5A.6 USING PSEUDO RAOB OBSERVATIONS TO STUDY GFS SKILL SCORE DROPOUTS

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1. INTRODUCTION

Numerical weather prediction (NWP) models use a wide array of conventional and non-conventional observations to estimate the state of the Earth's environment for their initial condition (IC). Successful assimilation of observations involves sophisticated algorithms and techniques for quality control (QC) to prepare observations for input to the analysis. Models that embody the physical laws governing the behaviour of the Earth's atmosphere, ocean and land surface, and computers with the power to run these models rapidly enough to make timely forecasts are an essential element of an effective environmental analysis and prediction system. The National Centers for Environmental Prediction (NCEP) Global Forecast System (GFS) model makes 3, 6, and 9-hour forecasts for each cycle every 6 hours generating a background (guess) for the next assimilation and analysis of the above mentioned observations. The analysis system in production at NCEP is the Gridpoint Statistical Interpolation (GSI) (Wu et al. 2002), a 3-dimensional variational process, which uses the background guess and all available conventional and non-conventional observations to generate an optimal analysis including the global surface pressure, and 3 dimensional dependent variables of motion, mass and moisture.

On approximately a monthly basis, poor forecasts or “Skill Score Dropouts” plague GFS performance. Other national center forecasts, for example, the European Centre for Medium-range Weather Forecasts (ECMWF), often do not exhibit this skill loss, for example, in Fig. 1. We attempt to quantify the skill differences between the GFS and ECMWF forecast system when there are dropouts, and define areas at IC time that have an impact on 5-day forecasts. Our goal is to find differences that can lead to algorithms to detect and correct QC problems, bias correction, and analysis issues in ICs before the forecast begins. To do this one needs to construct experiments that will objectively compare results from these national center forecast systems. For the experiments, we use the ECMWF standard 15 level pressure, longitude/latitude, 1°x1° ICs converted to simulated or “pseudo” RAOB observations. To analyze low model forecast skill, we compare the operational GFS and ECMWF analyses as well as forecasts from these analyses. Treating the ECMWF gridded ICs as pseudo-observations, and using them as sole input into the GSI analysis, which then acts as a “grand interpolator”, new ICs are generated that inherit ECMWF analysis system characteristics. These are labelled as “ECM” runs, described in more detail in section 3. From these ICs, GFS forecast experiments, (at T382L64), are made for comparison with NCEP’s operational forecasts or other control to detect differences between these systems in time and space for measuring the effectiveness of QC and other investigations.

Generally, it is found that the ECM results show improvement in GFS 5-day skill scores in practically all Southern Hemisphere (SH) and most Northern Hemisphere (NH) cases. In addition, application of GSI pseudo-observations derived from similar (same number of vertical levels, etc…) standard GFS (instead of ECMWF) post processed ICs produces forecasts similar to GFS production for typical and dropout cases. This provides a way to make comparisons between forecast systems and to isolate differences in QC of observations. ECM runs can be used to find the locations that are responsible for dropouts and then the input observations can be manipulated by type, level, and location to test the impact on forecasts to improve QC algorithms.

We find that the regions that influence the forecast skill can be found by creating a hybrid IC from selectively using the ECMWF or GFS pseudo-observations as input data for the GSI analysis. A region is chosen where “patches” over special areas are substituted in the pseudo-observation file, e.g., areas where there is

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ambiguity in observation quality, perhaps from areas of cloudiness and other observation contamination, or in latitude bands to isolate bias and quality control problems that alter 5-day forecasts. Kumar et al. (2009) shows that areas of meteorological potential as measured by dynamical indexes such as Eady's Baroclinic Index (EBI) or Rossby Radius of curvature are necessary conditions for some low skill forecast events. These cases are used to magnify the observation problems where we endeavour to remove errors that cause skill loss in forecasts but keep as much as possible, the information content to better define the initial state. Once the ECM analysis experiments are run, one can use the results interpolated to individual observation locations to analyze how the GSI and ECMWF analyses "draw" to these observations. The resulting differences in statistics can be used to discover quality control issues and create algorithms for complex QC, and implement real-time QC detection/correction schemes as in (Ballish et al. 2009). In this report, we update the method and cases begun in Alpert et al. (2009). As new instruments are orbited their contribution may need to be measured by the improving special cases such as dropouts.

2. "ECM" DESCRIPTION

To determine when a dropout occurs, a suitable, but admittedly arbitrary criteria, using the GFS 5-day Anomaly Correlation (AC) 500 hPa forecast height score as described in Fig. 1.

Using this criterion we update the list of IC dates, YYYYMMDDHH where HH is the cycle time at 00 or 12Z in Table 1. A number of these ICs are selected for experiments and comparison with ICs supplied from ECMWF analysis. Analyses that are derived from the ECMWF information by use of the GFS/GSI were called ECM runs in Alpert et al. (2009). The GSI analysis with ECMWF pseudo-observations is initiated using the GFS operational analysis as the background guess. The resulting output analysis is used as the background guess along with the ECMWF pseudo-observations for a second iteration of the GSI. It was found that using an analysis twice instead of a model forecast as background guess created noise in the resulting analysis and subsequently in the early hours of the forecast. Even though this noise does not influence the forecast skill, it is present in the initial condition, and within a 12 hour forecast, and influences secondary calculations such as the EBI (see Ballish et al. 2009 for its use in this context). Therefore to decrease the GFS influence or memory stored in the background, and reduce noise, we cycle this analysis in a similar way to that in production described in Section 3.

3. "ECMCYC" EXPERIMENTS

ECMWF forecasts do not often exhibit the loss of skill that occasions the GFS forecasts, so we chose it as a proxy for ground truth to compare with GFS analysis. That is, we choose fields from ECMWF to engineer GFS analyses suitable for comparison, and useful as a means to construct controlled experiments. We have updated the approach used to make ECM analyses by organizing the ECM program closer to operational methods.

