txt
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/KMA KMA_test23_goes16_abi_ch14_amv_201910201900.asc
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NWC INTERCOMP2021_NWCSAFTEST23.txt

#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NOA ASCII_AMV-4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/EUM AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/BRZ 4th_AMVIC_INPE_Test_2b_final
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/JMA JMA_test22_1200.txt
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/KMA KMA_test22_goes16_abi_ch14_amv_201910201200.asc
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NWC INTERCOMP2021_NWCSAFTEST22.txt
#
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NOA ASCII_AMV-4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/EUM AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
```

```
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/BRZ 4th_AMVIC_INPE_Test_1_final
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/JMA JMA_test11_1200.txt
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/KMA KMA_test11_goes16_abi_ch14_amv_201910201200.asc
#./doit /data/rdworak/Intercomp/2021/input/Datasets2021/NWC INTERCOMP2021_NWCSAFTEST11.txt
```

doit_coll_exp1

```
#!/bin/bash

path=$1
exp=$2
mdir=/home/rdworak/Intercomp/mfiles/
echo $path/$exp > inputfile_exp1
/opt/matlab/2014b/bin/matlab -nosplash < ${mdir}raobdiff_exp1_coll.m
exit
```

runit_coll_exp1

```
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_brz_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_eum_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_jma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_kma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_noa_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp22 Exp_22_conf_nwc_col.txt

#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_brz_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_eum_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_jma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_kma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_noa_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2018/Winds_Match_QINF/exp21 Exp_21_conf_nwc_col.txt

#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_brz_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_eum_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_jma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_kma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_noa_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI50 Exp_1_conf_nwc_col.txt

#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_brz_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_eum_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_jma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_kma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_noa_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp1/QI80 Exp_1_conf_nwc_col.txt

#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_brz_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_eum_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_jma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_kma_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_noa_col.txt
#./doit_coll /data/rdworak/Intercomp/Output2021/Winds_Match_CQI/exp22/QI80 Exp_22_conf_nwc_col.txt
#
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_brz_QINF_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_eum_QINF_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_jma_QINF_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_kma_QINF_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_noa_QINF_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_nwc_QINF_50.txt

./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_brz_QINF_80.txt
./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_eum_QINF_80.txt
./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_jma_QINF_80.txt
./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_kma_QINF_80.txt
./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_noa_QINF_80.txt
./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_nwc_QINF_80.txt

#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_brz_CQI_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_eum_CQI_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_jma_CQI_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_kma_CQI_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_noa_CQI_50.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_nwc_CQI_50.txt
#
```

```
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_brz_CQI_80.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_eum_CQI_80.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_jma_CQI_80.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_kma_CQI_80.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_noa_CQI_80.txt
#./doit_coll_exp1 /home/daves/intercomparison2021/analysis/scripts Exp_1_conf_nwc_CQI_80.txt
```

runit_qi_00_50

```
#!/bin/sh

###### Exp 1 QI 00 09 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 00 09; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 00 09;./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 00 09;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 00 ”9; .’test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 00 09; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
00 09” &

###### Exp 22 QI 00 09 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 00 09; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 00 09; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 00 09;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
‘KMA Exp22’ CQI 00 09; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 00 09; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 00 09” &

###### Exp 1 QI 10 19 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 10 19;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 10 19; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
10 19” &

###### Exp 22 QI 10 19 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 10 19;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 10 ”9; .’test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 10 19; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 10 19” &

###### Exp 1 QI 20 29 ######
```

```
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 20 29;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMaexp1
‘KMA Exp1’ CQI 20 29; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
20 29” &

###### Exp 22 QI 20 29 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 20 29;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 20 ”9; .’test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 20 29; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 20 29” &

###### Exp 1 QI 30 39 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 30 39;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
‘KMA Exp1’ CQI 30 39; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
30 39” &

###### Exp 22 QI 30 39 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 30 39;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 30 39; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 30 39; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 30 39” &

###### Exp 1 QI 40 49 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 40 49; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 40 49; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 40 49;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 40 ”9; .’test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 40 49; ./test_noplot_daves.py
```

```
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
40 49” &

###### Exp 22 QI 40 49 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 40 49; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 40 49; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 40 49;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
‘KMA Exp22’ CQI 40 49; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 40 49; ./test_no’lot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 40 49” &

###### Exp 1 QI 50 59 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  ‘BRZ Exp1’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  ‘EUM Exp1’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  ‘JMA Exp1’ CQI 50 59;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 50 ”9; .’test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  ‘NOA Exp1’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  ‘NWC Exp1’ CQI
50 59” &

###### Exp 22 QI 50 59 ######
bash -c “./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  ‘BRZ Exp22’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  ‘EUM Exp22’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  ‘JMA Exp22’ CQI 50 59;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 50 59; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  ‘NOA Exp22’ CQI 50 59; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  ‘NWC Exp22’
CQI 50 59” &
```

runit_qi_60_100

```
#!/bin/sh

###### Exp 1 QI 60 69 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  'BRZ Exp1' CQI 60 69; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  'EUM Exp1' CQI 60 69;./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  'JMA Exp1' CQI 60 69;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 60 69; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  'NOA Exp1' CQI 60 69; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  'NWC Exp1' CQI
60 69" &

###### Exp 22 QI 60 69 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  'BRZ Exp22' CQI 60 69; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  'EUM Exp22' CQI 60 69; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  'JMA Exp22' CQI 60 69;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 60 69; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  'NOA Exp22' CQI 60 69; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  'NWC Exp22'
CQI 60 69" &

###### Exp 1 QI 70 79 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  'BRZ Exp1' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  'EUM Exp1' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  'JMA Exp1' CQI 70 79;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 70 79; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  'NOA Exp1' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  'NWC Exp1' CQI
70 79" &

###### Exp 22 QI 70 79 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  'BRZ Exp22' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  'EUM Exp22' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  'JMA Exp22' CQI 70 79;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 70 79; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  'NOA Exp22' CQI 70 79; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  'NWC Exp22'
CQI 70 79" &

###### Exp 1 QI 80 89 ######
```

```
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  'BRZ Exp1' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  'EUM Exp1' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  'JMA Exp1' CQI 80 89;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 80 89; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  'NOA Exp1' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  'NWC Exp1' CQI
80 89" &

###### Exp 22 QI 80 89 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  'BRZ Exp22' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  'EUM Exp22' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  'JMA Exp22' CQI 80 89;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 80 89; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  'NOA Exp22' CQI 80 89; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  'NWC Exp22'
CQI 80 89" &

###### Exp 1 QI 90 100 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_1_final.txt
BRZexp1  'BRZ Exp1' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
EUMexp1  'EUM Exp1' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test11_1200.txt   JMAexp1  'JMA Exp1' CQI 90 100;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test11_goes16_abi_ch14_amv_201910201200.asc   KMAexp1
'KMA Exp1' CQI 90 100; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT   NOAexp1  'NOA Exp1' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST11.txt   NWCexp1  'NWC Exp1' CQI
90 100" &

###### Exp 22 QI 90 100 ######
bash -c "./test_noplot_daves.py /home/daves/intercomparison2021/BRZ/4th_AMVIC_INPE_Test_2b_final.txt
BRZexp22  'BRZ Exp22' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/EUM/AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
EUMexp22  'EUM Exp22' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/JMA/JMA_test22_1200.txt   JMAexp22  'JMA Exp22' CQI 90 100;
./test_noplot_daves.py
/home/daves/intercomparison2021/KMA/KMA_test22_goes16_abi_ch14_amv_201910201200.asc KMAexp22
'KMA Exp22' CQI 90 100; ./test_noplot_daves.py /home/daves/intercomparison2021/NOAA/ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT NOAexp22  'NOA Exp22' CQI 90 100; ./test_noplot_daves.py
/home/daves/intercomparison2021/NWC/INTERCOMP2021_NWCSAFTEST22.txt NWCexp22  'NWC Exp22'
CQI 90 100" &
```

20. Appendix D: Best-Fit Python Scripts

These scripts compute the Best-Fit pressure.

test_amv.py

```
#!/usr/bin/env python

import matplotlib
matplotlib.use('agg')

import os, os.path
import sys

import numpy as np
import amv as amv

import matplotlib as mpl
import matplotlib.pyplot as plt
from mpl_toolkits.basemap import Basemap

from matplotlib.colors import LogNorm
from pylab import *

undef = -9999.

# Pick up parameters
file_amv=sys.argv[1]
source=sys.argv[2]
qc_type=sys.argv[4]
#qc_min=int(sys.argv[5])
qc_min=80
#print qc_min
#qc_max=int(sys.argv[6])
qc_max=100
#print qc_max

if qc_type == 'QINF' :
   qc_pos=16  # 0 is first position
   qc_str='QINF:'+str(qc_min) + '-' + str(qc_max)
   qc_txt='.qinf_'+str(qc_min) + '-' + str(qc_max)

if qc_type == 'QIWF' :
   qc_pos=17
   qc_str='QIWF:'+str(qc_min) + '-' + str(qc_max)
   qc_txt='.qiwf_'+str(qc_min) + '-' + str(qc_max)

if qc_type == 'CQI' :
   qc_pos=18
   qc_str='CQI:'+str(qc_min) + '-' + str(qc_max)
   qc_txt='.cqi_'+str(qc_min) + '-' + str(qc_max)

fig_title=sys.argv[3] + qc_str
```

```
#files
omb_u_fig='omb_u.'+source+qc_txt+'.png'
omb_v_fig='omb_v.'+source+qc_txt+'.png'
omb_s_fig='omb_s.'+source+qc_txt+'.png'
omb_vd_fig='omb_vd.'+source+qc_txt+'.png'
main_fig='bfit.'+source+qc_txt+'.png'
amv_fig='amv_location.'+source+qc_txt+'.png'
bfit_fig='bfit_location.'+source+qc_txt+'.png'


print("Reading amv data file: "  + file_amv)
delimiter=','
#delimiter=None
#amv data is mcidas west positive -180 to 180, data is flipped and rotated to
0-360 longitude
#amv_data =
amv.read_txt(file_amv,qc_pos,qc_min,qc_max,delimiter=delimiter,lonflip=True,lon
0=180.,shift=-1)
#amv_data =
amv.read_txt(file_amv,qc_pos,qc_min,qc_max,delimiter=delimiter,lonflip=True,lon
0=180.)
amv_data =
amv.read_txt(file_amv,qc_pos,qc_min,qc_max,delimiter=delimiter,lonflip=None,lon
0=180.)
#lay_loc = [(amv_data[4,:] >=700.)]
#print lay_loc

print("filtering invalid lat and lon data")
spd = []
dir = []
lat = []
lon = []
prs = []
qc = []
for i in range(amv_data.shape[1]):
    dist_km = amv.great_circle(0, -75, amv_data[2, i], amv_data[3, i])
    if dist_km <= 6670:
        spd.append(amv_data[0, i])
        dir.append(amv_data[1, i])
        lat.append(amv_data[2, i])
        lon.append(amv_data[3, i])
        prs.append(amv_data[4, i])
        qc.append(amv_data[5, i])

amv_data = np.array([spd, dir, lat, lon, prs, qc])

print("Reading forecast file")
#file_fcst =
'/home/daves/BestFit/DecodedForecast_20120917070613Z_20120917120000Z_12_O_MPFS0
3'
#fcst_data = amv.read_DecodedForecast_MSG(file_fcst)
#file_fcst = '/home/snebuda/icomp/data/ECM_EI_AN_20160721_PL.grb'
#file_fcst = '/data/rdworak/Intercomp/model/ECM_EI_AN_20160721_PL.grb'
# file_fcst =
'/home/daves/intercomparison2021/ERA5/ERA5_UV_prs_20191020_hourly.grib'
#file_fcst =
'/Users/sreiner/Documents/stratus/datafiles/ERA5_UV_prs_20191020_hourly.grib'
file_fcst = '/data/sreiner/datafiles/ERA5_UV_prs_20191020_hourly.grib'
#file_fcst = '/data/rdworak/Intercomp/model/ECM_EI_AN_20160721_PL.grb'
```

```
#datetime=2016072112
datetime=2019102012
#forecast data is 0-360 Longitude which works for H8 AMV data
#no handling of lon mismatch in amv.locate
fcst_data, dt_out = amv.read_MSG_grib(file_fcst,datetime=datetime)

print("Finding grid location")
grid_i,grid_j = amv.locate(amv_data,fcst_data)
#print("value of i".format(grid_i[1]))
#print("value of j".format(grid_j[1]))
print("Finding best fit")

amv_num = amv_data.shape[1]
amv_u=np.empty(amv_num)
amv_v=np.empty(amv_num)
bfit_u=np.empty(amv_num)
bfit_v=np.empty(amv_num)
bfit_prs=np.empty(amv_num)
bfit_flag=np.empty(amv_num)
bfit_spd=np.empty(amv_num)
bfit_dir=np.empty(amv_num)
bg_u=np.empty(amv_num)
bg_v=np.empty(amv_num)
bg_spd=np.empty(amv_num)
bg_dir=np.empty(amv_num)

print("Number of AMV {0}".format(amv_num))

amv_spd = amv_data[0,:]
amv_dir = amv_data[1,:]

n = 0
while (n < amv_num):
    amv_single = amv_data[:,n]
    fcst_profile = fcst_data[grid_i[n],grid_j[n],:,:]

    verbose = False
    bfit_u[n],bfit_v[n],bfit_prs[n],bfit_flag[n] =
amv.bestfit(amv_single,fcst_profile,verbose)
    if bfit_prs[n] != undef:
        bfit_spd[n],bfit_dir[n] = amv.spddir(bfit_u[n],bfit_v[n])
    else:
        bfit_spd[n] = undef
        bfit_dir[n] = undef

    bg_u[n],bg_v[n] = amv.bg(amv_single,fcst_profile,verbose)
    bg_spd[n],bg_dir[n] = amv.spddir(bg_u[n],bg_v[n])
    amv_u[n],amv_v[n] = amv.uvcomp(amv_spd[n],amv_dir[n])

    n += 1

amv_prs = amv_data[4,:]
amv_lat = amv_data[2,:]
amv_lon = amv_data[3,:]
amv_qc = amv_data[5,:]

# Compute change in pressure for AMV best fit (sometimes there are bestfit
heights, but not original match of AMV to background
# when the AMV height is higher than the lowest background pressure)
#bfit_loc = [bfit_prs !=undef]
#bfit_loc = [(bfit_prs !=undef) & (bg_spd !=undef)]
```

