Recent Advances in the Processing, Targeting and Data Assimilation Applications of Satellite-Derived Atmospheric Motion Vectors (AMVs)

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Abstract

Atmospheric Motion Vectors (AMVs) derived from geostationary environmental satellites have been a long-standing component of the global observational database available to NWP. With the advances in data assimilation and targeted observing techniques, numerical analysis and forecast model resolution, and computing capacity, it is prudent to explore ways to improve both the processing and applications of these datasets. Approaches to meet these objectives are being investigated by a team of researchers experienced in AMV production (CIMSS), and application/assimilation (NRL-MRY and RSMAS/Miami). On the production side, the focus is on improving the availability of high-quality wind information provided by enhanced AMV datasets. The enhancement comes in the form of 1) expanded vector quantities by increasing the temporal processing of the AMV datasets (i.e. hourly production), and exploring rapid-scanning strategies (i.e. 15-min and 4-min image sampling to produce higher resolution AMV fields); 2) testing continues with AMV quality flags (EE and QI) passed to the user and/or assimilation system for more effective application of the AMV information content; and 3) tests assigning each AMV a specified layer-height rather than a single level are underway to try and minimize some of the height assignment uncertainty inherent in AMV production.

AMVs datasets with the above attributes are being experimentally produced by CIMSS, and have been made available to NRL-MRY and other centers for applications in NWP impact studies and targeting approaches. This talk will describe the enhanced AMV datasets, and discuss the impact experiments that are underway. In particular, we will focus on processing and application strategies for selected meteorological events that occurred during the THORPEX-Pacific Asian Regional Campaign (TPARC).

Introduction

Both optimal production and assimilation of AMVs are crucial for positive numerical model impact. Good quality AMVs can significantly improve an NWP forecast. But as model analysis background fields improve, it is becoming more difficult to sustain this impact. To address this, AMV producers have been researching improved quality control procedures and indicators, as well as methods for understanding and mitigating known AMV height assignment errors. This paper will focus on recent research conducted at CIMSS, in conjunction with NOAA/NESDIS, on improving vector quality confidence flags, and investigations into treating AMV height assignments in term of tropospheric layers, rather than discreet levels. It will then describe data support and model impact experiments as part of the THORPEX Pacific Asian Regional Campaign (TPARC). It will conclude with future data impact experiment plans further connecting AMV production improvements and d data assimilation.

AMV Quality Confidence Indicators

Most operational AMV producers utilize the Quality Indicator (QI, Holmlund 1998) approach for their quality control post-processing step. A derivative of the QI is the Expected Error (EE, LeMarshall *et al.,* 2004), which has been adopted and modified at CIMSS to operate within NESDIS AMV processing. Each method has its strengths and weaknesses, and our study aims to combine the use of the two approaches in an optimal way in order to maximize AMV dataset quality passed on to the data assimilation user.

The Expected Error (EE) Quality Flag

The EE uses five QI vector/forecast tests along with other vector and model information to assign estimated values of vector root mean square error. The estimates are obtained by using an updated library of regressed past AMV datasets against collocated RAOB values, and their differences. The regression coefficients can then be used to predict real time AMV errors. The regression predictors are shown in table 1. In order to eliminate the rare negative EE that can be a symptom of simple regression, we perform a log-linear regression, which maintains the skill of the EE while eliminating the possibility of a physically-unreasonable EE value.

1) QI Speed Test
2) QI Direction Test
3) QI Vector Difference
4) QI Local Consistency Test
5) Qi Forecast Test
6) AMV Speed
7) Assigned Pressure Level
8) Wind Shear (200 hPa Above – 200 hPa below)
9) Temperature Gradient (200 hPa Above – 200 hPa below)

Table 1: **Expected Error predictors. The first 5 are part of the QI test suite, the 6th and 7th are AMV descriptors, and the 8th and 9th are taken from an NWP model and describe the ambient environment.**

The skill of the EE is shown in figure 1. Each point on the plot represents the RMS error between AMVs and RAOBs for all AMVs with EEs less than or equal to the values on the x-axis. The colors of the lines represent AMVs grouped by assigned pressures (hPa), with the blue curve showing the statistics for the full dataset. As the plot shows, the measured RMS errors decrease as the EE maximum decreases, with a skillful predictive relationship forming below about EE=6m^{-1}.