The analysis system, as used by NCEP production, is a never ending cycle of 3, 6, 9-hour model forecasts (background guess), which account for model influence including the models physics package. This means that not only the model influences the analysis but also previous analysis cycles each in combination with the available observations. We call the upgraded analysis the "ECMCYC" analysis with a 6-hour cycling method schematically shown in Fig. 2. A 3, 6, and 9-hour forecast is used as the background guess with the pseudo RAOB observations, to produce another 3, 6, and 9-hour forecast as background guess for the next cycle. To start the ECMCYC cycling the first background guess is taken from the GFS operations, the remaining cycles background guess are made from each previous cycle. The resulting ECMCYC analysis will have little influence from the startup GFS background guess after several cycles and does not contain the noise from using an analysis as the background guess instead of a model forecast. In Fig. 3 a less noisy initial condition EBI calculation is shown for a typical day in April and can be compared with that in Fig. 9 of Alpert et al. (2009).

The ECMWF operational medium range prediction model is spectral T799 with 91 vertical levels. The fields used for this study are from 15 standard pressure levels, interpolated, and post processed files on a 1°x1° equally spaced cylindrical projection longitude/latitude grid. Each file contains surface pressure, u-, v-components of the wind, temperature and relative humidity on 15 standard levels (including the surface pressure) 1000., 925., 850., 700., 500., 400., 300., 250., 200., 150., 100.,50., 20., and 10 hPa. The GFS operational model, by comparison, also is a spectral model with truncation T382 and uses a physics Gaussian grid of about 0.3 degrees with 64 vertical levels.

An orography from GFS operations is interpolated to the 1°x1° grid and a new surface pressure is constructed hydrostatically taking account of these elevations for the pseudo-observations. Specific humidity, wind and temperature are calculated from the given variables and converted to profiles with appropriate coding and headers to have them appear as profiles of pseudo RAOB observations for the above given pressure levels at the grid points. The GSI observation input is confined to these pseudo-observations.

The resulting product is an analysis that can be considered as a “grand interpolation” for GFS ICs from the original ECMWF information. These analyses are used in conjunction with surface and fix fields from GFS production archives as ICs for 5-day forecast experiments. The 5-day AC scores for 15-29 April 2009 is shown in Fig. 4 using the ECMCYC analysis. It compares with the skill of past ECM runs and exceeds current production as shown in Alpert et al. (2009). The NH 500 hPa mean AC score shows over the period ECMWF, ECM, and GFS scores of 0.90, 0.89, and 0.85 respectively. In the SH where there is less skill ECMWF and the ECM 5-day forecasts are within one AC point near 0.87 compared to GFS at 0.82. It is remarkable that model skill can be maintained through day 5 with only 14 standard levels. Extending this idea of pseudo-observations, one can make forecast experiments by “patching” in sections of one analysis over the other to confirm the locations of the source of the dropout, should such areas exit. The hypothesis that observations may have bias or other QC problems can then be studied over these areas and perhaps alleviated.

4. OVERLAY OF A DROPOUT CASE

An example of a NH dropout is the 2007102212 GFS production IC (F00) resulting in a 5-day forecast that verified with an AC skill score of 0.61, as shown on the banner at the top of Fig. 5. This particular case by definition is a dropout based on criterion in Fig. 1 earning a place on the dropout list (Table 1). The production ECMWF 5-day forecast had AC score of 0.87 and the ECM run was 0.89 (Fig. 5), both do not show skill degradation. Comparison of the 500 hPa geopotential of the GFS and ECMWF production (similar to Fig. 5c) IC show very little difference and confirms that a slight difference is sufficient at IC time to cause very different day 5 forecasts. The differences that are present between these two national center model ICs ranges as much as ± 20m in height with virtually all large differences located within a broad trough in the Central Pacific (within the box drawn in Fig. 5c as shown by the red color fill in that area). The height fields at other levels (not shown) give a similar result, and similar differences in temperature (not shown) are predominately from this same Pacific location. A number of wind maximums are present in both the ECMWF and GFS analyses (not shown but consider the height gradients) which completes a synoptic picture of a volatile broad trough with a number of short waves moving within. The red color fill area indicates higher heights for the GFS (Fig. 5c). This shows that the GFS IC difference is largely an amplitude problem and not from a phase error. The largest 5-day forecast error at 500 hPa, in this case, is found to the east of Greenland and is largely responsible for the low AC score as shown in Fig. 5 under the GFS column.

To test that the dropout originated from the IC differences in the Pacific region we integrate an “Overlay” (OVRLY) forecast experiment for 5-days with GFS pseudo-observations but with ECM pseudo-observations only over a prescribed area or “patch” in the Pacific as shown by the box in Fig. 5c. The pseudo-observations used for the GFS and the ECM overlay include all the dependent variables and surface pressure at each latitude. This “hybrid” set of pseudo-observations is used as the only observation input to the GSI analysis system. The GFS production analysis is used as the background guess and GFS production fixed fields such as albedo, snow, etc… are needed to start the analysis as described in Fig. 2, and the resulting analysis is used to make a 5-day forecast called the “OVRLY run”. The 5-day forecast height and their difference to the verifying analysis for this OVRLY run (GFS IC with the ECM overlay substituted only over the patch area) at 500 hPa, is shown in Fig. 6b. The color fill in Fig. 6a compared with that in 6b shows much greater forecast error in the GFS production thus, the ECM values over the Pacific OVRLY patch area are sufficient to alleviate the dropout. The OVRLY skill score shown in the banner of Fig. 6 confirms this finding. For a 5-day forecast, the GFS forecast errors are largest east of Greenland extending across the 0 meridian but these errors are greatly reduced in the OVRLY experiment. The associated trough error in the Greenland area 5-day forecast can be traced back to the Pacific OVRLY region described above in Fig. 5c at IC time. The resulting analysis is a hybrid of the two national center analyses, but the information content of the dependent variables from the better scoring ECMWF analysis is placed only over the Pacific area in question as shown in Fig. 5c. The resulting 5-day OVRLY experiment forecast skill score is shown on the banner of Fig. 5 and is 0.90 confirming that the problem area is the outlined Pacific area. Smaller rectangles centered on the broad Pacific trough were studied with similar results; however when the OVRLY is moved to an area far away from the Pacific, the system reverts to the production GFS and the dropout reoccurs with similar loss of skill. A number of dropout cases are shown with the overlay patch in the same position.