```
bfit_loc = np.logical_and(bfit_prs != undef, bg_spd != undef)
#bfit_loc = [(bfit_prs !=undef) & (bg_spd !=undef) & (amv_prs < 700.) &
(amv_prs > 400.)]
tmp = bfit_prs[bfit_loc]
bfit_num = tmp.shape[0]
dp = bfit_prs[bfit_loc] - amv_prs[bfit_loc]
dp_x = amv_lon[bfit_loc]
dp_y = amv_lat[bfit_loc]
dp_x_none = amv_lon[bfit_prs == undef]
dp_y_none = amv_lat[bfit_prs == undef]
dp_x_down = amv_lon[bfit_prs > amv_prs]
dp_y_down = amv_lat[bfit_prs > amv_prs]
dp_x_up = amv_lon[(bfit_prs != undef) & (bfit_prs < amv_prs)]
dp_y_up = amv_lat[(bfit_prs != undef) & (bfit_prs < amv_prs)]

#set new background fields as if amv was moved to best fit pressure
bg_u_new = bg_u.copy()
bg_u_new[bfit_loc] = bfit_u[bfit_loc]
bg_v_new = bg_v.copy()
bg_v_new[bfit_loc] = bfit_v[bfit_loc]
bg_spd_new = bg_spd.copy()
bg_spd_new[bfit_loc] = bfit_spd[bfit_loc]

#Compute OMB for U, V, Spd, Vector at AMV prs and best fit prs
u_omb_bf = amv_u[bfit_loc] - bfit_u[bfit_loc]
v_omb_bf = amv_v[bfit_loc] - bfit_v[bfit_loc]
spd_omb_bf = amv_spd[bfit_loc] - bfit_spd[bfit_loc]
vd_omb_bf = np.sqrt( (amv_u[bfit_loc]-bfit_u[bfit_loc])**2 + (amv_v[bfit_loc]-
bfit_v[bfit_loc])**2 )

u_omb_bf_orig = amv_u[bfit_loc] - bg_u[bfit_loc]
v_omb_bf_orig = amv_v[bfit_loc] - bg_v[bfit_loc]
spd_omb_bf_orig = amv_spd[bfit_loc] - bg_spd[bfit_loc]
vd_omb_bf_orig = np.sqrt( (amv_u[bfit_loc]-bg_u[bfit_loc])**2 +
(amv_v[bfit_loc]-bg_v[bfit_loc])**2 )

u_omb_bg = amv_u[bg_u !=undef] - bg_u[bg_u !=undef]
v_omb_bg = amv_v[bg_v !=undef] - bg_v[bg_v !=undef]
spd_omb_bg = amv_spd[bg_spd !=undef] - bg_spd[bg_spd !=undef]
vd_omb_bg = np.sqrt( (amv_u[bg_spd !=undef]-bg_u[bg_spd !=undef])**2 +
(amv_v[bg_spd !=undef]-bg_v[bg_spd !=undef])**2 )

u_omb_new = amv_u[bg_u_new !=undef] - bg_u_new[bg_u_new !=undef]
v_omb_new = amv_v[bg_v_new !=undef] - bg_v_new[bg_v_new !=undef]
spd_omb_new = amv_spd[bg_spd_new !=undef] - bg_spd_new[bg_spd_new !=undef]
vd_omb_new = np.sqrt( (amv_u[bg_spd_new !=undef]-bg_u_new[bg_spd_new
!=undef])**2 + (amv_v[bg_spd_new !=undef]-bg_v_new[bg_spd_new !=undef])**2 )

mean_vd_bg = np.mean(vd_omb_bg)
std_vd_bg = np.std(vd_omb_bg)
rms_vd_bg = np.sqrt( mean_vd_bg**2 + std_vd_bg**2 )

mean_vd_new = np.mean(vd_omb_new)
std_vd_new = np.std(vd_omb_new)
rms_vd_new = np.sqrt( mean_vd_new**2 + std_vd_new**2 )

#Write out stats to a file
fo = open("amv_vd_stats.txt","a")
statsvd = "{0} {1} Total Number, Best Fit Number, VD OMB Mean,RMSE and VD OMB
after fit Mean, RMSE: {2} {3} {4:.2f} {5:.2f} {6:.2f} {7:.2f}\n" \
.format(file_amv,qc_str,amv_num,bfit_num,mean_vd_bg,rms_vd_bg,mean_vd_new,rms_v
```

```
d_new)
fo.write( statsvd);
fo.close()


frac = np.empty(4)
flag_title=['Found','Not Constrained','No sufficient minimum','No forecast
pressure match']
for f in range (4):
    frac[f] = float((bfit_flag == f).sum()) / float(amv_num)

# Page 1


fig = plt.figure(figsize=(12,12))

xmin=-40.
xmax= 40.
statx=0.05
staty=0.9
bins=np.arange(81) - 40.
label = 'U Component AMV-Forecast [m/s]'

ax=plt.subplot(2,2,1)
title = 'Before Fit'
values = u_omb_bg
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,2)
title = 'After Fit'
values = u_omb_new
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,3)
title = 'Subset of BFIT points Before Fit'
values = u_omb_bf_orig
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,4)
title = 'Subset of BFIT points After Fit'
values = u_omb_bf
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
```

```
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

#plt.show()
plt.gcf().set_size_inches(13, 13)
plt.savefig(omb_u_fig)
plt.clf()

print("wrote figure file: "  + omb_u_fig)

# Page 2


fig = plt.figure(figsize=(12,12))

xmin=-20.
xmax= 20.
statx=0.05
staty=0.9
bins=np.arange(81)*0.5 - 20.
label = 'V Component AMV-Forecast [m/s]'

ax=plt.subplot(2,2,1)
title = 'Before Fit'
values = v_omb_bg
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,2)
title = 'After Fit'
values = v_omb_new
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,3)
title = 'Subset of BFIT points Before Fit'
values = v_omb_bf_orig
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)
```

```
ax=plt.subplot(2,2,4)
title = 'Subset of BFIT points After Fit'
values = v_omb_bf
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

#plt.show()
plt.gcf().set_size_inches(13, 13)
plt.savefig(omb_v_fig)
plt.clf()

print("wrote figure file: "  + omb_v_fig)

# Page 3


fig = plt.figure(figsize=(12,12))

xmin=-40.
xmax= 40.
statx=0.05
staty=0.9
bins=np.arange(81) - 40.
label = 'Speed AMV-Forecast [m/s]'

ax=plt.subplot(2,2,1)
title = 'Before Fit'
values = spd_omb_bg
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,2)
title = 'After Fit'
values = spd_omb_new
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,3)
title = 'Subset of BFIT points Before Fit'
values = spd_omb_bf_orig
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
```

```
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,4)
title = 'Subset of BFIT points After Fit'
values = spd_omb_bf
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='left',va='center',transform=ax.transAxes)

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

#plt.show()
plt.gcf().set_size_inches(13, 13)
plt.savefig(omb_s_fig)
plt.clf()

print("wrote figure file: "  + omb_s_fig)

# Page 4


fig = plt.figure(figsize=(12,12))

xmin=0.
xmax= 40.
statx=0.9
staty=0.9
bins=np.arange(81)*0.5
label = 'Vector Difference AMV-Forecast [m/s]'

ax=plt.subplot(2,2,1)
title = 'Before Fit'
values = vd_omb_bg
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='right',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,2)
title = 'After Fit'
values = vd_omb_new
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='right',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,3)
```

```
title = 'Subset of BFIT points Before Fit'
values = vd_omb_bf_orig
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='right',va='center',transform=ax.transAxes)

ax=plt.subplot(2,2,4)
title = 'Subset of BFIT points After Fit'
values = vd_omb_bf
n,bins,patches = plt.hist(values,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
plt.xlabel(label)
plt.ylabel('Number')
plt.title(title)
stats="Mean {0:.2f} STD {1:.2f}".format(np.mean(values),np.std(values))
text(statx,staty,stats,ha='right',va='center',transform=ax.transAxes)

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

#plt.show()
plt.gcf().set_size_inches(13, 13)
plt.savefig(omb_vd_fig)
plt.clf()

print("wrote figure file: "  + omb_vd_fig)


# Page 5
x=amv_lon
y=amv_lat


fig = plt.figure(figsize=(12,12))

plt.subplot(3,2,1)
num_bins=50
n,bins,patches = plt.hist(x,num_bins,facecolor='green',alpha=0.5)
n,bins,patches = plt.hist(dp_x,num_bins,facecolor='orange',alpha=0.5)
plt.xlim(210.,360.)
#plt.xlim(-60.,60.)
#plt.ylim(0.,600.)
plt.xlabel('Longitudes')
plt.ylabel('Number')
plt.title(r'Green all AMV, Yellow found best fit')

plt.subplot(3,2,3)
num_bins=50
n,bins,patches = plt.hist(y,num_bins,facecolor='green',alpha=0.5)
n,bins,patches = plt.hist(dp_y,num_bins,facecolor='orange',alpha=0.5)
plt.xlim(-60.,60.)
#plt.ylim(0.,600.)
plt.xlabel('Latitudes')
plt.ylabel('Number')
#plt.title(r'Green all AMV, Yellow found best fit')

plt.subplot(4,2,7)
```

```
#not enough flag=3 to plot for these test cases
labels=flag_title[0:3]
sizes=frac[0:3]
colors=['lightblue','orange','lightgreen','red']
plt.pie(sizes,labels=labels,colors=colors,autopct='%.0f%%')
plt.axis('equal')

plt.subplot(2,2,2)
num_bins=50
n,bins,patches = plt.hist(dp,num_bins,facecolor='blue',alpha=0.5)
plt.xlim(-300.,300.)
#plt.ylim(0.,100.)
plt.xlabel('dp')
plt.ylabel('Number')
plt.title(r'Histogram of AMV Best Fit - Original Pressure')

plt.subplot(2,2,4)
plt.scatter(dp_x_none,dp_y_none,s=1,color='0.8')
plt.scatter(dp_x_up,dp_y_up,s=1,color='r')
plt.scatter(dp_x_down,dp_y_down,s=1,color='b')
#m = Basemap(projection='cyl',llcrnrlat=-80.,urcrnrlat=80.,llcrnrlon=-
130.,urcrnrlon=-20.,resolution='c')
m = Basemap(projection='cyl',llcrnrlat=-
80.,urcrnrlat=80.,llcrnrlon=225.,urcrnrlon=345.,resolution='c')
m.drawcoastlines()
plt.title(r'Grey no fit, Red BFIT up, Blue BFIT down ')

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

#plt.show()
plt.gcf().set_size_inches(13, 13)
plt.savefig(main_fig)
plt.clf()

print("wrote figure file: "  + main_fig)


# Page 6

fig = plt.figure(figsize=(12,12))

ax=plt.subplot(2,1,1)
lat = amv_lat
lon = amv_lon
prs = amv_prs
low_lat = lat[prs >=700.]
low_lon = lon[prs >=700.]
mid_lat = lat[(prs < 700.) & (prs >400.)]
mid_lon = lon[(prs < 700.) & (prs >400.)]
hig_lat = lat[prs <=400.]
hig_lon = lon[prs <=400.]
plt.scatter(low_lon,low_lat,s=1,color='darkblue')
plt.scatter(mid_lon,mid_lat,s=1,color='g')
plt.scatter(hig_lon,hig_lat,s=1,color='orange')
#m = Basemap(projection='cyl',llcrnrlat=-80.,urcrnrlat=80.,llcrnrlon=-
130.,urcrnrlon=-20.,resolution='c')
#m = Basemap(projection='cyl',llcrnrlat=-
80.,urcrnrlat=80.,llcrnrlon=60.,urcrnrlon=220.,resolution='c')
m = Basemap(projection='cyl',llcrnrlat=-
80.,urcrnrlat=80.,llcrnrlon=225.,urcrnrlon=345.,resolution='c')
```

```
m.drawcoastlines()
plt.xlabel(r'Blue 700 hPa, Green 700-400 hPa, Yellow Above 400 hPa')
plt.title(r'AMV Location')


ax=plt.subplot(2,2,3)
plt.gca().invert_yaxis()
xmin=-60.
xmax=60.
ymin=1000.
ymax=100.
plt.xlim(xmin,xmax)
#plt.ylim(ymin,ymax)
#plt.scatter(lat,prs,s=1,color='0.8')
colors=['purple','blue','cyan','green','yellow','orange','red','magenta','black
']
spd_min=0.
spd_max=10.
count=0
while (spd_max < 100):
    lat_bin=lat[(amv_spd>=spd_min) & (amv_spd<spd_max)]
    prs_bin=prs[(amv_spd>=spd_min) & (amv_spd<spd_max)]
    plt.scatter(lat_bin,prs_bin,s=1,color=colors[count])
    count+=1
    spd_min=spd_max
    spd_max=spd_max+10.

plt.xlabel('Latitude [deg]')
plt.ylabel('Pressure [hPa]')
plt.title(r'Color indicates speed - purple slow, red fast')


ax=plt.subplot(2,2,4)
xmin=0.
xmax=100.
bins=np.arange(101)
n,bins,patches = plt.hist(amv_qc,bins=bins,facecolor='green',alpha=0.5)
plt.xlim(xmin,xmax)
#plt.ylim(0.,600.)
plt.xlabel('QI')
plt.ylabel('Number')

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')

plt.gcf().set_size_inches(13, 13)
plt.savefig(amv_fig)
plt.clf()
print("wrote figure file: "+amv_fig)

# Page 7

plt.subplot(2,2,1)
bfp = bfit_prs[(bfit_prs !=undef)]
amvp = amv_prs[(bfit_prs !=undef)]

dp_low = bfp[(amvp>=700.)] - amvp[(amvp>=700.)]
dp_mid = bfp[(amvp<700.) & (amvp>400.)] - amvp[(amvp<700.) & (amvp>400.)]
dp_hig = bfp[(amvp<=400.)] - amvp[(amvp<=400.)]