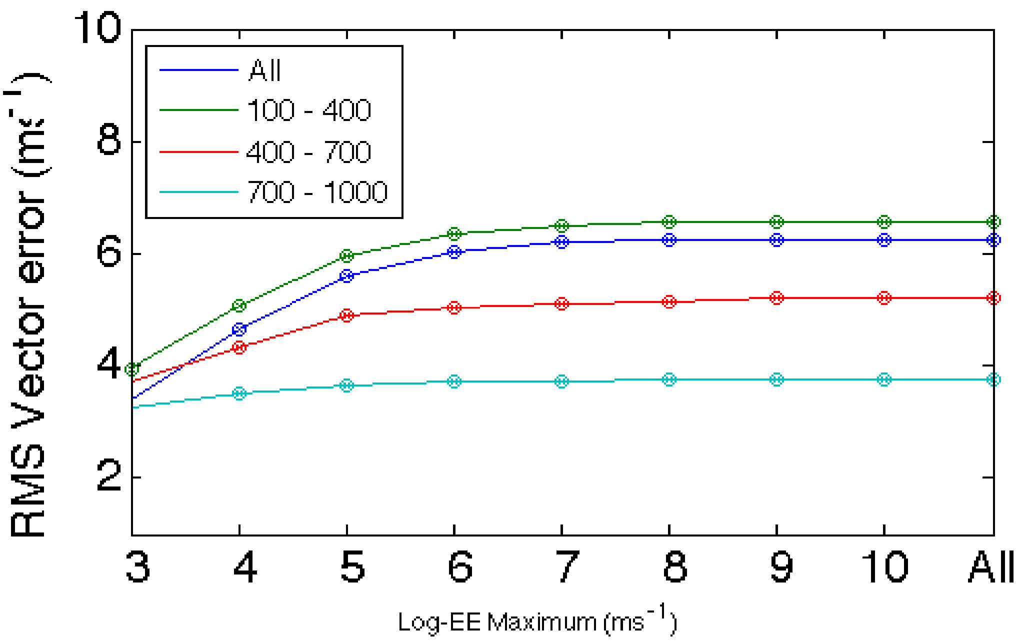

Figure 1: **Measured AMV – RAOB RMS error as a function of maximum Log-EE (predicted error). The colors represent the stats for various pressure levels (hPa). As the plots show, the errors decrease as the maximum log-EE threshold decreases.**

QI/EE Combination

Although the results of figure 1 are encouraging, the reduction in error comes at a cost: application of the EE alone reduces the number of AMVs compared to the QI, and eliminates more of the faster vectors. The QI, while not as strongly related to error as the EE, has the attribute of favoring coherent fast-moving AMVs. Thus, theoretically, smartly using the two schemes in combination could provide an optimal approach for AMV quality assessment and application. To test this, we implement a simple philosophy:

1) For slower AMVs, use a hard EE threshold for QC.
2) For faster AMVs, retain vectors that have high QI values regardless of their EE value.

Setting and optimizing these thresholds has been the goal of our recent work. To illustrate the impact on this scheme from several chosen thresholds, figure 2 shows the bias (y-axis), the RMSE (x-axis) and the average AMV speed (colored points) of various QI/Speed thresholds for a log-EE threshold maximum of 4.0. The two numbers near the plotted points are the QI and the minimal speed (ms^{-1}) thresholds. The points to the lower left show only AMVs with QIs of exactly 1.0 (highest quality) and with minimum speed thresholds shown. As one moves to the upper right in the figure, the QI is relaxed to 0.9, and it is shown by the average speed (color of points) that the QI retains more high-speed AMVs. This results in a smaller average vector bias and increases the average retained AMV speed (both good things), but also increases the average vector RMSE. The latter negative effect might be mitigated by optimizing the threshold used for EE in the combined approach. This is an area of further study.