In Fig. 7, eight NH overlay experiments are run for a number of dropout forecasts, including that shown in Figs. 5 and 6 where we show the skill scores compared with the GFS, ECMWF (operations) as well as the ECM (pseudo ob) run. The overlay area in the central Pacific as shown in Fig. 5 is kept the same for all these experiments. The above mentioned 2007102212 and 00Z overlay experiments both alleviate the dropouts but this is not the case 12 hours before or after this period where low skill persists. The period of 4 consecutive dropouts shown in Fig. 7 could indicate that the information necessary to improve the skill was not in the overlay rectangle location so the low skill forecasts did not gain the benefit from the ECMWF information. ECMWF operations are not immune from skill loss as shown on 2008030112, and ECM runs dropout as well (2008030400) but normally improve skill on average. For all the cases listed in Table 1 the ECM runs dropout about 10%.

This gives rise to the idea of possible areas of analysis/model sensitivity and we note the lack of conventional observations over NH ocean and in the SH causing the analysis system to rely more on non-conventional observations. In the SH, the differences between the GFS and ECMWF ICs are seldom centered in a single area, but scattered throughout the mid-latitudes as shown in Alpert et al. 2009). Therefore, in SH, instead of using a rectangle overlay, two different overlay latitude bans: 20-60S and 60-90S were used. However, neither overlay area experiment returned the high skill found in ECM forecast runs from global application of ECMWF pseudo-observations shown in Fig. 6 of Alpert et al. (2009), but they did alleviate the dropout according to our criteria in the cases.

5. SOUTHERN HEMISPHERE ECM EXPERIMENTS

The AC skill for 10 SH dropout cases, selected from Table 1, for the first half of 2008 are shown in Fig. 8. Even more so in the SH the ECM forecast skill is close to that of ECMWF operations except for the ECMWF dropout on 2008031812. Noted on this figure is the CNTRL (green) experiment skill which is from an updated GSI system. It is an improvement over the previous one shown in Black on Fig. 8. The upgraded GSI has alleviated half of the dropout cases by our criteria and improved the average AC skill. The addition of new observation types and other improvements show progress in our understanding as new implementations are made. In spite of the improvement of the forecast skill in the SH, the question remains as to the cause of the degradation. One possible cause we can investigate, using ECM experiments, is to quantify what an observation type contributed to the degradation. Work has been done in this area using adjoint methods (Zhu and Gelaro 2008), as well as an Ensemble approach (Liu and Kalnay, 2008) but it is instructive to run a set of ECM experiments that vary the observation input by type, e.g, including only one observation type to test the influence on the analysis and subsequent forecast skill. This experiment was done for the 2008020300 dropout case (Alpert et al. 2009) which originally had a skill score of 0.65 from GFS operations. The CNTRL GSI system includes all satellite radiance data over 6-h ingest window and when run for this case had a skill score of 0.70. It is shown with 9 other dropout cases in Fig. 9 for AC scores and the root-mean-error (RMS) scores in Fig. 10 for the impact of each satellite radiance contribution.

The conventional data, including RAOBS, ships, buoys, aircraft, satellite cloud track winds, and other conventional observation types, but not including the radiance observations, are called “PREPB” runs after the file name that stores them. The impact of satellite radiance data on SH dropouts for each of several satellite radiance observation types: Advanced Microwave Sounding Units; (AMSUA and AMSUB), Microwave Humidity Sounder (MHS), GPS Radio Occultation

(GPSRO), and the Atmospheric Infrared Sounder (AIRS) are in their turn used in an analysis/forecast experiment including the PREPB conventional observations. A MINDATA category is also run which includes only TRMM and SSMI data as a proxy for a "no observation data" experiment (meaning the analysis should be the same as the background guess) as these instruments contribute small data counts and the GSI requires the presence of at least some observations in order to run. The GSPRO, MHS and AMSUB have the largest contributions to skill in the SH for most of these dropout cases especially the case of 2008020300 where this combination alone alleviated the dropout (Alpert et al. 2009). The AMSUA and CNTRL forecasts are similar which could indicate that the contributions of the other types do not improve the skill or that the AMSUA observations were in some way affecting the skill. The RMS scores show the same contributions (low score for improvement) as the AC scores.

A composite summary of all the data on Fig. 11, the impact of satellite radiance observation type contributions is shown for 3- and 5-day AC scores. The satellite radiance data shows positive impact for the NH 3- and 5-day forecasts. In the SH, conventional and satellite observations (PREPB) show a negative impact (8 points) in 5-day forecasts. The addition of satellite radiance data to the conventional observations shows a positive impact for 5-day forecasts. AMSUA along with PREPB conventional observations show the largest positive impact in the NH. In general these cases are shown to have individual characteristics requiring incisive diagnostics to distinguish between independent causes.