#num_bins=50
```

```
#n,bins,patches = plt.hist(dp,num_bins,facecolor='blue',alpha=0.5)
bins=arange(61)*10. - 300.
hist1,binedges = np.histogram(dp_low,bins=bins)
x1=0.5*(binedges[1:]+binedges[:-1])
hist2,binedges = np.histogram(dp_mid,bins=bins)
x2=0.5*(binedges[1:]+binedges[:-1])
hist3,binedges = np.histogram(dp_hig,bins=bins)
x3=0.5*(binedges[1:]+binedges[:-1])
plt.plot(x1,hist1,'darkblue',x2,hist2,'g',x3,hist3,'orange')
plt.xlim(-300.,300.)
#plt.ylim(0.,100.)
plt.xlabel('BFIT pressure - AMV pressure [hPa]')
plt.ylabel('Number')
plt.title(r'Blue - low, Green - mid, Yellow - high')

plt.subplot(2,2,2)
lat = amv_lat[bfit_prs != undef]
lon = amv_lon[bfit_prs != undef]
prs = amv_prs[bfit_prs != undef]
low_lat = lat[prs >=700.]
low_lon = lon[prs >=700.]
mid_lat = lat[(prs < 700.) & (prs >400.)]
mid_lon = lon[(prs < 700.) & (prs >400.)]
hig_lat = lat[prs <=400.]
hig_lon = lon[prs <=400.]

plt.scatter(low_lon,low_lat,s=1,color='darkblue')
plt.scatter(mid_lon,mid_lat,s=1,color='g')
plt.scatter(hig_lon,hig_lat,s=1,color='orange')
#m = Basemap(projection='cyl',llcrnrlat=-80.,urcrnrlat=80.,llcrnrlon=-
130.,urcrnrlon=-20.,resolution='c')
#m = Basemap(projection='cyl',llcrnrlat=-
80.,urcrnrlat=80.,llcrnrlon=60.,urcrnrlon=220.,resolution='c')
m = Basemap(projection='cyl',llcrnrlat=-
80.,urcrnrlat=80.,llcrnrlon=225.,urcrnrlon=345.,resolution='c')
m.drawcoastlines()
plt.xlabel(r'Blue Below 700 hPa, Green 700-400 hPa, Yellow Above 400 hPa')
plt.title(r'BFIT AMV Location')

ax=plt.subplot(2,2,3)
plt.gca().invert_yaxis()
xmin=-60.
xmax=60.
ymin=1000.
ymax=100.
lat_none = amv_lat[bfit_prs == undef]
prs_none = amv_prs[bfit_prs == undef]
lat_down = amv_lat[bfit_prs > amv_prs]
prs_down = amv_prs[bfit_prs > amv_prs]
lat_up = amv_lat[(bfit_prs != undef) & (bfit_prs < amv_prs)]
prs_up = amv_prs[(bfit_prs != undef) & (bfit_prs < amv_prs)]
plt.xlim(xmin,xmax)
#plt.ylim(ymin,ymax)
plt.scatter(lat_none,prs_none,s=1,color='0.8')
plt.scatter(lat_up,prs_up,s=1,color='r')
plt.scatter(lat_down,prs_down,s=1,color='b')
plt.xlabel('Latitude [deg]')
plt.ylabel('Pressure [hPa]')
plt.title(r'Red BFIT up, Blue BFIT down, Grey no BFIT')

plt.subplot(2,2,4)
```

```
plt.gca().invert_yaxis()
xmin = 0.
xmax = 70.
ymin = 1000.
ymax = 100.
spd_none = amv_spd[bfit_prs == undef]
prs_none = amv_prs[bfit_prs == undef]
spd_down = amv_spd[bfit_prs > amv_prs]
prs_down = amv_prs[bfit_prs > amv_prs]
spd_up = amv_spd[(bfit_prs != undef) & (bfit_prs < amv_prs)]
prs_up = amv_prs[(bfit_prs != undef) & (bfit_prs < amv_prs)]

plt.xlim(xmin,xmax)
#plt.ylim(ymin,ymax)
plt.scatter(spd_none,prs_none,s=1,color='0.8')
plt.scatter(spd_down,prs_down,s=1,color='b')
plt.scatter(spd_up,prs_up,s=1,color='r')
plt.title(r'Red BFIT up, Blue BFIT down, Grey no BFIT')
plt.xlabel(r'Speed [m/s]')
plt.ylabel(r'Pressure [hPa]')

plt.figtext(0.5,0.96,fig_title,ha='center',color='black',weight='bold',size='la
rge')


plt.gcf().set_size_inches(13, 13)
plt.savefig(bfit_fig)
plt.clf()

print("wrote figure file: "+bfit_fig)
```

amv.py

```
#!/usr/bin/env python

import os, os.path
import sys
import numpy as np
import math
from math import radians, sin, cos, acos
import pygrib


def read_txt(file,qc_pos,qc_min,qc_max,delimiter=None,lonflip=None,lon0=None,
vprs=[100, 1000]):

#lonflip not equal to None will flip the sign on longitude
#lon0 two options, 0= -180 to 180 lon
#                  180 = 0 to 360 lon
#                  any other value, lon will not be changed

    undef = -9999.0


# count the valid AMV
    amv_num = 0
    with open(file,'r') as f:
        for line in f:
            try:

amv_list=parse_amv(line,qc_pos,qc_min,qc_max,delimiter=delimiter,vpressure=vprs
)
                if (amv_list[0] != undef):
                    amv_num +=1
            except:
                continue
    f.closed

# allocate np arrays
    print('number of amv in read_txt = {0}'.format(amv_num))
    amv_spd = np.empty(amv_num)
    amv_dir = np.empty(amv_num)
    amv_prs = np.empty(amv_num)
    amv_lat = np.empty(amv_num)
    amv_lon = np.empty(amv_num)
    amv_qc  = np.empty(amv_num)

#TargetID;Latitude;Longitude;TSize;SSize;Speed;Direction;Height;LLC;ModelSpeed;
ModelDir;Albedo;MaxCorr;TM;HeightError;HAM;QI;QIF;CQI

# read again to fill np arrays
    count = 0
    with open(file,'r') as f:
        for line in f:
            try:

amv_list=parse_amv(line,qc_pos,qc_min,qc_max,lonflip=lonflip,lon0=lon0,delimite
r=delimiter,vpressure=vprs)
```

```
                if (amv_list[0] != undef):
                    amv_spd[count] = amv_list[0]
                    amv_dir[count] = amv_list[1]
                    amv_lat[count] = amv_list[2]
                    amv_lon[count] = amv_list[3]
                    amv_prs[count] = round(amv_list[4])
                    amv_qc[count] = amv_list[5]
                    count +=1
            except:
                continue
    f.closed

# place in one variable for convenience
    amv_data = np.vstack((amv_spd,amv_dir,amv_lat,amv_lon,amv_prs,amv_qc))

    return amv_data



def
parse_amv(line,qc_pos,qc_min,qc_max,lonflip=None,lon0=None,delimiter=None,vpres
sure=[100, 1000]):

# contain format of text file and data checking in one function

    undef = -9999.0
    #print('in parse delimiter={0}'.format(delimiter))

#TargetID;Latitude;Longitude;TSize;SSize;Speed;Direction;Height;LLC;ModelSpeed;
ModelDir;Albedo;MaxCorr;TM;HeightError;HAM;QI;QIF;CQI
#2018 intercomparison

#last intercomparison
    tlat = 1 ; vlat=[-61.,61.]
    #tlon = 2 ; vlon=[-61.,61.]
    tlon = 2 ; vlon=[-180.,360.]
    tspd = 5 ; vspd=[0.,150.]
    tdir = 6 ; vdir=[0.,361.]
    tprs = 7 ; vprs=vpressure
    tqc  = qc_pos ; vqc =[qc_min,qc_max]

    if delimiter==None:
        token=line.split()
    else:
        token=line.split(delimiter)

    lat=undef
    lon=undef
    spd=undef
    dir=undef
    prs=undef
    qc =undef
    #print('lat {0} lon {1} spd {2} dir {3} prs {4} qc
{5}'.format(token[tlat],token[tlon],token[tspd],token[tdir],token[tprs],token[q
c_pos]))

# basic valid data check, could add QI or other flag check here
    valid=True
    if (float(token[tlat]) < vlat[0]) or (float(token[tlat]) > vlat[1]):
        valid=False
    if (float(token[tlon]) < vlon[0]) or (float(token[tlon]) > vlon[1]):
```

```
        valid=False
    if (float(token[tspd]) < vspd[0]) or (float(token[tspd]) > vspd[1]):
        valid=False
    if (float(token[tdir]) < vdir[0]) or (float(token[tdir]) > vdir[1]):
        valid=False
    if (float(token[tprs]) < vprs[0]) or (float(token[tprs]) > vprs[1]):
        valid=False
    if (float(token[tqc])  < vqc[0])  or (float(token[tqc])  > vqc[1]):
        valid=False


    if (valid):
        lat = float(token[tlat])
        lon = float(token[tlon])
        spd = float(token[tspd])
        dir = float(token[tdir])
        prs = float(token[tprs])
        qc  = float(token[tqc])
    if lonflip!=None:
        lon = -lon
    if lon0==0. and lon>180.:
        lon=lon-360.
    if lon0==180. and lon<0.:
        lon=lon+360.

    amv_list = [spd,dir,lat,lon,prs,qc]

    return amv_list



def write_txt(file,amv_data):

    amv_num  = np.size(amv_data,axis=1)

    with open(file,'w') as f:
        out_string=file+" spd,dir,lat,lon,prs"
        f.write(out_string)
        f.write("\n")
        i = 0
        while (i<amv_num):
            out_string="{0} {1} {2} {3} {4} 
{5}".format(amv_data[0,i],amv_data[1,i],amv_data[2,i],amv_data[3,i],amv_data[4,
i],amv_data[5,i])
            f.write(out_string)
            f.write("\n")

            i +=1
    f.closed

    return

def read_DecodedForecast_MSG(file):

    """Usage: DecFcst = read_DecodedForecast_MSG(file)
    where, e.g.:
    file = '[...]/DecodedForecast_20120503070606Z_20120503120000Z_12_V_MPFS07'
    """

#    Decoded forecast header (4,776 bytes)
#    Decoded_Forecast_Header = BYTARR(4776)
```

```
#    Decoded forecast data point (40 bytes)
#    Decoded_Forecast_Point = {Latitude      : FLOAT(0), $
#                             Longitude     : FLOAT(0), $
#                             Pressure      : FLOAT(0), $
#                             Geopotential  : FLOAT(0), $
#                             Temperature   : FLOAT(0), $
#                             WVMixingRatio : FLOAT(0), $
#                             O3MixingRatio : FLOAT(0), $
#                             WindSpeed     : FLOAT(0), $
#                             WindDirection : FLOAT(0), $
#                             DewPointTemp  : FLOAT(0)}
#   Decoded forecast data array (29,160,000 bytes)
#   Decoded_Forecast_Array = REPLICATE(Decoded_Forecast_Point, 40L * 135L * 
135L)

# This could input defined
    num_x = 721
    num_y = 1440
    num_var = 10
    num_lev = 40
    num_pt = num_x * num_y
    arrout = np.zeros((num_x,num_y,10,40))

#   Open file and skip header
    fo = open(file)
    fo.seek(4776)

    print('Program is reading decoded forecast data:{0}'.format(file))

#   '>f4' is float which is big-endian
    forecast=np.fromfile(fo,dtype=('>f4'))
    fo.close()
    fore=np.reshape(forecast,(num_pt,num_lev,num_var))

    latitude      = fore[:,:,0]
    longitude     = fore[:,:,1]
    pressure      = fore[:,:,2]
    geopotential  = fore[:,:,3]
    temperature   = fore[:,:,4]
    wvmixingratio = fore[:,:,5]
    o3mixingratio = fore[:,:,6]
    windspeed     = fore[:,:,7]
    winddirection = fore[:,:,8]
    dewpointtemp  = fore[:,:,9]

    for j in range(num_pt):

#hardwired for this input file
        x = np.floor(longitude[j,0] + 67)
        y = np.floor(latitude[j,0] + 67)

        arrout[x,y,0,:] = pressure[j,:]
        arrout[x,y,1,:] = geopotential[j,:]
        arrout[x,y,2,:] = temperature[j,:]
        arrout[x,y,3,:] = wvmixingratio[j,:]
        arrout[x,y,4,:] = o3mixingratio[j,:]
        arrout[x,y,5,:] = windspeed[j,:]
        arrout[x,y,6,:] = winddirection[j,:]
        arrout[x,y,7,:] = dewpointtemp[j,:]
        arrout[x,y,8,:] = latitude[j,:]
```

```
        arrout[x,y,9,:] = longitude[j,:]

    return arrout


def locate(amv_data,fcst_data):

    amv_num  = np.size(amv_data,axis=1)
    grid_i = np.zeros(amv_num,dtype=int)
    grid_j = np.zeros(amv_num,dtype=int)
    fcst_lat  = fcst_data[:,:,8,0]
    fcst_lon  = fcst_data[:,:,9,0]
    #toplon=361.
    #max_lon = max(fcst_lon.all,toplon)
    #print('Longitudes'.format(max_lon))
    numx = np.size(fcst_data,axis=0)
    numy = np.size(fcst_data,axis=1)

    n = 0
    while (n<amv_num):
        #print('n={0}'.format(n))
        amv_lat  = amv_data[2,n]
        amv_lon  = amv_data[3,n]
        grid_diff = (amv_lat-fcst_lat)**2 + (amv_lon-fcst_lon)**2
        indx= np.argmin(grid_diff)
        indx_2d=np.unravel_index(indx,(numx,numy))
        grid_i[n] = indx_2d[0]
        grid_j[n] = indx_2d[1]
        n +=1

    return grid_i,grid_j



def bestfit(amv_data,fcst_data,verbose):

    """Finds the background model best fit pressure associated with the AMV.
       The model best-fit pressure is the height (in pressure units) where the
       vector difference between the observed AMV and model background is a
       minimum.  This calculation may only work approximately 1/3 of the time.

       Reference:
       Salonen et al (2012), "Characterising AMV height assignment error by
       comparing best-fit pressure statistics from the Met Office and ECMWF
       System."  Proceedings of the 11th International Winds Workshop,
       Auckland, New Zealand, 20-24 February 2012.