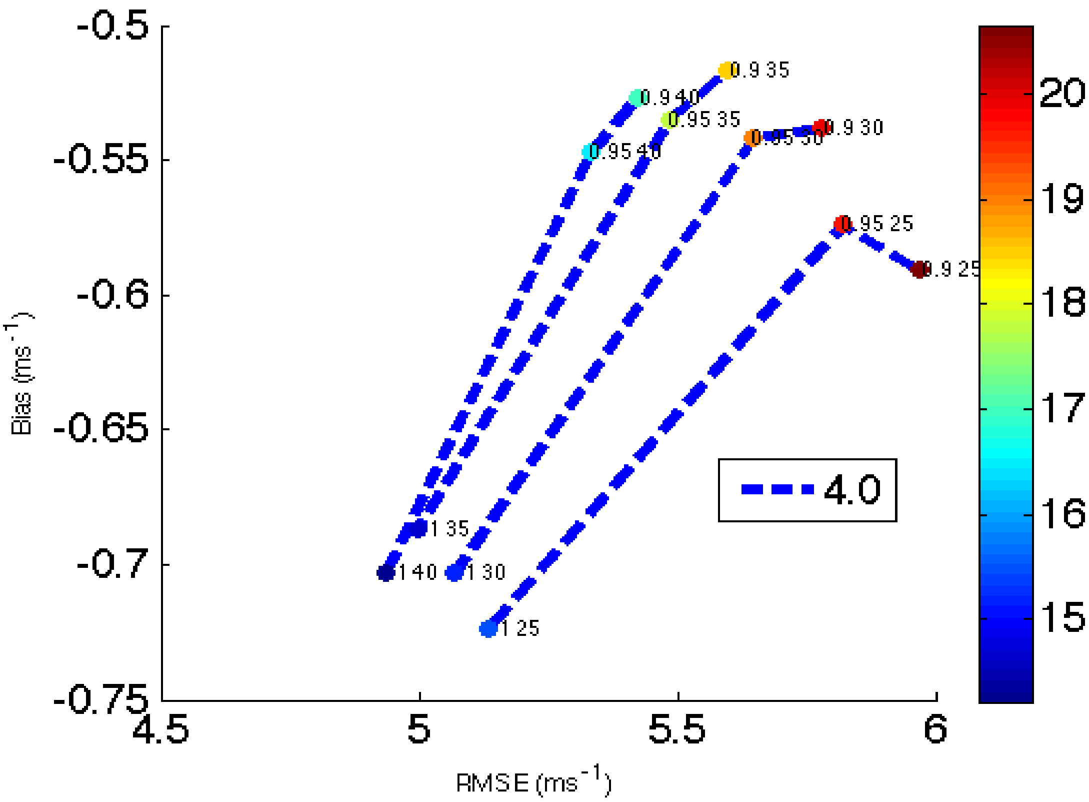

Figure 2: **AMV – RAOB Bias and RMSE for selected vector QI and speed thresholds with a set log-EE threshold of 4.0 ms^{-1}. The colored points represent the average AMV speed (ms^{-1}, color bar on the right). The labels on each point represent the QI and speed minimum value (ms^{-}) for each threshold. Each dashed line is showing the statistical results of a fixed speed threshold but changing QI threshold. As one lowers the QI threshold, more fast AMVs are being retained, thus increasing the average dataset speed, decreasing the bias, but increasing the RMSE. Trade-offs like these will have to be considered to optimize the effectiveness of the combined indicator approach.**

Layer height Attribution

Another way to improve AMVrepresentation of AMVs is by examining their height assignments, long known to be the largest source of errors. Experiments are underway to test the use of AMVs assigned to tropospheric layers, rather than the traditional single level height assignment. These layers were generated based on work by Velden and Bedka (2009), in which they compared AMVs to co-located rawinsonde wind profiles from U.S. Department of Energy Atmospheric Radiation Measurement Program sites. Optimal layer thicknesses to be assigned to individual vectors were determined based on parameters such as the AMV's geographic location (latitude), and the ambient environmental wind shear, and which sensor channel produced the vectors.