6. SATELLITE COUNTS AND OTHER MEASURES

There is a half billion observations in each 6 hour GFS cycle. Each satellite instrument has a unique number of spectral channels measuring radiation. Not all the data can be utilized by the assimilation process so there is windowing of the data and further selection process for assimilated data. The amount of data received, selected and assimilated is shown in Fig. 12 for a typical 6 hour cycle (2009030412). The percentage is given for each instruments contribution. The newest addition is IASI which represents 43% of the total radiance data received and about half of the total selected by the assimilation process and a third of that included in the assimilation. Before the introduction of IASI AMSUA and AIRS were the dominant contributors. One should note the large amount of data that is filtered out by the selection process.

If a sufficient amount of data is missing from a particular cycle for a long enough period, then there could be an effect on model skill. An apparent lack of observational data was the apparent cause for the SH dropout shown in Fig. 13 occurring on 2009010800. Counting back on Fig. 13 gives the initial time as 3JAN. On Fig. 14 are the data counts for most of the satellite radiance contributions for the initial condition as well as a few previous cycles. The loss of data on this particular period was large for most of the positive contributors mentioned in the previous section. The ECMWF forecast was also compromised as its skill score fell to 0.8, still far above the GFS at 0.4 and ECMWF may have experienced data loss as well. It should be remembered that the accumulation time for ECMWF is 12 hours long compared to 6 hours for the GFS and there is a chance that some of the missing data might have been recovered. In any event, one could use ECM experiments to locate where the forecast was impacted and check for the potential of weather systems to be mis-forecast.

7. SUMMARY

The use of ECMWF analysis pressure files to generate "pseudo-observations" for input to the Gridded Statistical Interpolation (GSI) and subsequent GFS 5-day forecasts, yield results that have the character of the ECMWF model in terms of forecast error and skill. These are called "ECM" or "ECMCYC" runs depending on their background guess. In either case the GFS operational skill is improved in the NH and more so in the SH for typical cases as well as when the GFS model 5-day forecast has very low skill which we have termed "dropouts". Dropouts seen in the GFS model seem to occur once a month in the NH and more often in the SH. A climatology of NH and SH dropouts has been updated and systematic differences have been described when the model has forecasts of very low skill. The goal is to diagnose problems in quality control and other analysis issues and implement operational improvements.

GFS runs from ECM analyses show dropouts can be alleviated in GFS forecasts but the number that can be improved vary greatly. Running the operational GSI after removing select observation types offers a systematic approach for assessing the impact of different observation types. Analyzing the contribution to the analysis from individual observation types, and constructing composites, has shown that sometimes withholding observations can improve the forecast. However, these results are not consistent. The goal remains to develop implementable algorithms for improving quality control, bias correction, and analysis weighting of observations. This is discussed in an accompanying report of Kumar et al. 2009).

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8. REFERENCES

Alpert, J. C., D. L. Carlis, B. A. Ballish, and V. K. Kumar, 2009: Improved forecast skill using pseudo-observations in the NCEP GFS. 13th AMS IOAS-AOLS, P2.1.

Ballish, B. A., J. Alpert, D. Carlis, and V. K. Kumar, 2009: What Causes NCEP GFS Model Forecast Skill “Dropouts”, 13th AMS IOAS-AOLS, 2.1

Kumar, V. K., J. Alpert, B. A. Ballish and D. Carlis, 2009: 23WAF,19NWP Conf, Omaha, NE.

Liu J. and E. Kalnay, 2008: Estimating observation impact without adjoint model in an ensemble Kalman filter. Q.J.R. Meteorol. Soc. 134: 1327-1335.

Wu, W., R. J. Purser, and D. F. Parrish, 2002: Three dimensional variational analysis with spatially inhomogeneous covariances. *Mon. Wea. Rev*., **130,** 2905-2916.

Zhu, Y., and R. Gelaro, 2008: Observation sensitivity calculations using the adjoint of the Gridpoint Statistical Interploation (GSI) analysis system. *Mon. Wea. Rev*., **136,** 335-351.

Table 1. Dates of Northern Hemisphere (NH) and Southern Hemisphere (SH) skill score dropout cases specified by initial condition date.

Dropout Table

Northern Hem.	Southern Hem.	Southern Hem. (Cont…)
2007102112	2007092912	2008080500
2007102200	2007100212	2008081500
2007102212	2007100412	2008081600
2007102312	2007100612	2008081912
2007111112	2007100700	2008090212
2007122012	2007101300	2008090300
2008012100	2007101400	2008100912
2008021712	2007102000	2008101212
2008030112	2007111912	2008101300
2008030400	2007121612	2008101912
2008030412	2007122000	2008102112
2008060400	2007122012	2008102200
2008060500	2008011100	2008110600
2008060600	2008011112	2008110612
2008062500	2008011212	2008110700
2008070200	2008020100	2008110900
2008070212	2008020112	2008110912
2008070300	2008020300	2008111400
2008070412	2008021512	2008120112
2008070600	2008021700	2008120812
2008070700	2008022000	2008121812
2008070712	2008030112	2009010212
2008070812	2008030212	2009010300
2008071000	2008030300	2009010312
2008071900	2008030312	2009021012
2008092300	2008030912	2009021100
2008092312	2008031012	2009022012
2008100400	2008031212	2009022100
2008100412	2008031300	2009022112
2008101012	2008031412	2009030912
2008101100	2008031800	2009031012
2008101112	2008031812	2009031112
2008101200	2008032012	2009031200
2008101212	2008040900	2009031212
2008101300	2008042500	2009032212
2008102100	2008042512	2009032300
2009021600	2008042600	2009032500
	2008050900	2009040412
	2008051000	2009040500
	2008051512	2009040600
	2008052200	2009040700
	2008052212	2009040900
	2008061212	2009040912
	2008062500	2004041000
	2008062512	
	2008072500	

Updated May 1, 2009

What is a “dropout”?