       Input contained in amv_data and fcst_data:
       amv_spd -  AMV speed m/s
       amv_dir -  AMV direction deg
       amv_prs -  AMV pressure hPa
       fcst_spd - (level) forecast speed m/s
       fcst_dir - (level) forecast direction (deg)
       fcst_prs - (level) forecast pressure (hPa)

       Output contained in bf_data:
       SatwindBestFitU - AMV best fit U component m, unconstrained value is
undef
       SatwindBestFitV - AMV best fit V component m, unconstrained value is
undef
       bfit_prs - AMV best fit pressure m/s, unconstrained value is undef
```

```
       flag - 0 found, 1 not contrained, 2 vec diff minimum not met, 3 failed
to find suitable fcst pressure match

       History:
       10/2012 - Steve Wanzong - Created in Fortran
       10/2013 - Sharon Nebuda - rewritten for python
    """
    undef = -9999.0

    amv_spd = amv_data[0]
    amv_dir = amv_data[1]
    amv_prs = round(amv_data[4])
    amv_lat = amv_data[2]
    amv_lon = amv_data[3]

    fcst_spd = fcst_data[5,:]
    fcst_dir = fcst_data[6,:]
    fcst_prs = fcst_data[0,:]
    fcst_lat = fcst_data[8,0]
    fcst_lon = fcst_data[9,0]

    fcst_num_levels = fcst_spd.shape[0]

#   verbose = True
#   verbose = False

    SatwindBestFitPress = undef
    SatwindBestFitU = undef
    SatwindBestFitV = undef

    PressDiff = 150.                      # pressure above and below AMV to
look for fit
    TopPress = 50.                        # highest level to allow search

    flag = 3
    bf_data = np.vstack((undef,undef,undef,flag))

    if (amv_prs<TopPress):
        if (verbose):
            print('AMV location lat,lon,prs ({0},{1},{2}) is higher than
pressure {3}'.format(amv_lat,amv_lon,amv_prs,TopPress))
        return bf_data

#Calculate the pressure +/- 150 hPa from the AMV pressure.
    PressMax = amv_prs + PressDiff
    PressMin = max((amv_prs-PressDiff),TopPress)

#1d array of indicies to consider for best fit location
    kk = np.where((fcst_prs<PressMax) & (fcst_prs>PressMin))
    if (len(kk[0]) ==0):
        if (verbose):
            print('AMV location lat,lon,prs ({0},{1},{2}) failed to find fcst
prs around AMV'.format(amv_lat,amv_lon,amv_prs))
        return bf_data

#Diagnostic field: Find the model minimum speed and maximum speed within
PressDiff of the AMV.
    if (verbose):
        SatwindMinSpeed = min(fcst_spd[kk])
        SatwindMaxSpeed = max(fcst_spd[kk])
```

```
#Compute U anv V for both AMVs and forecast
    amv_uwind = -amv_spd * np.sin(math.radians(amv_dir))
    amv_vwind = -amv_spd * np.cos(math.radians(amv_dir))
#   fcst_uwind = -fcst_spd[:] * np.sin(math.radians(fcst_dir[:]))
#   fcst_vwind = -fcst_spd[:] * np.cos(math.radians(fcst_dir[:]))
    dr=0.017453
    fcst_uwind = -fcst_spd * np.sin(dr*fcst_dir)
    fcst_vwind = -fcst_spd * np.cos(dr*fcst_dir)

#Calculate the vector difference between the AMV and model background at all
levels.
    VecDiff = np.sqrt((amv_uwind - fcst_uwind) ** 2 + (amv_vwind - fcst_vwind)
** 2)

#Find the model level of best-fit pressure, from the minimum vector difference.
    MinVecDiff = min(VecDiff[kk])
    imin=-1
    for i, item in enumerate(VecDiff):
        if MinVecDiff == VecDiff[i]:
            if i in kk[0]:
                imin = i

#   if(imin != -1): print('{0:8.2f} {1:8.2f} {2:8.0f} {3:8.2f},{4:8.2f}
{5:8.2f} {6:8.2f} {7:8.0f}'.format(amv_lat,amv_lon,amv_prs,amv_uwind,
amv_vwind, fcst_uwind[imin],fcst_vwind[imin], fcst_prs[imin]))
    if (imin ==-1 ):
        if (verbose):
            print('AMV location lat,lon,prs ({0},{1},{2}) failed to find min
vector difference in layers around AMV'.format(amv_lat,amv_lon,amv_prs))

        return bf_data


#Use a parabolic fit to find the best-fit pressure.
#p2 - Minimized model pressure at level imin (hPa)
#v2 - Minimized vector difference at level imin (m/s)
#p1 - 1 pressure level lower in atmosphere than p2
#p3 - 1 pressure level above in atmosphere than p2
#v1 - Vector difference 1 pressure level lower than p2
#v3 - Vector difference 1 pressure level above than p2

    p2 = fcst_prs[imin]
    v2 = VecDiff[imin]

# assumes fcst data level 0 at surface and (fcst_num_levels-1) at model top
#if bottom model level
    if imin == 0:
        SatwindBestFitPress = p2
    else:
        p3 = fcst_prs[imin+1]
        p1 = fcst_prs[imin-1]
        v3 = VecDiff[imin+1]
        v1 = VecDiff[imin-1]

#if top of allowed region
        if p3 < TopPress:
            SatwindBestFitPress = p2

#check not collinear
        elif (v1 != v2 and v2 != v3):
            SatwindBestFitPress = p2 - (0.5 *
```

```
            ((((p2 - p1) * (p2 - p1) * (v2 - v3)) - ((p2 - p3) * (p2 - p3) *
(v2 - v1))) /
            (((p2 - p1) * (v2 - v3)) - ((p2 - p3) * (v2 - v1)))))
            if (SatwindBestFitPress < p3) or (SatwindBestFitPress > p1):
                if (verbose):
                    print('Best Fit not found between two pressure layers')
                    print('SatwindBestFitPress {0} p1 {1} p2 {2} p3 {3} imin
{4}'.format(SatwindBestFitPress,p1,p2,p3,imin))
                SatwindBestFitPress = p2
        else:
            SatwindBestFitPress = p2

#Find best fit U and V by linear interpolation.
    if p2 == SatwindBestFitPress:
        SatwindBestFitU = fcst_uwind[imin]
        SatwindBestFitV = fcst_vwind[imin]
    else:
        if p2 < SatwindBestFitPress:
            LevBelow = imin - 1
            LevAbove = imin
            Prop = (SatwindBestFitPress - p1) / (p2 - p1)
        else:
            LevBelow = imin
            LevAbove = imin + 1
            Prop = (SatwindBestFitPress - p2) / (p3 - p2)

        SatwindBestFitU = fcst_uwind[LevBelow] * (1.0 - Prop) +
fcst_uwind[LevAbove] * Prop
        SatwindBestFitV = fcst_vwind[LevBelow] * (1.0 - Prop) +
fcst_vwind[LevAbove] * Prop



# Check to see if the best fit pressure is constrained.

    SatwindGoodConstraint = 0
    flag = 2

    if MinVecDiff <= 4.0:

        SatwindGoodConstraint = 1
        flag = 1

        for ilev in range(fcst_num_levels):
            if fcst_prs[ilev] >= TopPress:

                if ((fcst_prs[ilev] < (SatwindBestFitPress - 100.)) or  \
                   (fcst_prs[ilev] > (SatwindBestFitPress + 100.))) and  \
                   (VecDiff[ilev] <= (MinVecDiff + 2.0)):
                   SatwindGoodConstraint = 0

    if SatwindGoodConstraint == 1:
        bfit_prs = SatwindBestFitPress
        bfit_u = SatwindBestFitU
        bfit_v = SatwindBestFitV
        flag = 0
    else:
        bfit_prs = undef
        bfit_u = undef
        bfit_v = undef
```

```
    if (verbose):
        print('*** AMV best-fit ***')
        print('AMV -> p/minspd/maxspd: {0} {1}
{2}'.format(amv_prs,SatwindMinSpeed,SatwindMaxSpeed))
        print('Bestfit -> p1,p2,p3,v1,v2,v3: {0} {1} {2} {3} {4}
{5}'.format(p1,p2,p3,v1,v2,v3))
        print('Bestfit -> pbest,bfu,bfv,amvu,amvv,bgu,bgv: {0} {1} {2} {3} {4}
{5} {6}'.format(

SatwindBestFitPress,SatwindBestFitU,SatwindBestFitV,amv_uwind,amv_vwind,fcst_uw
ind[imin],fcst_vwind[imin]))
        print('Good Constraint: {0}'.format(SatwindGoodConstraint))
        print('Minimum Vector Difference: {0}'.format(VecDiff[imin]))
        print('Vector Difference Profile: ')
        print(VecDiff)
        print('Pressure Profile: ')
        print(fcst_prs)

        if (abs(SatwindBestFitU - amv_uwind) > 4.0) or  (abs(SatwindBestFitV -
amv_vwind) > 4.0):
            print('U Diff: {0}'.format(abs(SatwindBestFitU - amv_uwind)))
            print('V Diff: {0}'.format(abs(SatwindBestFitV - amv_vwind)))

    bf_data = np.vstack((bfit_u,bfit_v,bfit_prs,flag))

    return bf_data




def bg(amv_data,fcst_data,verbose):

    """Finds the background model U and V components at the AMV pressure level
       5/2014 - Sharon Nebuda
    """
    undef = -9999.0

    amv_prs = round(amv_data[4])

    fcst_spd = fcst_data[5,:]
    fcst_dir = fcst_data[6,:]
    fcst_prs = fcst_data[0,:]

    fcst_num_levels = fcst_spd.shape[0]

    bg_u = undef
    bg_v = undef

    bg_data = np.vstack((bg_u,bg_v))

#Compute U anv V for forecast
#   fcst_uwind = -fcst_spd[:] * np.sin(math.radians(fcst_dir[:]))
#   fcst_vwind = -fcst_spd[:] * np.cos(math.radians(fcst_dir[:]))
    dr=0.017453
    fcst_uwind = -fcst_spd * np.sin(dr*fcst_dir)
    fcst_vwind = -fcst_spd * np.cos(dr*fcst_dir)

    if (verbose):
        print(fcst_uwind)
```

```
# assumes fcst data level 0 at surface and (fcst_num_levels-1) at model top
# data not well behaved (level 0 = level 1, level at top = 0 or -9999)
# hard wired this search
#   if (fcst_prs[1] < fcst_prs[0]):
    k = 0
    while (k < (fcst_num_levels-1)):

        if ((fcst_prs[k] >= amv_prs) and (amv_prs >= fcst_prs[k+1])):

            LevBelow = k
            LevAbove = k + 1
            Prop = (amv_prs - fcst_prs[LevAbove]) / (fcst_prs[LevBelow] -
fcst_prs[LevAbove])

            bg_u = fcst_uwind[LevBelow] * Prop + fcst_uwind[LevAbove] * (1.-
Prop)
            bg_v = fcst_vwind[LevBelow] * Prop + fcst_vwind[LevAbove] * (1.-
Prop)
            k=fcst_num_levels
            if (verbose):
                print('{0} {1} {2} {3}
{4}'.format(k,fcst_uwind[LevBelow],fcst_uwind[LevAbove],Prop,bg_u))

        k+=1


# assumes fcst data level (fcst_num_levels-1) at surface and 0 at model top
#   else:
#       print('k=0 prs {0} k=1 prs {1}'.format(fcst_prs[0],fcst_prs[1])
#       k = fcst_num_levels-1
#       while (k > 0 and fcst_prs[k] > -999.):
#
#           if ((fcst_prs[k] >= amv_prs) and (amv_prs >= fcst_prs[k-1])):
#
#               LevBelow = k
#               LevAbove = k - 1
#               Prop = (amv_prs - fcst_prs[LevAbove]) / (fcst_prs[LevAbove] -
fcst_prs[LevBelow])
#
#               bg_u = fcst_uwind[LevBelow] * Prop + fcst_uwind[LevAbove] *
(1.-Prop)
#               bg_v = fcst_vwind[LevBelow] * Prop + fcst_vwind[LevAbove] *
(1.-Prop)
#               print('shouldnt be here {0} {1} {2} {3}
{4}'.format(k,fcst_prs[k],amv_prs,bg_u,bg_v))
#
#           k-=1


#   if (bg_u == undef):
#       print('Did not find U {0} {1} {2}'.format(amv_prs, fcst_prs[0],
fcst_prs[fcst_num_levels-1])
    bg_data = np.vstack((bg_u,bg_v))

    return bg_data


def spddir(ucomp,vcomp):

    """Computes speed and direction (wind barb convention) from U and V wind
components
```

```
    """

    undef = -9999.

    if (ucomp != undef and vcomp !=undef):
        speed = np.sqrt( (ucomp*ucomp) + (vcomp*vcomp) )
        r2d = 180./np.pi
        direction = 90. - np.arctan(vcomp/ucomp) * r2d
    else:
        speed = undef
        direction = undef

    return speed, direction


def uvcomp(speed,direction):

    """Computes U and V components from speed and direction
    """
    undef = -9999.

    if (speed != undef and direction !=undef):
        uwind = -speed * np.sin(math.radians(direction))
        vwind = -speed * np.cos(math.radians(direction))
    else:
        uwind = undef
        vwind = undef

    return uwind, vwind


def read_MSG_grib(file,datetime=None):

    """Usage: Fcst, timeout = read_MSG_grib(file,time=time)
       Returns a pressure, lat, lon, speed, direction in a
       padded array for backwards compatibility
       time in YYYYMMDDHH format, long integer
       number of levels and number of time samples is hardwired
       if time is not specified, first time is returned
       if time is does not match file times, first time is returned
    """

    grbs=pygrib.open(file)
    uall=grbs.select(name='U component of wind')
    vall=grbs.select(name='V component of wind')
    #or grb=grbs.select(name='Temperature')[0]  # for one 2d grib message
    #without [0] get all levels and all times in a list of numpy arrays of
complex data type
    #print(grb[0].keys())
    #print(grb[0].level)
    #print(grb[0].year)
    #print(grb[0])

    nlev = 37
    ntim = 24

    dt_file = np.zeros(ntim,dtype=int)
    for n in range(ntim):
        nm = n*nlev  # grib message number
        date = uall[nm].dataDate
        time = uall[nm].hour
```

```
        #string_datetime = '{0}{1:2d}'.format(date1,time1)
        dt_file[n] = date*100 + time

    nm=1
    dt_out = dt_file[0]
    if datetime!=None:
        for n in range(ntim):
            if datetime == dt_file[n]:
                nm = n
                dt_out = dt_file[n]

    nstart = nlev * nm

    prs = np.zeros(nlev)
    for n in range(nlev):
        prs[n] = uall[n].level

    lats, lons = uall[0].latlons()
    dims = lats.shape

    nlon = dims[0]
    nlat = dims[1]

    fcst_data=np.zeros((nlon,nlat,10,nlev))
    uwnd=np.zeros((nlon,nlat))
    vwnd=np.zeros((nlon,nlat))
    wspd=np.zeros((nlon,nlat))
    wdir=np.zeros((nlon,nlat))
    for n in range(nlev):
        ns = nstart + n
        nl = nlev - n - 1 # flip so data is surface to model top
        uwnd[:,:]=uall[ns].values  # same as uall[ns]['values']
        vwnd[:,:]=vall[ns].values
        wspd = np.square(uwnd) + np.square(vwnd)
        wspd = np.sqrt(wspd)
        wdir = 270.-np.arctan2(vwnd,uwnd)*180./np.pi
        fix = np.where(wdir>= 360)
        wdir[fix] = wdir[fix] - 360.