The optimal layers found by Velden and Bedka constitute a look-up table that can be used to assign layer heights for each AMV. An example of the sensitivity of AMV RMS error to layer height assignments is shown in Figure 3. Each curve represents the mean vector RMS between collocated AMVs and RAOBS for different local vertical shear regimes. For each shear regime, the plots show the VRMS errors for AMVs that use the traditional single level height assignment (point on the y-axis) and for those same AMVs but considering layer-averaged height assignments (points to the right of the y-axis). As seen in the plot, averaging the AMV-RAOB errors over a layer reduces the VRMS error as compared to the single level, particularly in the higher vertical shear regimes where the height uncertainty is likely to have the greatest impact on the observation error. It is hoped that this information can provide a better representation of AMV motion, and might be used in data assimilation as part of an improved AMV forward operator. Experiments are in progress with the UK Met Office to investigate this idea.

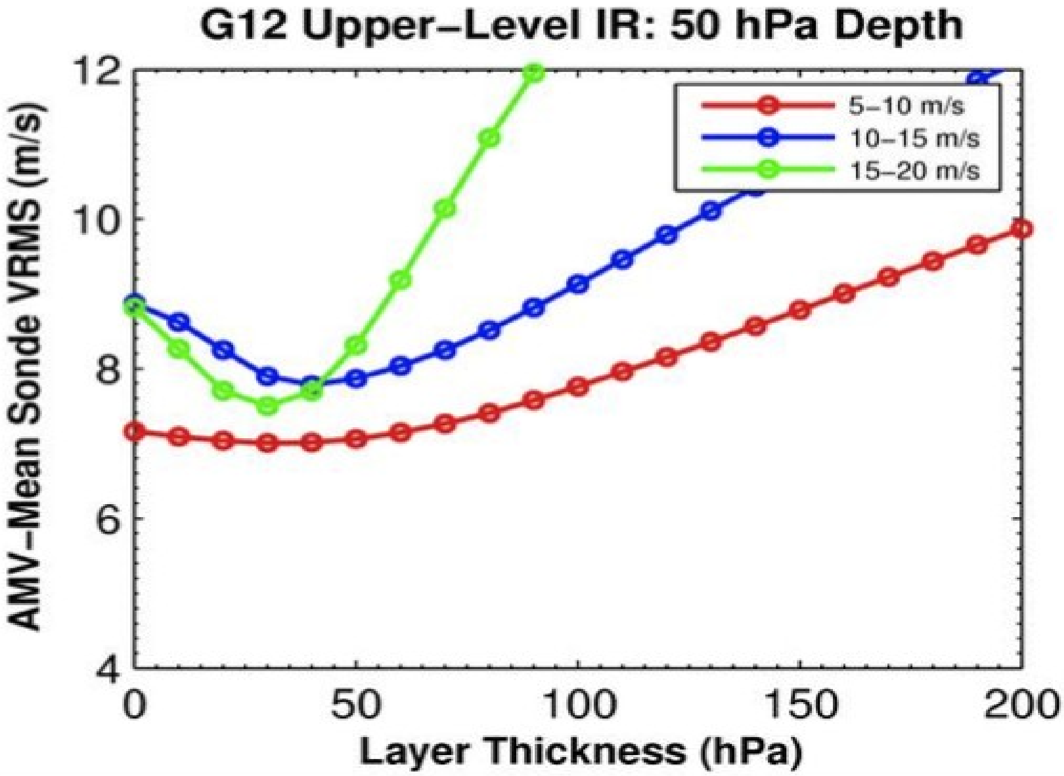

Figure 3: **Vector RMS differences between GOES-12 upper-level IR AMVs and collocated rawinsonde profiles for varying height assignment layer thicknesses (10–200 hPa), represented by the colored curves [with the corresponding single-level-based height assignment VRMS values plotted on the y axis]. The analyses are with respect to varying local vertical wind shear regimes (curve colors). The term "vertical wind shear" here refers to the vector difference between the two collocated rawinsonde values +/- 25 hPa from the original AMV height assignment level (Velden and Bedka, 2009)**