The criteria that a 5-day 500 mb Anomaly Correlation (AC) height score must meet in order to be considered a dropout (Alpert et al, 2009) :

- At least one of the following criteria must be met:
  - a) ECMWF minus GFS ≥ 15 AC points
  - b) GFS AC ≤ 0.70
  - c) ECMWF AC ≤ 0.75
  - d) Monthly avg GFS AC score minus GFS forecast ≥ 15
  - e) Monthly avg ECMWF AC score minus ECMWF forecast ≥ 15
- Criteria is for NH and SH dropouts.

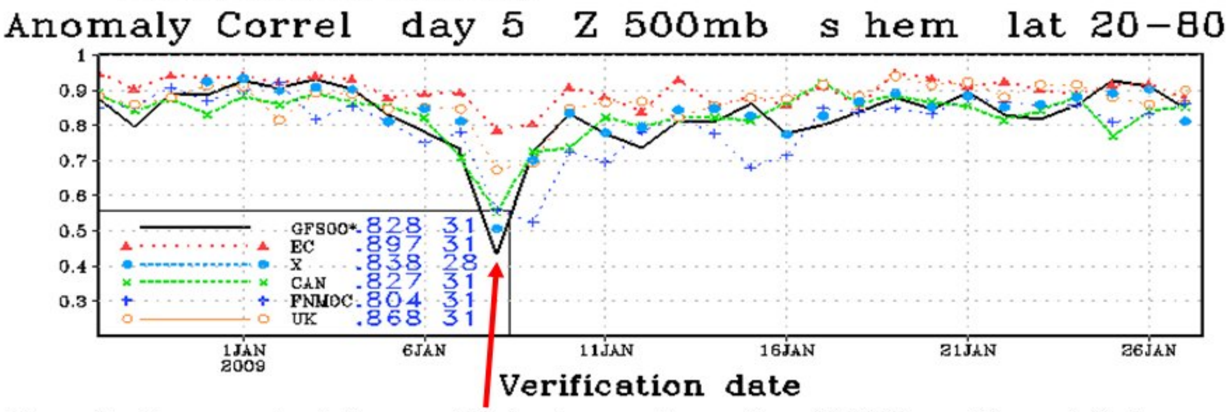

Figure 1. On approximately a monthly basis, poor forecasts or “Skill Score Dropouts” plague GFS performance. GFS production in Black, ECMWF in Red.

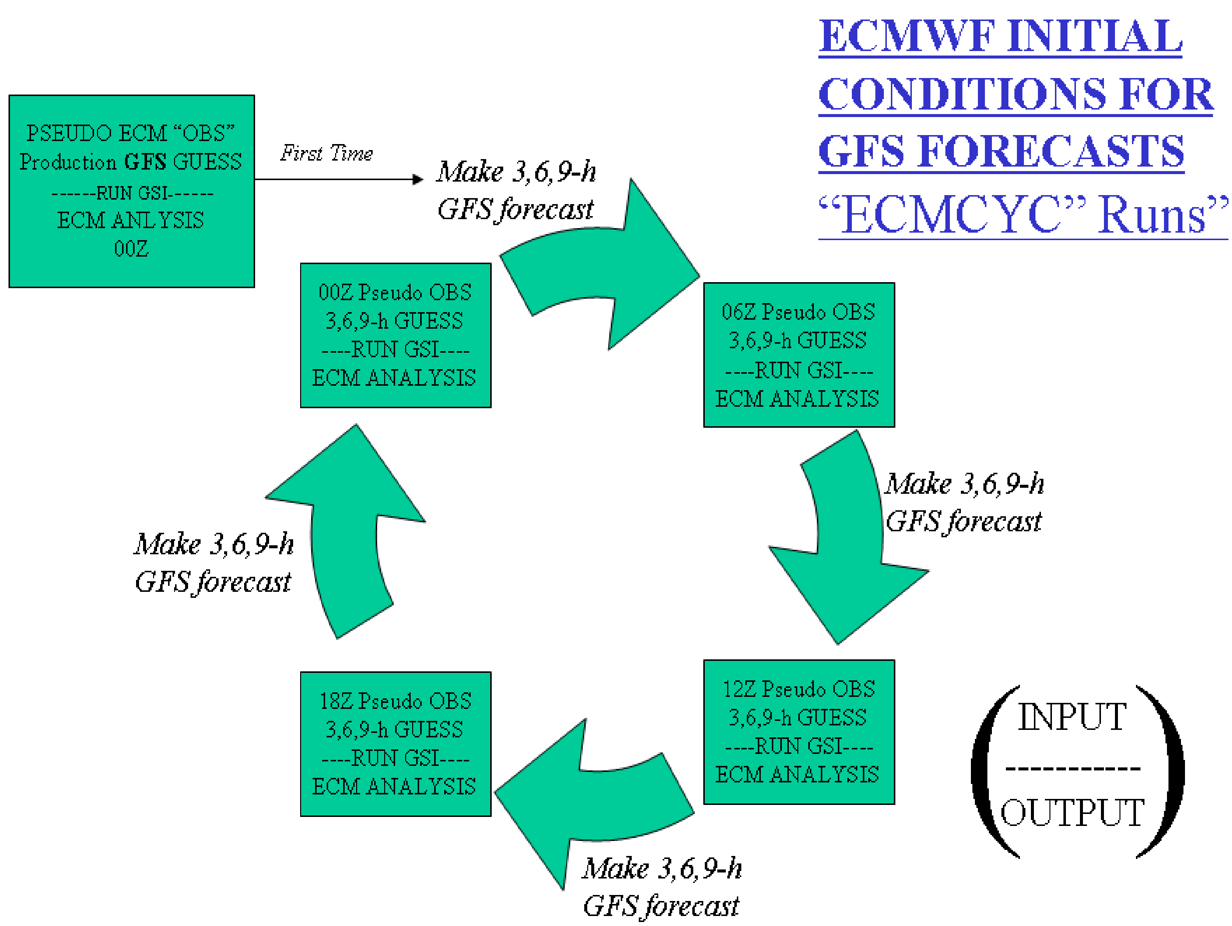

Figure 2. Schematic representation of an ECM run using the GSI/GFS system and ECMWF 14 level pressure and 1x1 degree analysis files.

