Evaluation of a New Quality Indicator to Estimate Satellite-Derived Atmospheric Motion Vector Observation Error

Howard Berger, Christopher Velden, and Steve Wanzong

Cooperative Institute for Meteorological Satellite Studies, University of Wisconsin,

Madison, Wisconsin, USA

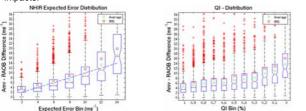
Introduction

Atmospheric motion vectors (AMVs) are derived by tracking cloud and water vapor features through a sequence of satellite images (Velden et al. 2005). Most numerical weather prediction (NWP) centers around the globe assimilate AMVs into their models. Although AMVs have shown positive impact on NWP forecasts, guality control and vector height assignment issues remain. The complex nature of AMV observations has made it difficult to accurately assess the true observation error: information that is crucial for data assimilation. To help address this question, we will describe experiments in progress at CIMSS aimed at exploring the application of a new AMV quality indicator.

The 'Expected Error' AMV Quality Index

The Expected Error (EE) is an AMV quality identifier that was originally developed by Dr. John LeMarshall whilst at the Bureau of Meteorology in Australia. It is essentially an extension of the currently available Quality Indicator (QI) developed at EUMETSAT, but provides an output in the form of most likely (expected) root-mean square (RMS) error for each vector. To calculate the EE for an AMV, the five vector consistency tests that make up the QI, along with the AMV's speed, pressure, and an NWP model vertical temperature gradient and wind shear surrounding the observation are needed. These values are linearly regressed against co-located AMV - RAOB (regional) vector differences over extended periods to develop regression coefficients, which are used to calculate real time AMV EEs.

To show the additional value and performance of the EE, we compare it to one of the standard AMV quality indicators used operationally: the QI. The boxand-whisker plots below compare EE and QI values to actual measured AMV-RAOB wind differences generated from co-located northern-hemisphere AMV-RAOB matches in August 2007. The plots show a clear (and generally statistically significant) relationship between the actual AMV -RAOB differences and the errors estimated by the EE. The QI distributions show a much weaker relationship. This gives confidence that the EE may provide a better measure for more effective data assimilation applications and NWP impacts.



Box-and-whisker plots showing actual AMV - RAOB differences as binned by selected Expected Error values (left) and OI (right). The edges of the box represent the upper and lower quartiles, while the red line represents the median of the distribution. The red-hash marks are outliers. The average (green-circle) and rms (red-square) of each distribution is also plotted. A dashed 1-1 line is graphed on the EE plots for reference. The EE plots shows an increase in expected error with increasing actual error (correlated at 48%). The QI, on the other hand, shows a weaker relationship with actual error (correlated negatively at 27%). These plots are for IR cloud-tracked AMVs;

Expected Error Predictor Tests

Concerns over model dependence within the expected error have led us to test the e ffect of various predictors on the expected error's skill. The following three regressions use the different sets of predictors shown below. To allow independent testing, the predictors are trained and evaluated against AMV-RAOB error using a jack-knife test that successively removes a single day of data from the training set and uses that for regression validation. This process is repeated for each day of the month.

I	Predictors	All Predictors	QI-Only	No-Model	
QI S	Speed Check	Х	х	X	
QI Di	rection Check	Х	Х	X	
QI \	/ector Check	Х	Х	X	
QI Loo	al Consistency	Х	Х	X	
QI Fo	precast Check	Х	Х		
AM۱	Wind Speed	Х		X	
AN	IV Pressure	Х		X	
Model Wind Shear		Х			
Model Temperature Shear		Х			
RMSE (vs. Acual Error) (m/s)	100 - 400 hPa	4.93	5.29	5.22	
	400 - 700 hPa	3.55	3.99	4.04	
	700 - 1000 hPa	2.34	3.61	2.43	
Bias (EE -Actual) (m/s)	100 - 400 hPa	-0.11	-0.02	-0.33	
	400 - 700 hPa	0.56	0.11	0.94	
	700 - 1000 hPa	0.38	0.09	2.86	
R ²		0.24	0.10	0.13	

Although the "All Predictors" regression performs the best, the "No Model" regression does have some skill. Both improve on simply using the QIpredictors alone

CIMSS Quality Control and Expected Error

Experiments are performed during July - September 2007 to investigate the impact of the expected error on CIMSS quality control processing. We are testing whether the expected error could be used to create a dataset that is statistically comparable to the recursive filter (RF) analysis (Velden et al. 2005). Thus, a pre-RF dataset and a post-RF dataset are matched in space and time (150 km, 25 hPa) with RAOBS. These two datasets are subsequently co-located to each other to examine accuracy only on observations that are in both datasets.