Experimental AMV Datasets

As part of the THORPEX Pacific Asian Regional Campaign (TPARC) in 2008, CIMSS produced experimental AMV datasets on an hourly basis from 30-min sequence MTSAT image triplets. As an example, Figure 4 shows the typical coverage of these AMV datasets, which were used in real-time mission planning and forecasting for the field campaign. In addition, the hourly data allow for detailed case-study analyses as well as data assimilation and forecast impact studies. A 4d-VAR system, in particular, could take advantage of the more-frequent wind observations. Preliminary results from such a data impact study are discussed below.

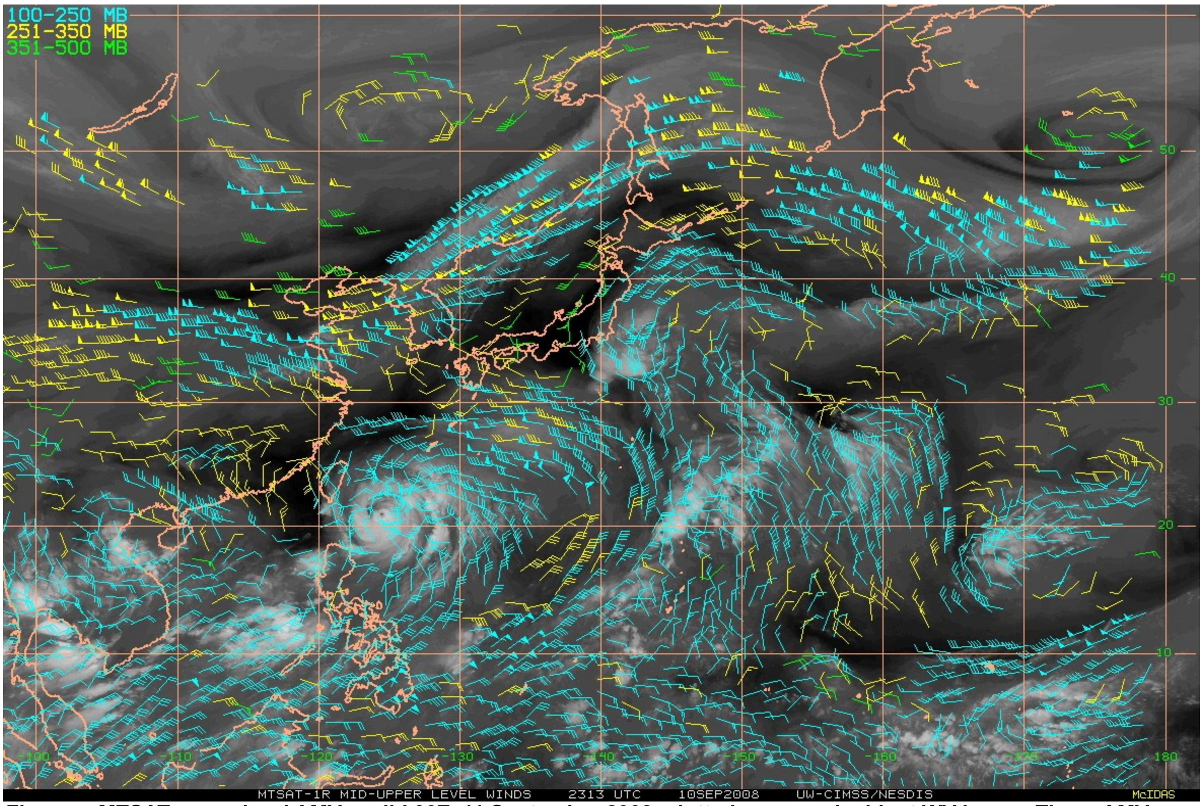

Figure 4: **MTSAT upper-level AMVs valid 00Z, 11 September 2008, plotted over a coincident WV image. These AMV datasets were produced on a hourly basis by CIMSS during the TPARC field experiment in August-September 2008, and are being used in 4D data assimilation experiments to test for model forecast impacts.**