        fcst_data[:,:,0,nl]=prs[n]
        fcst_data[:,:,5,nl]=wspd[:,:]
        fcst_data[:,:,6,nl]=wdir[:,:]
        fcst_data[:,:,8,nl]=lats[:,:]
        fcst_data[:,:,9,nl]=lons[:,:]

    grbs.close()

    return fcst_data, dt_out

# old decoder
#       arrout[x,y,0,:] = pressure[j,:]
#       arrout[x,y,1,:] = geopotential[j,:]
#       arrout[x,y,2,:] = temperature[j,:]
#       arrout[x,y,3,:] = wvmixingratio[j,:]
#       arrout[x,y,4,:] = o3mixingratio[j,:]
#       arrout[x,y,5,:] = windspeed[j,:]
#       arrout[x,y,6,:] = winddirection[j,:]
#       arrout[x,y,7,:] = dewpointtemp[j,:]
#       arrout[x,y,8,:] = latitude[j,:]
#       arrout[x,y,9,:] = longitude[j,:]
```

```
#uwnd, vwnd, prs, lons, lats, timeout =
amv.read_MSG_grib_uv(file,datetime=datetime)
def read_MSG_grib_uv(file,datetime=None):

    """Usage: uwnd,vwnd,prs,lons,lats, timeout =
read_MSG_grib_uv(file,time=time)
       Returns a pressure, lat, lon, speed, direction in a
       padded array for backwards compatibility
       time in YYYYMMDDHH format, long integer
       number of levels and number of time samples is hardwired
       if time is not specified, first time is returned
       if time is does not match file times, first time is returned
    """

    grbs=pygrib.open(file)
    uall=grbs.select(name='U component of wind')
    vall=grbs.select(name='V component of wind')
    #or grb=grbs.select(name='Temperature')[0]  # for one 2d grib message
    #without [0] get all levels and all times in a list of numpy arrays of
complex data type
    #print(grb[0].keys())
    #print(grb[0].level)
    #print(grb[0].year)
    #print(grb[0])

    nlev = 37
    ntim = 24

    dt_file = np.zeros(ntim,dtype=int)
    for n in range(ntim):
        nm = n*nlev  # grib message number
        date = uall[nm].dataDate
        time = uall[nm].hour
        #string_datetime = '{0}{1:2d}'.format(date1,time1)
        dt_file[n] = date*100 + time

    nm=1
    dt_out = dt_file[0]
    if datetime!=None:
        for n in range(ntim):
            if datetime == dt_file[n]:
                nm = n
                dt_out = dt_file[n]

    nstart = nlev * nm

    prs = np.zeros(nlev)
    for n in range(nlev):
        prs[n] = uall[n].level

    lats, lons = uall[0].latlons()
    dims = lats.shape

    nlon = dims[0]
    nlat = dims[1]

    uwnd=np.zeros((nlon,nlat,nlev))
    vwnd=np.zeros((nlon,nlat,nlev))
    for n in range(nlev):
```

```
        ns = nstart + n
        nl = nlev - n - 1 # flip so data is surface to model top
        uwnd[:,:,nl]=uall[ns].values  # same as uall[ns]['values']
        vwnd[:,:,nl]=vall[ns].values

    grbs.close()

    return uwnd,vwnd,prs,lons,lats, dt_out

# old decoder
#       arrout[x,y,0,:] = pressure[j,:]
#       arrout[x,y,1,:] = geopotential[j,:]
#       arrout[x,y,2,:] = temperature[j,:]
#       arrout[x,y,3,:] = wvmixingratio[j,:]
#       arrout[x,y,4,:] = o3mixingratio[j,:]
#       arrout[x,y,5,:] = windspeed[j,:]
#       arrout[x,y,6,:] = winddirection[j,:]
#       arrout[x,y,7,:] = dewpointtemp[j,:]
#       arrout[x,y,8,:] = latitude[j,:]
#       arrout[x,y,9,:] = longitude[j,:]


# https://medium.com/@petehouston/calculate-distance-of-two-locations-on-earth-
using-python-1501b1944d97
def great_circle(lat1, lon1, lat2, lon2):
    """Calculate the great circle distance between two points
    on the earth (specified in decimal degrees)"""

    lon1, lat1, lon2, lat2 = map(radians, [lon1, lat1, lon2, lat2])
    return 6371 * (
        acos(sin(lat1) * sin(lat2) + cos(lat1) * cos(lat2) * cos(lon1 - lon2))
    )
```

21. Appendix E: Matlab Scripts

The Matlab scripts were based on those used in the previous AMV intercomparison study.

Winds_Bulk.m

```
function success = Winds_Bulk_CQI(exp,inpd,char_qitype,qival)

if ( char_qitype == "QINF" )
     qitype=17
end

if ( char_qitype == "CQI" )
     qitype=19
end

indir=sprintf('%s',inpd)
outflnm=sprintf('Exp_%i_Bulk_%s_%i_statsout.txt',exp, char_qitype, qival);

fal1= {'EUM',  'BRZ', 'JMA', 'NOA' , 'KMA', 'NWC'};


% new data columns
% 1. IDN
% 2. LAT[DEG]
% 3. LONG[DEG]
% 4. TBOX[PIX]
% 5. SBOX[PIX]
% 6. SPD[MPS]
% 7. DIR[DEG]
% 8. P[HPA]
% 9. LOWL
% 10.MSPD[MPS]
% 11.MDIR[DEG]
% 12.ALB[%]
% 13.CORR[%]
% 14.TMET
% 15.PERR[HPA]
% 16.HMET
% 17.QINF[%]
% 18.QIF[%]
% 19.CQI[%]

%clear;


if (exp == 1 )
    %EUM: AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
    %BRZ: 4th_AMVIC_INPE_Test_1_final.txt
    %JMA: JMA_test11_1200.txt
    %NOA: ASCII_AMV-4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
    %KMA: KMA_test11_goes16_abi_ch14_amv_201910201200.asc
```

```
    %NWC: INTERCOMP2021_NWCSAFTEST11.txt
    fall= {'AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt',
'4th_AMVIC_INPE_Test_1_final.txt', 'JMA_test11_1200.txt', 'ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT' ,
'KMA_test11_goes16_abi_ch14_amv_201910201200.asc',
'INTERCOMP2021_NWCSAFTEST11.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[16 16 16 15 16 16];

end

if (exp == 21 )
    %EUM: AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt
    %BRZ: 4th_AMVIC_INPE_Test_2a_final.txt
    %JMA: JMA_test21_1130.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT
    %KMA: KMA_test21_goes16_abi_ch14_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST21.txt
    fall= {'AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt',
'4th_AMVIC_INPE_Test_2a_final.txt', 'JMA_test21_1130.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT' ,
'KMA_test21_goes16_abi_ch14_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST21.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[16 16 7 19 16 24];

end

if (exp == 22 )
    %EUM: AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
    %BRZ: 4th_AMVIC_INPE_Test_2b_final.txt
    %JMA: JMA_test22_1200.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT
    %KMA: KMA_test22_goes16_abi_ch14_amv_201910201200.asc
    %NWC: INTERCOMP2021_NWCSAFTEST22.txt
    fall= {'AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt',
'4th_AMVIC_INPE_Test_2b_final.txt', 'JMA_test22_1200.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT' ,
'KMA_test22_goes16_abi_ch14_amv_201910201200.asc',
'INTERCOMP2021_NWCSAFTEST22.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[16 16 7 19 16 24];
end


if (exp == 23 )
    %EUM: AMVIntm_Chan14_20191020190000Z_GOES_ASCII_Test23.txt
    %BRZ: 4th_AMVIC_INPE_Test_2c_final.txt
    %JMA: JMA_test23_1900.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1900.CH_14.FD.CT
    %KMA: KMA_test23_goes16_abi_ch14_amv_201910201900.asc
    %NWC: INTERCOMP2021_NWCSAFTEST23.txt
    fall= {'AMVIntm_Chan14_20191020190000Z_GOES_ASCII_Test23.txt',
'4th_AMVIC_INPE_Test_2c_final.txt', 'JMA_test23_1900.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1900.CH_14.FD.CT' ,
'KMA_test23_goes16_abi_ch14_amv_201910201900.asc',
'INTERCOMP2021_NWCSAFTEST23.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[16 16 7 19 16 24];
end
```

```
if (exp == 3 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt
    %BRZ: 4th_AMVIC_INPE_Test_3_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test31_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST31.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt',
'4th_AMVIC_INPE_Test_3_final.txt', '', 'ASCII_AMV-
4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test31_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST31.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[24 16 16 15 16 24];
end

if (exp == 4 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt
    %BRZ: 4th_AMVIC_INPE_Test_4_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test41_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST41.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt',
'4th_AMVIC_INPE_Test_4_final.txt', '', 'ASCII_AMV-
4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test41_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST41.txt'};
    fsym= {'b.', 'g^', 'y', 'k+', 'ro', 'ms'};
    tbsize=[24 18 16 15 16 24];
end

%    figure;
fid=fopen(outflnm,'w');
for i=1:6
    fname=fall{i};
    fnameo=fal1{i};

    if (fname == "")
         continue
    end

    a=dlmread([indir,fall{i}],',',0,0);

    %Remove records with invalid pressure
    abad=find(a(:,8)==0);
    a(abad,:)=[];

    %Remove records with invalid latitude
    abad=find(a(:,2) >  90);
    a(abad,:)=[];
    abad=find(a(:,2) < -90);
    a(abad,:)=[];

    %Remove records with bad direction
    abad=find(a(:,7) < 0 | a(:,7) > 360);
    a(abad,:)=[];

    spd25=find(a(:,6)>=2.5);
    a=a(spd25,:);
```

```
    good_50=find(a(:,qitype)>=50);
    good_80=find(a(:,qitype)>=80);
    good_qi=find(a(:,qitype)>=qival);
    figure;
    set(gcf, 'visible', 'off')
    subplot(2,3,1);
    hold on;
    %plot(a(:,3),a(:,2),'r.');
    scatter(a(:,3),a(:,2),2,'r.');
    scatter(a(good_50,3),a(good_50,2),2,'b.');
    scatter(a(good_80,3),a(good_80,2),2,'g.');
    names={'All AMV','QI>=50','QI>=80'};
    label(1)=names(1);
    label(2)=names(2);
    label(3)=names(3);

legend(gca,label(:),'FontSize',4,'FontWeight','bold','Location','Northwest');
    %legend('All AMV',
'QI>=50','QI>=80','Location','northwest','Orientation','horizontal');
    xlabel('Lon');
    ylabel('Lat');
    title(fnameo);
     xlim([-135 -15])
%    set(gca,'xdir','reverse')
     ylim([-60  60])

%    set(gca,'XTick',[ -135 -95 -55 -15 ])
%    set(gca,'XTickLabel',[-135 -95 -55 -15])
%     hold on;

    disp('**************************');
    %disp(fname);

    fprintf(fid,'For File: %s \n',fname);
    fprintf(fid,'Target box size in pixels: %d \n',tbsize(i));
    fprintf(fid,'Total num winds: %d \n',length(a(:,1)));
    fprintf(fid,'Winds QI>=%d: %d \n',qival,length(good_qi));

    fprintf(fid,'Lat_min, %6.2f \n', min(a(:,2)));
    fprintf(fid,'Lat_max, %6.2f \n', max(a(:,2)));
    fprintf(fid,'Lon_west, %6.2f \n', min(a(:,3)));
    fprintf(fid,'Lon_east, %6.2f \n', (360-max(a(:,3))));

    fprintf(fid,' \n');
    fprintf(fid,'*** For AMV with QI>=%d ***\n', qival);

    alow=find(a(good_qi,8)>=700);
    amid=find(a(good_qi,8)<700 & a(good_qi,8)>400);
    ahigh=find(a(good_qi,8)<=400);

    fprintf(fid,'SPD_min, %6.2f \n', min(a(good_qi,6)));
    fprintf(fid,'SPD_max, %6.2f \n', max(a(good_qi,6)));
    fprintf(fid,'SPD_mean, %6.2f \n', mean(a(good_qi,6)));

    fprintf(fid,'P_min, %6.2f \n', min(a(good_qi,8)));
    fprintf(fid,'P_max, %6.2f \n', max(a(good_qi,8)));
    fprintf(fid,'P_mean, %6.2f \n', mean(a(good_qi,8)));

    fprintf(fid,'Low_winds, %6.2f \n', 100*length(alow)/length(good_qi) );
```

```
    fprintf(fid,'Mid_winds, %6.2f \n', 100*length(amid)/length(good_qi) );
    fprintf(fid,'High_winds, %6.2f \n', 100*length(ahigh)/length(good_qi) );

    aa=a(good_qi,:);
    fprintf(fid,'Low_SPD_min, %6.2f \n', min(aa(alow,6)));
    fprintf(fid,'Low_SPD_max, %6.2f \n', max(aa(alow,6)));
    fprintf(fid,'Low_SPD_mean, %6.2f \n', mean(aa(alow,6)));

    fprintf(fid,'Low_P_min, %6.2f \n', min(aa(alow,8)));
    fprintf(fid,'Low_P_max, %6.2f \n', max(aa(alow,8)));
    fprintf(fid,'Low_P_mean, %6.2f \n', mean(aa(alow,8)));

    fprintf(fid,'Mid_SPD_min, %6.2f \n', min(aa(amid,6)));
    fprintf(fid,'Mid_SPD_max, %6.2f \n', max(aa(amid,6)));
    fprintf(fid,'Mid_SPD_mean, %6.2f \n', mean(aa(amid,6)));

    fprintf(fid,'Mid_P_min, %6.2f \n', min(aa(amid,8)));
    fprintf(fid,'Mid_P_max, %6.2f \n', max(aa(amid,8)));
    fprintf(fid,'Mid_P_mean, %6.2f \n', mean(aa(amid,8)));

    fprintf(fid,'High_SPD_min, %6.2f \n', min(aa(ahigh,6)));
    fprintf(fid,'High_SPD_max, %6.2f \n', max(aa(ahigh,6)));
    fprintf(fid,'High_SPD_mean, %6.2f \n', mean(aa(ahigh,6)));

    fprintf(fid,'High_P_min, %6.2f \n', min(aa(ahigh,8)));
    fprintf(fid,'High_P_max, %6.2f \n', max(aa(ahigh,8)));
    fprintf(fid,'High_P_mean, %6.2f \n', mean(aa(ahigh,8)));

    subplot(2,3,2);
    hist(a(good_qi,qitype),11); % QI
    v=axis;
    axis([qival 100 v(3) v(4)]);
    title(['QI' ' ' fnameo]);

    subplot(2,3,3);
    hist(a(good_qi,6),11); % SPD
    v=axis;
    axis([0 100 v(3) v(4)]);
    title(['SPD' ' ' fnameo]);

    subplot(2,3,4);
    hist(a(good_qi,7),45); % DIR
    v=axis;
    axis([0 360 v(3) v(4)]);
    title(['DIR' ' ' fnameo]);

    subplot(2,3,5);
    hist(a(good_qi,8),21); % H
    v=axis;
    axis([100 1000 v(3) v(4)]);
    title(['P' ' ' fnameo]);

    char_qival=sprintf('%i',qival);
    char_exp=sprintf('%i',exp);

    saveas(gcf, ['Exp_' char_exp '_' fnameo '_' char_qitype '_' char_qival '_'
fname(1:6)], 'tif');

end;

fclose(fid);
```

```
close(figure(1:6))
 success='yes';
```

Winds_Match_EUM.m

```
function success = Winds_Match_EUM(exp,inpd,char_qitype,dist,qi)
% collocaton of the cgms study datastes - search for a spatial match
% within less than a specified distance
% make sure to organize set_out by own configuration target box size from
smallest to largest