Dataset	Height (hpa)	Pre-RF	Post-RF
Number	100 - 400	22622	23133
	400 - 700	3638	3399
	700 - 1000	1649	1377
Spd Bias	100 - 400	-1.15	-0.33
	400 - 700	-0.55	-1.06
	700 - 1000	-0.14	-0.42
RMS	100 - 400	7.50	6.97
Vector Difference	400 - 700	5.86	5.39
Binciciice	700 - 1000	4.70	4.63

Bulk statistics for the Pre- and Post-RF datasets as compared to RAOBS.

Expected Error Max		3	4	5	6	7	8	9	10	11	12
Number of matches	100 - 400	993	4370	10048	16012	19705	21519	22181	22462	22579	22607
	400 - 700	328	1169	2141	2943	3317	3490	3553	3597	3616	3626
	700 - 1000	718	1173	1464	1602	1638	1646	1649	1649	1649	1649
Spd Bias (AMV Š RAOB)	100 - 400	-1.17	-1.33	-1.49	-1.46	-1.36	-1.25	-1.24	-1.20	-1.16	-1.15
	400 - 700	-1.05	-1.02	-1.06	-0.91	-0.82	-0.79	-0.75	-0.68	-0.63	-0.61
	700 - 1000	-0.45	-0.49	-0.32	-0.22	-0.17	-0.14	-0.14	-0.14	-0.14	-0.14
RMS Vector Diff. (vs RAOB)	100 - 400	5.02	5.58	6.23	6.71	7.04	7.24	7.36	7.44	7.48	7.49
	400 - 700	4.36	4.72	5.18	5.39	5.51	5.62	5.68	5.74	5.78	5.80
	700 - 1000	3.91	4.15	4.45	4.63	4.68	4.69	4.70	4.70	4.70	4.70

Pre-RF dataset as thresholded by expected error values. The RMS values decrease as expected, but the slow biases become worse. This could suggest giving higher speed winds a higher ee-threshold.

NRL Expected Error Experiment

The first NWP test of the expected error as a thresholding tool are applied in a data impact experiment during April 2007 on the Navy NOGAPS model. AMVs from all operational centers are assimilated in the model along with complementary AMVs from CIMSS. This preliminary test only used the expected error values on the CIMSS AMVs.

NRL superobs their AMVs into 2x2 degree boxes. Several checks within the superobbing process help avoid assimilating AMVs with too much variance. The expected error thresholds are used to remove AMVs from the superobs that are thought to be of poor quality. In this experiment, AMVs with speeds lower than 50 ms⁻¹ are removed if their expected errors are greater than 7.5 ms⁻¹. The threshold is raised to 15 ms⁻¹ if the speed is greater than 50 in order to allow more high-speed AMVs into the assimilation process. The preliminary results of these experiments were neutral, with some positive impacts in the southern-hemisphere and slightly negative results in the southern hemisphere.

Summary

This study shows that the expected error (EE) index can be a useful measure of Atmospheric Motion Vector quality. Including the original predictors showed the highest skill, removing some of the predictors tied to a numerical weather prediction model was still useful. As model independence is crucial for NWP, this result suggests revisiting these predictors in the future. The expected error can also have a place in CIMSS real-time quality control, particularly in reducing the RMS against RAOBS. Finally, initial NWP experiments using the EE have shown neutral results. Further experiments are necessary to take full advantage of the indicator in the NWP context.

References

Velden et al. 2005: Recent Innovations in Deriving Tropospheric Winds from Meteorological Satellites. Bul Amer. Meteorol. Soc. 2 205-223

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