Rapid-Scan Datasets

In addition to providing AMV data sets more frequently during TPARC, CIMSS also produced AMV datasets from special 15-minute and 4-minute rapid scans (r/s) during Typhoons Sinlaku and Jangmi. These r/s were kindly provided by the Japanese Meteorological Agency and their MTSAT-2 as part of TPARC special observing periods. The higher temporal resolution imagery provides more coherent tracers for tracking clouds, allowing the AMVs to better capture TC flow characteristics that can impact motion and intensity changes.

Figure 5 illustrates a comparison of the routine vs. r/s AMV coverages for a selected time period during Typhoon Sinlaku. Appreciably more AMVs are evident when the r/s images are employed for the cloud tracking. Although the 30-minute AMVs suggest the clockwise outflow to the north and east of Sinlaku, the pattern is more-clearly seen in the r/s data sets. The r/s AMVs also show a stronger outflow, which is important to the dynamics of TC intensity modulation. These differences can influence the initial conditions of Sinlaku within NWP models, and should help better forecast intensity changes, particularly within a high-resolution mesoscale model.

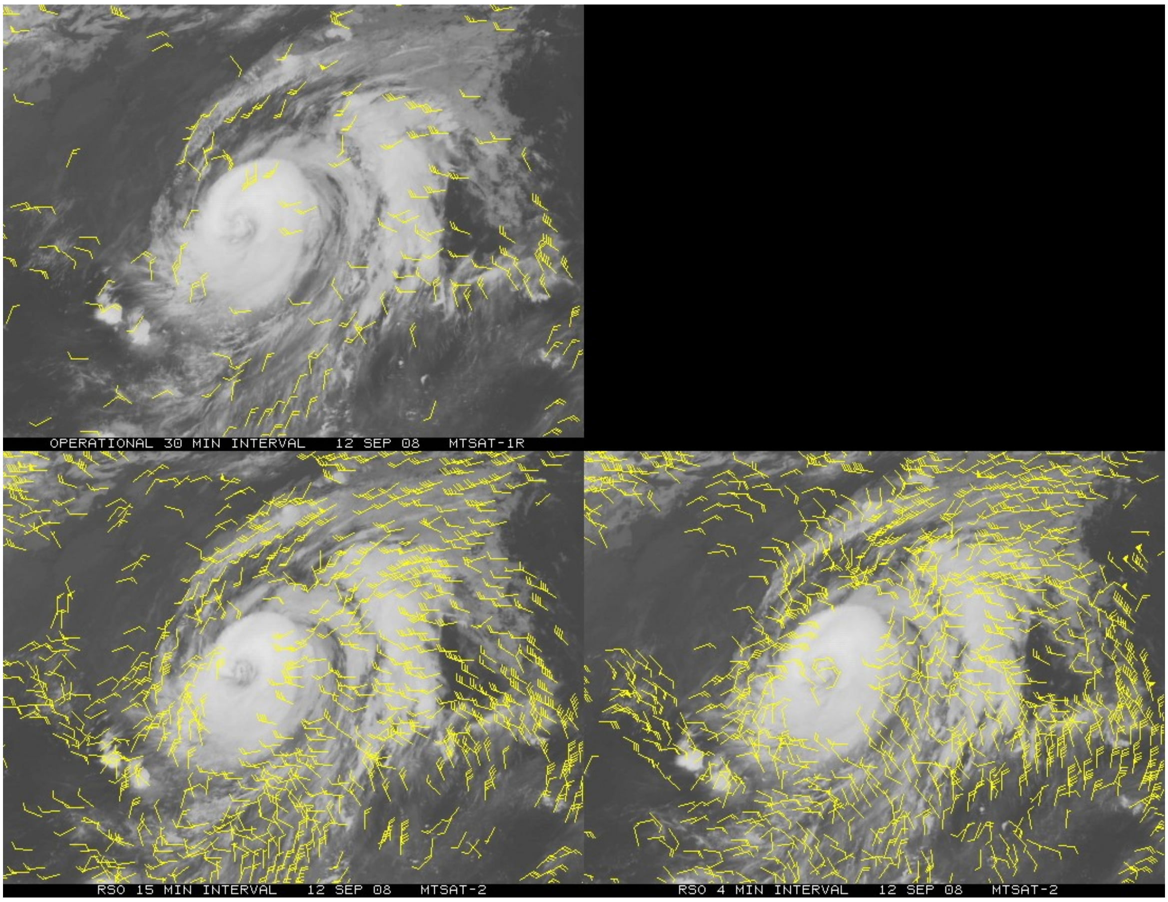

Figure 5: **Comparison of AMVs derived from a coincident sequence of 30-minute (upper-left), 15-minute (lower-left) and 4-minute (lower-right) MTSAT-2 IR images provided during TPARC for Typhoon Sinlaku on Sept. 12th. The increased AMV coverage provided by the r/s imagery is evident in defining the flow characteristics around Sinlaku.**

Data Impact Experiments

The hourly TPARC AMVs are currently being tested in a 4D-VAR version of the U.S. Navy NOGAPS model. Because 4D-VAR better utilizes high-temporal-availability data than the operational 3D-VAR, assimilating the AMV information at hourly intervals should in theory impact typhoon track forecasting within NOGAPS. To test this, a control run was generated based on an assimilation of all of the operational NOGAPS data and the special observations (except for aircraft dropsondes, but including the CIMSS hourly AMVs) during