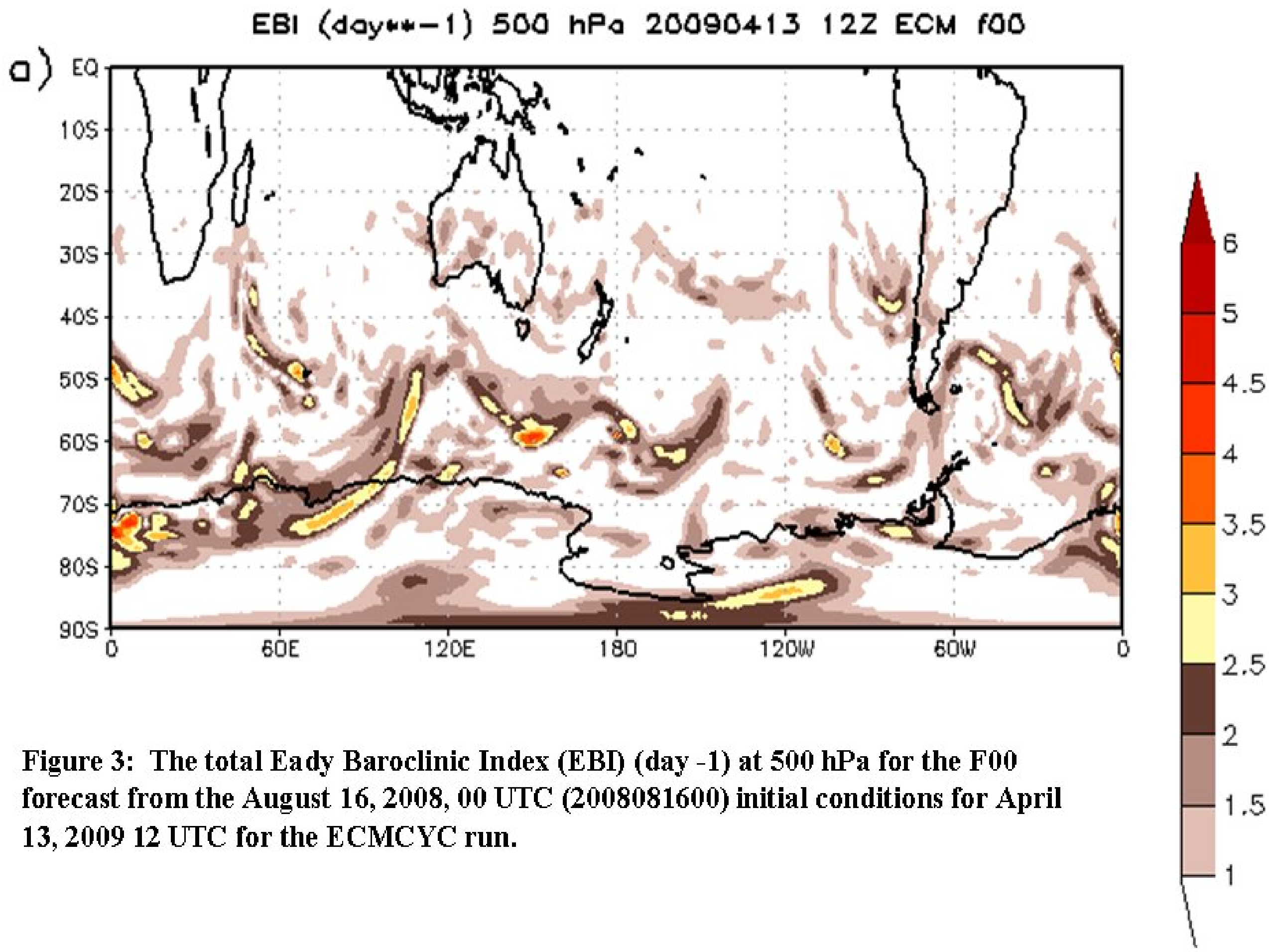

Figure 3: The total Eady Baroclinic Index (EBI) (day -1) at 500 hPa for the F00 forecast from the August 16, 2008, 00 UTC (2008081600) initial conditions for April 13, 2009 12 UTC for the ECMCYC run.