%clear;
indir=sprintf('%s',inpd)

if ( char_qitype == "QINF" )
        qitype=17
end

if ( char_qitype == "CQI" )
        qitype=19
end

if (exp == 1 )
    %EUM: AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt
    %BRZ: 4th_AMVIC_INPE_Test_1_final.txt
    %JMA: JMA_test11_1200.txt
    %NOA: ASCII_AMV-4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT
    %KMA: KMA_test11_goes16_abi_ch14_amv_201910201200.asc
    %NWC: INTERCOMP2021_NWCSAFTEST11.txt
    fall= {'AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test11.txt',
'4th_AMVIC_INPE_Test_1_final.txt', 'JMA_test11_1200.txt', 'ASCII_AMV-
4thInt_TEST1.GOES16.2019293.1200.CH_14.FD.CT' ,
'KMA_test11_goes16_abi_ch14_amv_201910201200.asc',
'INTERCOMP2021_NWCSAFTEST11.txt'};

end

if (exp == 21 )
    %EUM: AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt
    %BRZ: 4th_AMVIC_INPE_Test_2a_final.txt
    %JMA: JMA_test21_1130.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT
    %KMA: KMA_test21_goes16_abi_ch14_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST21.txt
    fall= {'AMVIntm_Chan14_20191020113000Z_GOES_ASCII_Test21.txt',
'4th_AMVIC_INPE_Test_2a_final.txt', 'JMA_test21_1130.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1130.CH_14.FD.CT' ,
'KMA_test21_goes16_abi_ch14_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST21.txt'};

end

if (exp == 22 )
    %EUM: AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt
    %BRZ: 4th_AMVIC_INPE_Test_2b_final.txt
    %JMA: JMA_test22_1200.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT
    %KMA: KMA_test22_goes16_abi_ch14_amv_201910201200.asc
    %NWC: INTERCOMP2021_NWCSAFTEST22.txt
    fall= {'AMVIntm_Chan14_20191020120000Z_GOES_ASCII_Test22.txt',
'4th_AMVIC_INPE_Test_2b_final.txt', 'JMA_test22_1200.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1200.CH_14.FD.CT' ,
'KMA_test22_goes16_abi_ch14_amv_201910201200.asc',
```

```
'INTERCOMP2021_NWCSAFTEST22.txt'};
end


if (exp == 23 )
    %EUM: AMVIntm_Chan14_20191020190000Z_GOES_ASCII_Test23.txt
    %BRZ: 4th_AMVIC_INPE_Test_2c_final.txt
    %JMA: JMA_test23_1900.txt
    %NOA: ASCII_AMV-4thInt_TEST2.GOES16.2019293.1900.CH_14.FD.CT
    %KMA: KMA_test23_goes16_abi_ch14_amv_201910201900.asc
    %NWC: INTERCOMP2021_NWCSAFTEST23.txt
    fall= {'AMVIntm_Chan14_20191020190000Z_GOES_ASCII_Test23.txt',
'4th_AMVIC_INPE_Test_2c_final.txt', 'JMA_test23_1900.txt', 'ASCII_AMV-
4thInt_TEST2.GOES16.2019293.1900.CH_14.FD.CT' ,
'KMA_test23_goes16_abi_ch14_amv_201910201900.asc',
'INTERCOMP2021_NWCSAFTEST23.txt'};
end

if (exp == 3 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt
    %BRZ: 4th_AMVIC_INPE_Test_3_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test31_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST31.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt',
'4th_AMVIC_INPE_Test_3_final.txt', '', 'ASCII_AMV-
4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test31_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST31.txt'};
end

if (exp == 4 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt
    %BRZ: 4th_AMVIC_INPE_Test_4_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test41_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST41.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt',
'4th_AMVIC_INPE_Test_4_final.txt', '', 'ASCII_AMV-
4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test41_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST41.txt'};
end


fsym= {'y.' ,  'r.' , 'k.' , 'b.' , 'g.' , 'm.' };

% Read and sort by EUM speed

set_eum_temp=dlmread([indir,fall{1}],',',0,0);
set_eum=sortrows(set_eum_temp,6);

%set_eum=dlmread([indir,fall{1}],',',0,0);
set_brz=dlmread([indir,fall{2}],',',0,0);
set_jma=dlmread([indir,fall{3}],',',0,0);
set_noa=dlmread([indir,fall{4}],',',0,0);
set_kma=dlmread([indir,fall{5}],',',0,0);
set_nwc=dlmread([indir,fall{6}],',',0,0);
```

```
qivar=[];
qivar=find(set_eum(:,qitype)>=qi);
set_eum=set_eum(qivar,:);

qivar=[];
qivar=find(set_kma(:,qitype)>=qi);
set_kma=set_kma(qivar,:);

qivar=[];
qivar=find(set_brz(:,qitype)>=qi);
set_brz=set_brz(qivar,:);

qivar=[];
qivar=find(set_noa(:,qitype)>=qi);
set_noa=set_noa(qivar,:);

qivar=[];
qivar=find(set_nwc(:,qitype)>=qi);
set_nwc=set_nwc(qivar,:);

qivar=[];
qivar=find(set_jma(:,qitype)>=qi);
set_jma=set_jma(qivar,:);

i_out=0;

for i_amv=1:length(set_eum(:,1))
%   disp(i_amv)

    [val1, loc1]=min( deg2km(distance(set_nwc(:,2), set_nwc(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

    if val1 < dist

            [val2, loc2]=min( deg2km(distance(set_brz(:,2), set_brz(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

            if val2 < dist

                [val3, loc3]=min( deg2km(distance(set_jma(:,2), set_jma(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                if val3 < dist

                    [val4, loc4]=min( deg2km(distance(set_noa(:,2),
set_noa(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                    if val4 < dist

                        [val5, loc5]=min( deg2km(distance(set_kma(:,2),
set_kma(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                        if val5 < dist

                    i_out=i_out+1;
                    set_out_lat(i_out,:) =[ set_jma(loc3,02) set_kma(loc5,02)
set_noa(loc4,02) set_eum(i_amv,02) set_brz(loc2,02) set_nwc(loc1,02) ];
                    set_out_lon(i_out,:) =[ set_jma(loc3,03) set_kma(loc5,03)
set_noa(loc4,03) set_eum(i_amv,03) set_brz(loc2,03) set_nwc(loc1,03) ];
                    set_out_spd(i_out,:) =[ set_jma(loc3,06) set_kma(loc5,06)
```

```
set_noa(loc4,06)  set_eum(i_amv,06) set_brz(loc2,06) set_nwc(loc1,06) ];
                    set_out_dir(i_out,:) =[ set_jma(loc3,07) set_kma(loc5,07)
set_noa(loc4,07)  set_eum(i_amv,07) set_brz(loc2,07) set_nwc(loc1,07) ];
                    set_out_pres(i_out,:)=[ set_jma(loc3,08) set_kma(loc5,08)
set_noa(loc4,08)  set_eum(i_amv,08) set_brz(loc2,08) set_nwc(loc1,08) ];
                    set_out_ham(i_out,:) =[ set_jma(loc3,16) set_kma(loc5,16)
set_noa(loc4,16)  set_eum(i_amv,16) set_brz(loc2,16) set_nwc(loc1,16) ];
                    set_out_qi(i_out,:)  =[ set_jma(loc3,qitype)
set_kma(loc5,qitype) set_noa(loc4,qitype)  set_eum(i_amv,qitype)
set_brz(loc2,qitype) set_nwc(loc1,qitype) ];

                    co_eum(i_out,:) = set_eum(i_amv,:);
                    co_kma(i_out,:) = set_kma(loc5,:);
                    co_brz(i_out,:) = set_brz(loc2,:);
                    co_noa(i_out,:) = set_noa(loc4,:);
                    co_nwc(i_out,:) = set_nwc(loc1,:);
                    co_jma(i_out,:) = set_jma(loc3,:);

                    end;
                end;
            end;
        end
    end;
end;



disp('**************');
disp(i_out);

figure;
set(gcf, 'visible', 'off')
x=1:i_out;
subplot(4,1,1);
plot(x,set_out_spd(:,1),fsym{1},x,set_out_spd(:,2),fsym{2},x,
set_out_spd(:,3),fsym{3},x,set_out_spd(:,4),fsym{4},x,set_out_spd(:,5),fsym{5},
x, set_out_spd(:,6), fsym{6} );
lngd=legend({'JMA', 'KMA', 'NOA', 'EUM', 'BRZ',
'NWC'},'Position',[0.86,0.86,0.1,0.1]);
subplot(4,1,2);
plot(x,set_out_dir(:,1),fsym{1},x,set_out_dir(:,2),fsym{2},x,
set_out_dir(:,3),fsym{3},x,set_out_dir(:,4),fsym{4},x,set_out_dir(:,5),fsym{5},
x, set_out_dir(:,6),fsym{6} );
subplot(4,1,3);
plot(x,set_out_pres(:,1),fsym{1},x,set_out_pres(:,2),fsym{2},x,
set_out_pres(:,3),fsym{3},x,set_out_pres(:,4),fsym{4},x,set_out_pres(:,5),fsym{
5},x, set_out_pres(:,6),fsym{6} );
subplot(4,1,4);
plot(x,set_out_qi(:,1),fsym{1},x,set_out_qi(:,2),fsym{2},x,
set_out_qi(:,3),fsym{3},x,set_out_qi(:,4),fsym{4},x,set_out_qi(:,5),fsym{5},x,s
et_out_qi(:,6),fsym{6} );

char_qi=sprintf('%i',qi);
char_exp=sprintf('%i',exp);

saveas(gcf,['Exp_' char_exp '_Match_EUM_' char_qitype '_' char_qi ],'tif');
save(['Exp_' char_exp '_conf_eum_' char_qitype '_' char_qi '.txt'], 'co_eum',
'-ascii');
save(['Exp_' char_exp '_conf_kma_' char_qitype '_' char_qi '.txt'], 'co_kma',
'-ascii');
save(['Exp_' char_exp '_conf_brz_' char_qitype '_' char_qi '.txt'], 'co_brz',
```

```
'-ascii');
save(['Exp_' char_exp '_conf_noa_' char_qitype '_' char_qi '.txt'], 'co_noa',
'-ascii');
save(['Exp_' char_exp '_conf_nwc_' char_qitype '_' char_qi '.txt'], 'co_nwc',
'-ascii');
save(['Exp_' char_exp '_conf_jma_' char_qitype '_' char_qi '.txt'], 'co_jma',
'-ascii');

figure;
set(gcf, 'visible', 'off')
plot(set_out_pres(:,4),set_out_pres(:,1),'y.',set_out_pres(:,4),set_out_pres(:,
2),'r.',set_out_pres(:,4), set_out_pres(:,3),'k.',set_out_pres(:,4),
set_out_pres(:,5),'g.', set_out_pres(:,4), set_out_pres(:,6),'m.');
names= {'EUM vs JMA','EUM vs KMA',' EUM vs NOA','EUM vs BRZ','EUM vs NWC'};
label(1)=names(1);
label(2)=names(2);
label(3)=names(3);
label(4)=names(4);
label(5)=names(5);
legend(gca,label(:),'FontSize',5,'FontWeight','bold','Location','NortheastOutsi
de');
xlabel('Pressure (EUM)');
ylabel('Pressure (Centres)');
title('Scatter Plot of AMV Pressure');

saveas(gcf,['Exp_' char_exp '_Match_EUM_pres_scat_' char_qitype '_' char_qi
],'tif');

%figure;
%set(gcf, 'visible', 'off')
%plot(x,abs(max(set_out_pres')-min(set_out_pres')),'.');
%xlabel('AMV Number');
%ylabel('Pressure difference');
%title('Maximum Pressure difference');