the TPARC period. A second experiment was then conducted, omitting all of the CIMSS-derived AMVs in the assimilation. The resulting forecast impacts for the tracks of typhoons Nuri and Sinlaku are shown in Tables 2 and 3, respectively. The results show the impacts of the AMVs are mixed, generally degrading the longer-range track forecasts for Nuri but improving those for Sinlaku. It should be noted the number of track forecasts compared are small (especially for Nuri), and therefore none of the impacts are statistically significant. Understanding why these impacts differ is being examined.

Forecast Hour	**0**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
Control (nm)	19	31	48	90	103	162	206	273	309	402	466
NO-AMV (nm)	19	31	46	93	103	141	167	223	252	363	455
# of forecasts	9	9	9	8	7	6	5	4	3	3	3

Table 2: **Homogenous track forecast error (nm) for Typhoon Nuri for the AMV (Control) and NO-AMV experiments**

Forecast Hour	**0**	**12**	**24**	**36**	**48**	**60**	**72**	**84**	**96**	**108**	**120**
Control (nm)	23	51	82	112	139	180	217	210	149	162	210
NO-AMV (nm)	25	52	83	113	145	178	237	230	201	227	283
# of forecasts	24	22	21	19	17	15	14	12	10	9	9

Table 3: **Homogeneous track forecast error (nm) for Typhoon Sinlaku for the AMV (Control) and NO-AMV experiments**

Conclusions and Future Work

The mixed results from the initial AMV model impact experiments suggest further study is needed, including the testing of the new AMV QC and layer-height strategies described above in the assimilation process. In addition, plans include NOGAPS experiments assimilating the rapid-scan AMVs over the T-PARC region. The r/s AMVs should provide additional flow information in the storm near-storm environment.

Iterating between improving the quality of AMVs and understanding how to better use them in data assimilation is the key to positive model forecast impacts. Issues with AMV height assignment error and quality control must continue to be addressed from both producers and users. Further research at CIMSS will focus on these issues and partnerships.

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