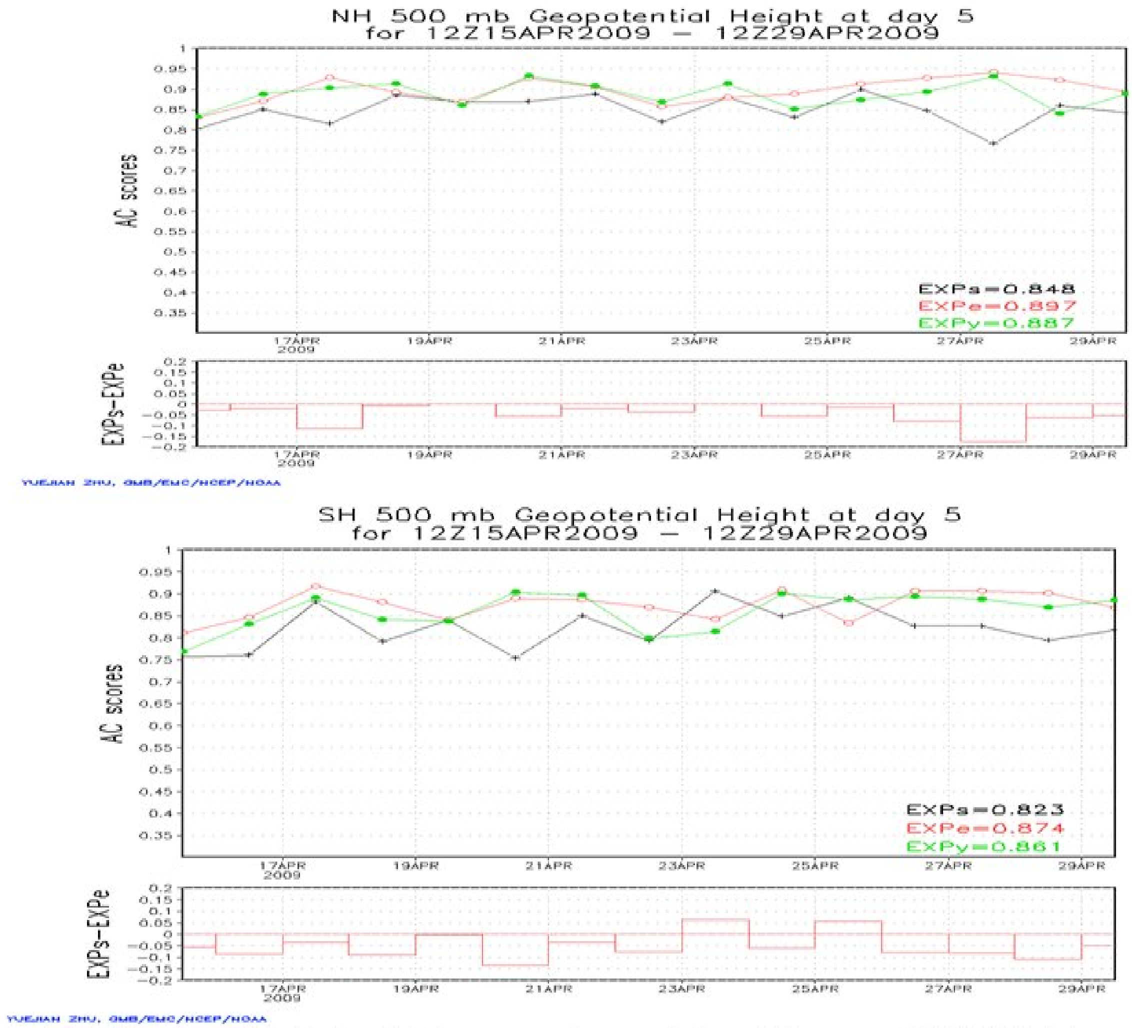

Figure 4. NH (top) and SH (bottom) 5-day anomaly correlation skill scores at 500 hPA. Forecasts from ECMCYC (EXPy) analysis in Green, GFS operations (EXPs) in Black, and (EXPe) are ECMWF operations for 2 weeks in April.

Lat/Lon Box	IC Date	GFS	ECMWF	ECM	OVRLY
20N→ 80N 150E→ 230E	2007102212	0.61	0.87	0.89	0.90