%if ( exp == 1)
%   saveas(gcf,'Exp_21_CQI_pres_hist.tif','tif');
%end

%if ( exp == 2)
%   saveas(gcf,'Exp_22_CQI_pres_hist.tif','tif');
%end

%if ( exp == 3)
%   saveas(gcf,'Exp_52_CQI_pres_hist.tif','tif');
%end

%if ( exp == 4)
%   saveas(gcf,'Exp_4_CQI_pres_hist.tif','tif');
%end

set_out_names = {'Japan', 'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF'}
set_out_spd1 = [set_out_spd(:,1), set_out_spd(:,2), set_out_spd(:,3),
set_out_spd(:,4), set_out_spd(:,5), set_out_spd(:,6),
((set_out_spd(:,4)+set_out_spd(:,2))/2)];
fall1 = {'Japan', 'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF','Correct'};

outflnm=sprintf('Exp_%i_Match_%s_%i_statsout.txt',exp, char_qitype, qi);
fid=fopen(outflnm,'w');

for i=1:5
```

```
    for n=i:5
        fprintf(fid,'%s "VS" %s \n', set_out_names{i}, set_out_names{n+1});
        [h,p,ci,stats]=ttest(set_out_spd(:,i),set_out_spd(:,n+1));
        fprintf(fid,'  Speed:     h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_dir(:,i),set_out_dir(:,n+1));
        fprintf(fid,'  Direction: h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_pres(:,i),set_out_pres(:,n+1));
        fprintf(fid,'  Pressure:  h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_qi(:,i),set_out_qi(:,n+1));
        fprintf(fid,'  QI:        h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
    end;
end;
fprintf('\n')
%
%
%"Correct" Speed Comparison
for i=1:6
    fprintf(fid,'%s %s \n', 'Speed Correct VS.', fall1{i});
    [h,p,ci,stats]=ttest(set_out_spd1(:,7),set_out_spd1(:,i));
    fprintf(fid,'Speed "Correct": h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), mean(set_out_spd1(:,7)-set_out_spd1(:,i)));
end;
fclose(fid);
close(figure(1:3))
 success='yes';
```

Winds_Match_EUM_noJMA.m

```
function success = Winds_Match_EUM_noJMA(exp,inpd,char_qitype,dist,qi)
% collocaton of the cgms study datastes - search for a spatial match
% within less than a specified distance
% make sure to organize set_out by own configuration target box size from
smallest to largest
% no JMA since they didn't do exp 3 and 4

%clear;
indir=sprintf('%s',inpd)

if ( char_qitype == "QINF" )
        qitype=17
end

if ( char_qitype == "CQI" )
        qitype=19
end

if (exp == 3 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt
    %BRZ: 4th_AMVIC_INPE_Test_3_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test31_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST31.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt',
'4th_AMVIC_INPE_Test_3_final.txt', 'ASCII_AMV-
4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test31_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST31.txt'};
end

if (exp == 4 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt
    %BRZ: 4th_AMVIC_INPE_Test_4_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test41_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST41.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt',
'4th_AMVIC_INPE_Test_4_final.txt', 'ASCII_AMV-
4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test41_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST41.txt'};
end

fsym= {'r.' ,  'k.' , 'b.' , 'g.' , 'm.' };

% Read and sort by EUM speed

set_eum_temp=dlmread([indir,fall{1}],',',0,0);
set_eum=sortrows(set_eum_temp,6);

%set_eum=dlmread([indir,fall{1}],',',0,0);
set_brz=dlmread([indir,fall{2}],',',0,0);
set_noa=dlmread([indir,fall{3}],',',0,0);
```

```
set_kma=dlmread([indir,fall{4}],',',0,0);
set_nwc=dlmread([indir,fall{5}],',',0,0);

qivar=[];
qivar=find(set_eum(:,qitype)>=qi);
set_eum=set_eum(qivar,:);

qivar=[];
qivar=find(set_kma(:,qitype)>=qi);
set_kma=set_kma(qivar,:);

qivar=[];
qivar=find(set_brz(:,qitype)>=qi);
set_brz=set_brz(qivar,:);

qivar=[];
qivar=find(set_noa(:,qitype)>=qi);
set_noa=set_noa(qivar,:);

qivar=[];
qivar=find(set_nwc(:,qitype)>=qi);
set_nwc=set_nwc(qivar,:);

i_out=0;

for i_amv=1:length(set_eum(:,1))
%   disp(i_amv)

    [val1, loc1]=min( deg2km(distance(set_nwc(:,2), set_nwc(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

    if val1 < dist

            [val2, loc2]=min( deg2km(distance(set_brz(:,2), set_brz(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

            if val2 < dist

                    [val4, loc4]=min( deg2km(distance(set_noa(:,2),
set_noa(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                    if val4 < dist

                        [val5, loc5]=min( deg2km(distance(set_kma(:,2),
set_kma(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                        if val5 < dist

                    i_out=i_out+1;
                    set_out_lat(i_out,:) =[ set_kma(loc5,02) set_noa(loc4,02)
set_eum(i_amv,02) set_brz(loc2,02) set_nwc(loc1,02) ];
                    set_out_lon(i_out,:) =[ set_kma(loc5,03) set_noa(loc4,03)
set_eum(i_amv,03) set_brz(loc2,03) set_nwc(loc1,03) ];
                    set_out_spd(i_out,:) =[ set_kma(loc5,06) set_noa(loc4,06)
set_eum(i_amv,06) set_brz(loc2,06) set_nwc(loc1,06) ];
                    set_out_dir(i_out,:) =[ set_kma(loc5,07) set_noa(loc4,07)
set_eum(i_amv,07) set_brz(loc2,07) set_nwc(loc1,07) ];
                    set_out_pres(i_out,:)=[ set_kma(loc5,08) set_noa(loc4,08)
set_eum(i_amv,08) set_brz(loc2,08) set_nwc(loc1,08) ];
                    set_out_ham(i_out,:) =[ set_kma(loc5,16) set_noa(loc4,16)
set_eum(i_amv,16) set_brz(loc2,16) set_nwc(loc1,16) ];
```

```
                    set_out_qi(i_out,:)  =[ set_kma(loc5,qitype)
set_noa(loc4,qitype)  set_eum(i_amv,qitype) set_brz(loc2,qitype)
set_nwc(loc1,qitype) ];

                    co_eum(i_out,:) = set_eum(i_amv,:);
                    co_kma(i_out,:) = set_kma(loc5,:);
                    co_brz(i_out,:) = set_brz(loc2,:);
                    co_noa(i_out,:) = set_noa(loc4,:);
                    co_nwc(i_out,:) = set_nwc(loc1,:);

                    end;
            end;
        end
    end;
end;



disp('**************');
disp(i_out);

set_out_spd(:,3)

figure;
set(gcf, 'visible', 'off')
x=1:i_out;
subplot(4,1,1);
plot(x,set_out_spd(:,1),fsym{1},x,set_out_spd(:,2),fsym{2},x,
set_out_spd(:,3),fsym{3},x,set_out_spd(:,4),fsym{4},x,set_out_spd(:,5),fsym{5}
);
lngd=legend({'KMA', 'NOA', 'EUM', 'BRZ',
'NWC'},'Position',[0.86,0.86,0.1,0.1]);
subplot(4,1,2);
plot(x,set_out_dir(:,1),fsym{1},x,set_out_dir(:,2),fsym{2},x,
set_out_dir(:,3),fsym{3},x,set_out_dir(:,4),fsym{4},x,set_out_dir(:,5),fsym{5}
);
subplot(4,1,3);
plot(x,set_out_pres(:,1),fsym{1},x,set_out_pres(:,2),fsym{2},x,
set_out_pres(:,3),fsym{3},x,set_out_pres(:,4),fsym{4},x,set_out_pres(:,5),fsym{
5} );
subplot(4,1,4);
plot(x,set_out_qi(:,1),fsym{1},x,set_out_qi(:,2),fsym{2},x,
set_out_qi(:,3),fsym{3},x,set_out_qi(:,4),fsym{4},x,set_out_qi(:,5),fsym{5} );

char_qi=sprintf('%i',qi);
char_exp=sprintf('%i',exp);

saveas(gcf,['Exp_' char_exp '_Match_EUM_' char_qitype '_' char_qi ],'tif');
save(['Exp_' char_exp '_conf_eum_' char_qitype '_' char_qi '.txt'], 'co_eum',
'-ascii');
save(['Exp_' char_exp '_conf_kma_' char_qitype '_' char_qi '.txt'], 'co_kma',
'-ascii');
save(['Exp_' char_exp '_conf_brz_' char_qitype '_' char_qi '.txt'], 'co_brz',
'-ascii');
save(['Exp_' char_exp '_conf_noa_' char_qitype '_' char_qi '.txt'], 'co_noa',
'-ascii');
save(['Exp_' char_exp '_conf_nwc_' char_qitype '_' char_qi '.txt'], 'co_nwc',
'-ascii');

figure;
set(gcf, 'visible', 'off')
```

```
plot(set_out_pres(:,3),set_out_pres(:,1),'r.',set_out_pres(:,3),set_out_pres(:,
2),'k.',set_out_pres(:,3), set_out_pres(:,4),'g.',set_out_pres(:,3),
set_out_pres(:,5),'m.');
names= {'EUM vs KMA',' EUM vs NOA','EUM vs BRZ','EUM vs NWC'};
label(1)=names(1);
label(2)=names(2);
label(3)=names(3);
label(4)=names(4);
legend(gca,label(:),'FontSize',5,'FontWeight','bold','Location','NortheastOutsi
de');
xlabel('Pressure (EUM)');
ylabel('Pressure (Centres)');
title('Scatter Plot of AMV Pressure');

saveas(gcf,['Exp_' char_exp '_Match_EUM_pres_scat_' char_qitype '_' char_qi
],'tif');

%figure;
%set(gcf, 'visible', 'off')
%plot(x,abs(max(set_out_pres')-min(set_out_pres')),'.');
%xlabel('AMV Number');
%ylabel('Pressure difference');
%title('Maximum Pressure difference');

%if ( exp == 1)
%   saveas(gcf,'Exp_21_CQI_pres_hist.tif','tif');
%end

%if ( exp == 2)
%   saveas(gcf,'Exp_22_CQI_pres_hist.tif','tif');
%end

%if ( exp == 3)
%   saveas(gcf,'Exp_52_CQI_pres_hist.tif','tif');
%end

%if ( exp == 4)
%   saveas(gcf,'Exp_4_CQI_pres_hist.tif','tif');
%end

set_out_names = {'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF'}
set_out_spd1 = [set_out_spd(:,1), set_out_spd(:,2), set_out_spd(:,3),
set_out_spd(:,4), set_out_spd(:,5), ((set_out_spd(:,4)+set_out_spd(:,2))/2)];
fall1 = {'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF','Correct'};

outflnm=sprintf('Exp_%i_Match_%s_%i_statsout.txt',exp, char_qitype, qi);
fid=fopen(outflnm,'w');

for i=1:4
    for n=i:4
        fprintf(fid,'%s "VS" %s \n', set_out_names{i}, set_out_names{n+1});
        [h,p,ci,stats]=ttest(set_out_spd(:,i),set_out_spd(:,n+1));
        fprintf(fid,'  Speed:     h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_dir(:,i),set_out_dir(:,n+1));
        fprintf(fid,'  Direction: h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_pres(:,i),set_out_pres(:,n+1));
        fprintf(fid,'  Pressure:  h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_qi(:,i),set_out_qi(:,n+1));
```

```
        fprintf(fid,'  QI:        h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
    end;
end;
fprintf('\n')
%
%
%"Correct" Speed Comparison
%for i=1:5
%    fprintf(fid,'%s %s \n', 'Speed Correct VS.', fall1{i});
%    [h,p,ci,stats]=ttest(set_out_spd1(:,7),set_out_spd1(:,i));
%    fprintf(fid,'Speed "Correct": h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), mean(set_out_spd1(:,7)-set_out_spd1(:,i)));
%end;
fclose(fid);
close(figure(1:3))
 success='yes';
```

Winds_Match_NWCref_noJMA.m

```
function success = Winds_Match_NWCref_noJMA(exp,inpd,char_qitype,dist,qi)
% collocaton of the cgms study datastes - search for a spatial match
% within less than a specified distance
% make sure to organize set_out by own configuration target box size from
smallest to largest
% no JMA since they didn't do exp 3 and 4

%clear;
indir=sprintf('%s',inpd)

if ( char_qitype == "QINF" )
        qitype=17
end

if ( char_qitype == "CQI" )
        qitype=19
end

if (exp == 3 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt
    %BRZ: 4th_AMVIC_INPE_Test_3_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test31_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST31.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test31.txt',
'4th_AMVIC_INPE_Test_3_final.txt', 'ASCII_AMV-
4thInt_TEST3.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test31_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST31.txt'};
end

if (exp == 4 )
    %EUM: AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt
    %BRZ: 4th_AMVIC_INPE_Test_4_final.txt
    %JMA: n/a
    %NOA: ASCII_AMV-4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS
    %KMA: KMA_test41_goes16_abi_ch08_amv_201910201130.asc
    %NWC: INTERCOMP2021_NWCSAFTEST41.txt
    fall= {'AMVIntm_Chan08_20191020113000Z_GOES_ASCII_Test41.txt',
'4th_AMVIC_INPE_Test_4_final.txt', 'ASCII_AMV-
4thInt_TEST4.GOES16.2019293.1130.CH_08.FD.CS' ,
'KMA_test41_goes16_abi_ch08_amv_201910201130.asc',
'INTERCOMP2021_NWCSAFTEST41.txt'};
end

fsym= {'r.' ,  'k.' , 'b.' , 'g.' , 'm.' };

% Read and sort by EUM speed

set_eum_temp=dlmread([indir,fall{1}],',',0,0);
set_eum=sortrows(set_eum_temp,6);

%set_eum=dlmread([indir,fall{1}],',',0,0);
set_brz=dlmread([indir,fall{2}],',',0,0);
set_noa=dlmread([indir,fall{3}],',',0,0);
```

```
set_kma=dlmread([indir,fall{4}],',',0,0);
set_nwc=dlmread([indir,fall{5}],',',0,0);

qivar=[];
qivar=find(set_eum(:,qitype)>=qi);
set_eum=set_eum(qivar,:);

qivar=[];
qivar=find(set_kma(:,qitype)>=qi);
set_kma=set_kma(qivar,:);

qivar=[];
qivar=find(set_brz(:,qitype)>=qi);
set_brz=set_brz(qivar,:);

qivar=[];
qivar=find(set_noa(:,qitype)>=qi);
set_noa=set_noa(qivar,:);

qivar=[];
qivar=find(set_nwc(:,qitype)>=qi);
set_nwc=set_nwc(qivar,:);

i_out=0;

for i_amv=1:length(set_eum(:,1))
%   disp(i_amv)

    [val1, loc1]=min( deg2km(distance(set_nwc(:,2), set_nwc(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

    if val1 < dist

            [val2, loc2]=min( deg2km(distance(set_brz(:,2), set_brz(:,3),
set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

            if val2 < dist

                    [val4, loc4]=min( deg2km(distance(set_noa(:,2),
set_noa(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                    if val4 < dist

                        [val5, loc5]=min( deg2km(distance(set_kma(:,2),
set_kma(:,3), set_eum(i_amv,2), set_eum(i_amv,3)))); % lat/lon metrics

                        if val5 < dist

                    i_out=i_out+1;
                    set_out_lat(i_out,:) =[ set_kma(loc5,02) set_noa(loc4,02)
set_eum(i_amv,02) set_brz(loc2,02) set_nwc(loc1,02) ];
                    set_out_lon(i_out,:) =[ set_kma(loc5,03) set_noa(loc4,03)
set_eum(i_amv,03) set_brz(loc2,03) set_nwc(loc1,03) ];
                    set_out_spd(i_out,:) =[ set_kma(loc5,06) set_noa(loc4,06)
set_eum(i_amv,06) set_brz(loc2,06) set_nwc(loc1,06) ];
                    set_out_dir(i_out,:) =[ set_kma(loc5,07) set_noa(loc4,07)
set_eum(i_amv,07) set_brz(loc2,07) set_nwc(loc1,07) ];
                    set_out_pres(i_out,:)=[ set_kma(loc5,08) set_noa(loc4,08)
set_eum(i_amv,08) set_brz(loc2,08) set_nwc(loc1,08) ];
                    set_out_ham(i_out,:) =[ set_kma(loc5,16) set_noa(loc4,16)
set_eum(i_amv,16) set_brz(loc2,16) set_nwc(loc1,16) ];
```

```
                    set_out_qi(i_out,:)  =[ set_kma(loc5,qitype)
set_noa(loc4,qitype)  set_eum(i_amv,qitype) set_brz(loc2,qitype)
set_nwc(loc1,qitype) ];

                    co_eum(i_out,:) = set_eum(i_amv,:);
                    co_kma(i_out,:) = set_kma(loc5,:);
                    co_brz(i_out,:) = set_brz(loc2,:);
                    co_noa(i_out,:) = set_noa(loc4,:);
                    co_nwc(i_out,:) = set_nwc(loc1,:);

                    end;
            end;
        end
    end;
end;



disp('**************');
disp(i_out);

set_out_spd(:,3)

figure;
set(gcf, 'visible', 'off')
x=1:i_out;
subplot(4,1,1);
plot(x,set_out_spd(:,1),fsym{1},x,set_out_spd(:,2),fsym{2},x,
set_out_spd(:,3),fsym{3},x,set_out_spd(:,4),fsym{4},x,set_out_spd(:,5),fsym{5}
);
lngd=legend({'KMA', 'NOA', 'EUM', 'BRZ',
'NWC'},'Position',[0.86,0.86,0.1,0.1]);
subplot(4,1,2);
plot(x,set_out_dir(:,1),fsym{1},x,set_out_dir(:,2),fsym{2},x,
set_out_dir(:,3),fsym{3},x,set_out_dir(:,4),fsym{4},x,set_out_dir(:,5),fsym{5}
);
subplot(4,1,3);
plot(x,set_out_pres(:,1),fsym{1},x,set_out_pres(:,2),fsym{2},x,
set_out_pres(:,3),fsym{3},x,set_out_pres(:,4),fsym{4},x,set_out_pres(:,5),fsym{
5} );
subplot(4,1,4);
plot(x,set_out_qi(:,1),fsym{1},x,set_out_qi(:,2),fsym{2},x,
set_out_qi(:,3),fsym{3},x,set_out_qi(:,4),fsym{4},x,set_out_qi(:,5),fsym{5} );

char_qi=sprintf('%i',qi);
char_exp=sprintf('%i',exp);

saveas(gcf,['Exp_' char_exp '_Match_EUM_' char_qitype '_' char_qi ],'tif');
save(['Exp_' char_exp '_conf_eum_' char_qitype '_' char_qi '.txt'], 'co_eum',
'-ascii');
save(['Exp_' char_exp '_conf_kma_' char_qitype '_' char_qi '.txt'], 'co_kma',
'-ascii');
save(['Exp_' char_exp '_conf_brz_' char_qitype '_' char_qi '.txt'], 'co_brz',
'-ascii');
save(['Exp_' char_exp '_conf_noa_' char_qitype '_' char_qi '.txt'], 'co_noa',
'-ascii');
save(['Exp_' char_exp '_conf_nwc_' char_qitype '_' char_qi '.txt'], 'co_nwc',
'-ascii');

figure;
set(gcf, 'visible', 'off')
```

```
plot(set_out_pres(:,5),set_out_pres(:,1),'r.',set_out_pres(:,5),set_out_pres(:,
2),'k.',set_out_pres(:,5), set_out_pres(:,4),'g.',set_out_pres(:,5),
set_out_pres(:,3),'m.');
names= {'NWC vs KMA',' NWC vs NOA','NWC vs BRZ','NWC vs EUM'};
label(1)=names(1);
label(2)=names(2);
label(3)=names(3);
label(4)=names(4);
legend(gca,label(:),'FontSize',5,'FontWeight','bold','Location','NortheastOutsi
de');
xlabel('Pressure (NWC)');
ylabel('Pressure (Centres)');
title('Scatter Plot of AMV Pressure');

saveas(gcf,['Exp_' char_exp '_Match_NWC_pres_scat_' char_qitype '_' char_qi
],'tif');

%figure;
%set(gcf, 'visible', 'off')
%plot(x,abs(max(set_out_pres')-min(set_out_pres')),'.');
%xlabel('AMV Number');
%ylabel('Pressure difference');
%title('Maximum Pressure difference');

%if ( exp == 1)
%   saveas(gcf,'Exp_21_CQI_pres_hist.tif','tif');
%end

%if ( exp == 2)
%   saveas(gcf,'Exp_22_CQI_pres_hist.tif','tif');
%end

%if ( exp == 3)
%   saveas(gcf,'Exp_52_CQI_pres_hist.tif','tif');
%end

%if ( exp == 4)
%   saveas(gcf,'Exp_4_CQI_pres_hist.tif','tif');
%end

set_out_names = {'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF'}
set_out_spd1 = [set_out_spd(:,1), set_out_spd(:,2), set_out_spd(:,3),
set_out_spd(:,4), set_out_spd(:,5), ((set_out_spd(:,4)+set_out_spd(:,2))/2)];
fall1 = {'Korea', 'NOAA', 'EUMETSAT', 'Brazil', 'NWCSAF','Correct'};

outflnm=sprintf('Exp_%i_Match_%s_%i_statsout.txt',exp, char_qitype, qi);
fid=fopen(outflnm,'w');

for i=1:4
    for n=i:4
        fprintf(fid,'%s "VS" %s \n', set_out_names{i}, set_out_names{n+1});
        [h,p,ci,stats]=ttest(set_out_spd(:,i),set_out_spd(:,n+1));
        fprintf(fid,'  Speed:     h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_dir(:,i),set_out_dir(:,n+1));
        fprintf(fid,'  Direction: h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_pres(:,i),set_out_pres(:,n+1));
        fprintf(fid,'  Pressure:  h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f
\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
        [h,p,ci,stats]=ttest(set_out_qi(:,i),set_out_qi(:,n+1));
```

```
        fprintf(fid,'  QI:        h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f 
\n\n', h, p, ci(1), ci(2), (ci(1)+ci(2))/2);
    end;
end;
fprintf('\n')
%
%
%"Correct" Speed Comparison
%for i=1:5
%    fprintf(fid,'%s %s \n', 'Speed Correct VS.', fall1{i});
%    [h,p,ci,stats]=ttest(set_out_spd1(:,7),set_out_spd1(:,i));
%    fprintf(fid,'Speed "Correct": h = %d, p = %.2f, ci = %.2f %.2f, Mean: %.2f 
\n', h, p, ci(1), ci(2), mean(set_out_spd1(:,7)-set_out_spd1(:,i)));
%end;
fclose(fid);
close(figure(1:3))
 success='yes';
```

raobdiff_exp1_norm.m

```
format long
warning off MATLAB:divideByZero;
clear figure;
clear z;
clear y;
clear r;

%fin=fopen('/Users/daves/Desktop/Intercomparison/RAOB/inputfile');
fin=fopen('/home/rdworak/Intercomp/scr/inputfile');
inputfile=fgetl(fin)

%y=load(inputfile);

%z=load('/home/rdworak/Intercomp/RAOBs/convraob.txt');
z=dlmread('/home/rdworak/Intercomp/RAOBs/convraob_cor20191020_12UTC.txt','',1,0
);
%convert sign of lon for raobs to Mcidas notation + west, - east
%z(:,2)=z(:,2)*-1;
distthres=150;
%qithres=50;
%qithres=80;

for qithres=50:30:80

clear r;

    %for qitype=17:1:19
    for qitype=19
           raobspdtot=0;
           y=dlmread(inputfile,',',1,0);
       % Ensure longitudes are +/-180
            atemplon=find(y(:,3) > 180);
            y(atemplon,3)=y(atemplon,3)-360;

       %y=dlmread(inputfile,'');
    %qitype=19
%y=y(find(y(:,19) >= qithres), :); %For CQI
%y=y(find(y(:,18) >= qithres), :); %For QIF
%y=y(find(y(:,17) >= qithres), :);  %For QINF
y=y(find(y(:,qitype) >= qithres), :);


k=0;
r=zeros(k,9);
sz=size(z,1);
sy=size(y,1);
for j=1:sy
    pdiffmin=100;
    for i=1:sz
        latdis=111*abs(z(i,1)-y(j,2));
        if latdis<=distthres
            angle=abs(cos(deg2rad(z(i,1))));
            londif=abs(z(i,2)-y(j,3));
            if londif<=180
                londis=londif*angle*111;
            else
                londis=(360-londif)*angle*111;
```

```
            end
            disp =sqrt(latdis^2+londis^2);
                if disp<=distthres
                   pdiff=y(j,8)-z(i,3);
                    if abs(pdiff)<=abs(pdiffmin)
                        %Include RAOB Sanity Check
                        %if (z(i,3)>=200 && z(i,3)<=1000) && (z(i,5)>=0 &&
z(i,5)<=360) && (z(i,6)>0 && z(i,6)<=200)
                       % if (z(i,3)>=700)
                        tdiff=0;
                        ddiff=abs(y(j,7)-z(i,5));
                        if ddiff>180
                            ddiff=360-ddiff;
                            if z(i,5)<y(j,7)
                                ddiff=-1*ddiff;
                            end
                        else
                            if z(i,5)>y(j,7)
                                ddiff=-1*ddiff;
                            end
                        end
                        mdiff=(y(j,6))-(z(i,6));
                        su=y(j,6)*sin(deg2rad(y(j,7)));
                        sv=y(j,6)*cos(deg2rad(y(j,7)));
                        ru=z(i,6)*sin(deg2rad(z(i,5)));
                        rv=z(i,6)*cos(deg2rad(z(i,5)));
                        UD=su-ru;
                        VD=sv-rv;
                        vdiff=sqrt(UD^2+VD^2);
                        pdiffmin=pdiff;
                        c=i;
                    raobspd=z(i,6);

                   % end
                end
                  end
              end
          end
          if abs(pdiffmin)<=50
              k=k+1;
             raobspdtot=raobspd+raobspdtot;
              r(k,1)=pdiffmin;
              r(k,2)=tdiff;
              r(k,3)=ddiff;
              r(k,4)=mdiff;
              r(k,5)=vdiff;
              r(k,6)=UD;
              r(k,7)=VD;
              r(k,8)=c;
              r(k,9)=j;
          end
      end


r;
k
avgrspd=raobspdtot/k
pbias=sum(r(:,1))/k
tbias=sum(r(:,2))/k
dbias=sum(r(:,3))/k
mbias=sum(r(:,4))/k
```

```
vbias=sqrt((sum(r(:,6))/k)^2+(sum(r(:,7))/k)^2)

prms=sqrt((sum((r(:,1).^2)))/k)
trms=sqrt((sum((r(:,2).^2)))/k)
drms=sqrt((sum((r(:,3).^2)))/k)
mrms=sqrt((sum((r(:,4).^2)))/k)
vrms=sqrt((sqrt(sum((r(:,6)).^2)/k))^2+(sqrt(sum((r(:,7)).^2)/k))^2)
nvrms=vrms/avgrspd;

if (qithres==50)&&(qitype==17)
fid1 =
fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_50QINF_
McIcor_norm','a');
fprintf(fid1,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid1);
end

if (qithres==80)&&(qitype==17)
fid2=fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_80
QINF_McIcor_norm','a');
fprintf(fid2,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid2);
end


if (qithres==50)&&(qitype==18)
fid3=fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_50
QIF_McIcor_norm','a');
fprintf(fid3,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid3);
end

if (qithres==80)&&(qitype==18)
fid4=fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_80
QIF_McIcor_norm','a');
fprintf(fid4,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid4);
end

if (qithres==50)&&(qitype==19)
fid5=fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_50
CQI_McIcor_norm','a');
fprintf(fid5,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid5);
end

if (qithres==80)&&(qitype==19)
fid6=fopen('/data/rdworak/Intercomp/Output2021/Raobdiff/exp1/raob.output_ALL_80
CQI_McIcor_norm','a');
fprintf(fid6,'%40s, %9.0f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f, %9.2f
%9.2f\n',inputfile,k,pbias,prms,mbias,mrms,dbias,vrms,nvrms);
fclose(fid6);
end
    end
end
%
```

```
% fid = fopen('/home/sarahl/rms.output','a');
% fprintf(fid,'%9.0f %9.2f %9.2f %9.2f %9.2f
%9.2f\n',k,prms,trms,drms,mrms,vrms);
% fclose(fid);

%fid = fopen('/home/sarahl/diff.output','w');
%for h=1:k
%fprintf(fid,'%9.0f %9.0f %9.0f %9.2f %9.2f %9.2f %9.2f
%9.2f\n',h,r(h,8),r(h,9),r(h,1),r(h,2),r(h,3),r(h,4),r(h,5));
%end
%fclose(fid);


%
% fid = fopen('/home/sarahl/bias.output','a');
% fprintf(fid,'%9.0f %9.2f %9.2f %9.2f %9.2f\n',k,pbias,tbias,dbias,mbias);
% fclose(fid);
%
% fid = fopen('/home/sarahl/rms.output','a');
% fprintf(fid,'%9.0f %9.2f %9.2f %9.2f %9.2f\n',k,prms,trms,drms,mrms);
% fclose(fid);

% figure(1)
% bin=[-20:1:20];
% h1=histc(r(:,4),bin);
% bar(bin, h1,'histc');
% ylabel('Frequency');
% xlabel('Mag diff');
% title('Frequencey of mag diff of prediced winds within dist thres to closest
raob level');
```