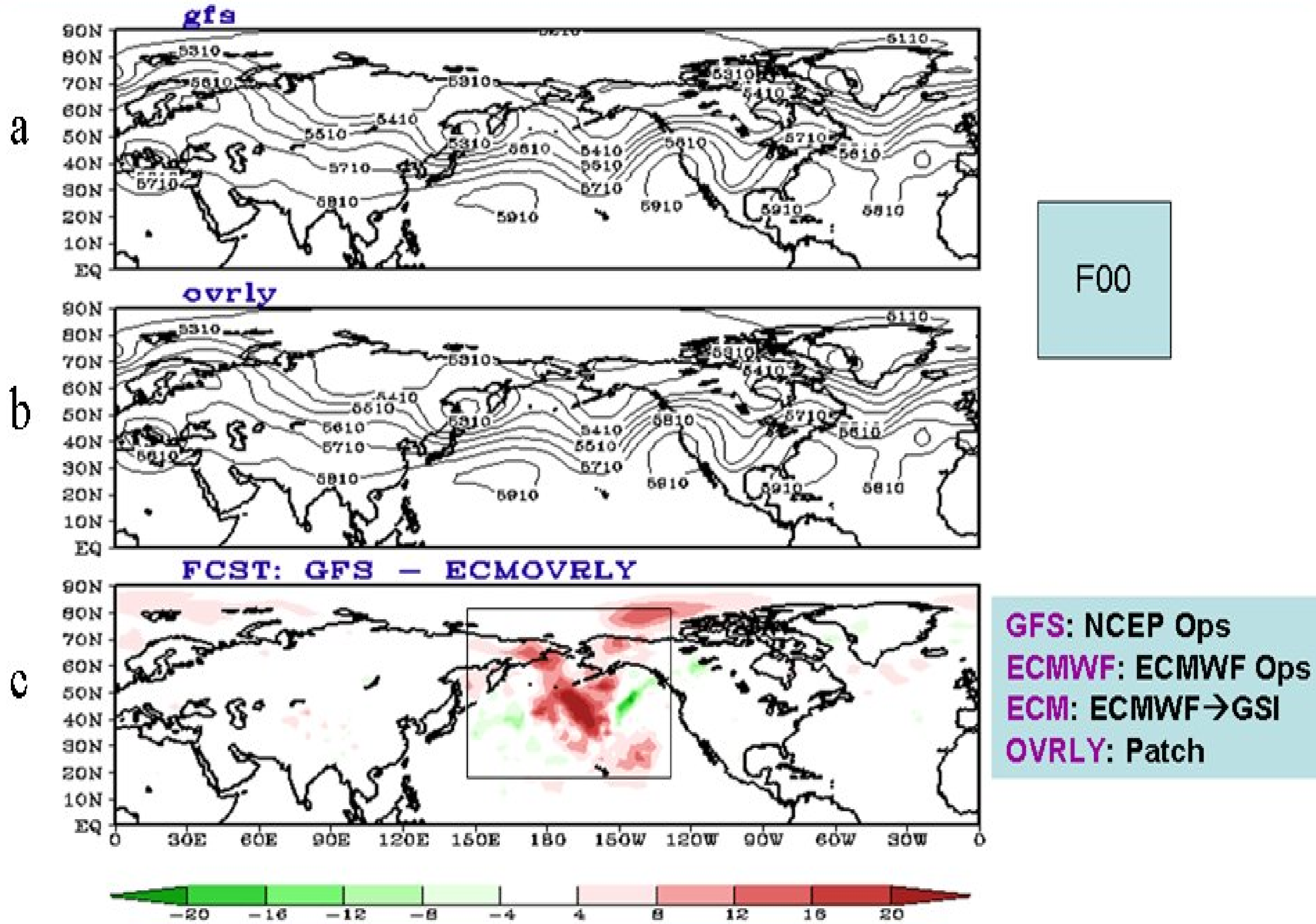

Figure 5. Central Pacific "overlay/patch" (OVRLY) run for a dropout case initialized on 2007102212. Patch is represented by box in (c). Top banner shows NH 5-day AC skill scores for the GFS, ECMWF, ECM, and OVRLY model runs. Graphical maps represent the 500 hPa heights at F00, the initial condition, for the GFS (a) and OVRLY or ECMOVRLY (b) runs. The forecast difference (GFS – OVRLY) map of the two F00 forecasts is shown in (c).

Lat/Lon Box	IC Date	GFS	ECMWF	ECM	OVRLY
20N→ 80N 150E→ 230E	2007102212	0.61	0.87	0.89	0.90

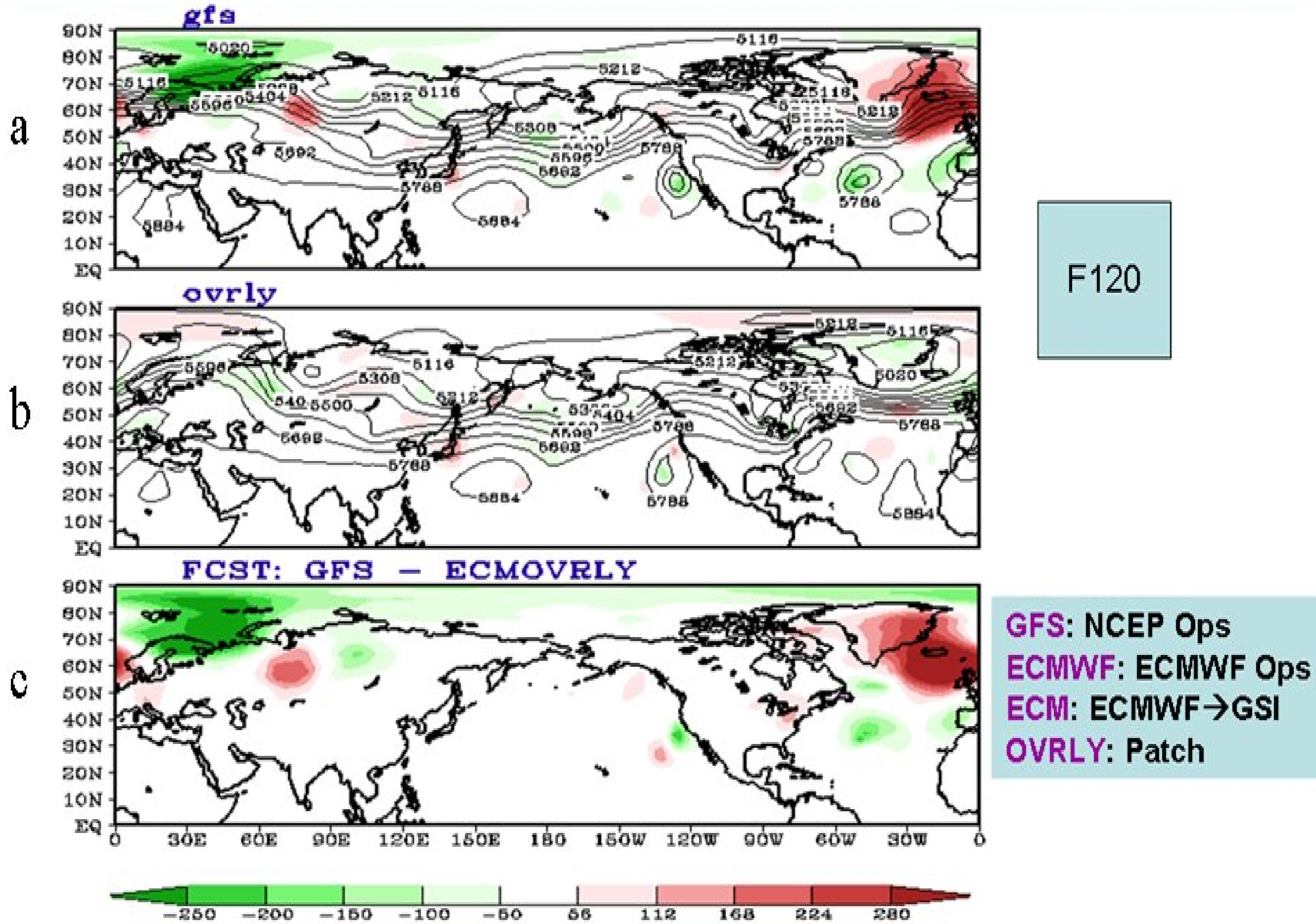

Figure 6. Banner is same as Fig. 5. The NH 5-day F120 forecast of 500 hPa heights (contours) for the GFS (a) and OVRLY (b) runs. Color fill in (a & b) represent the forecast minus verifying analysis differences for both model runs. The F120 GFS minus OVRLY difference is color filled in (c).

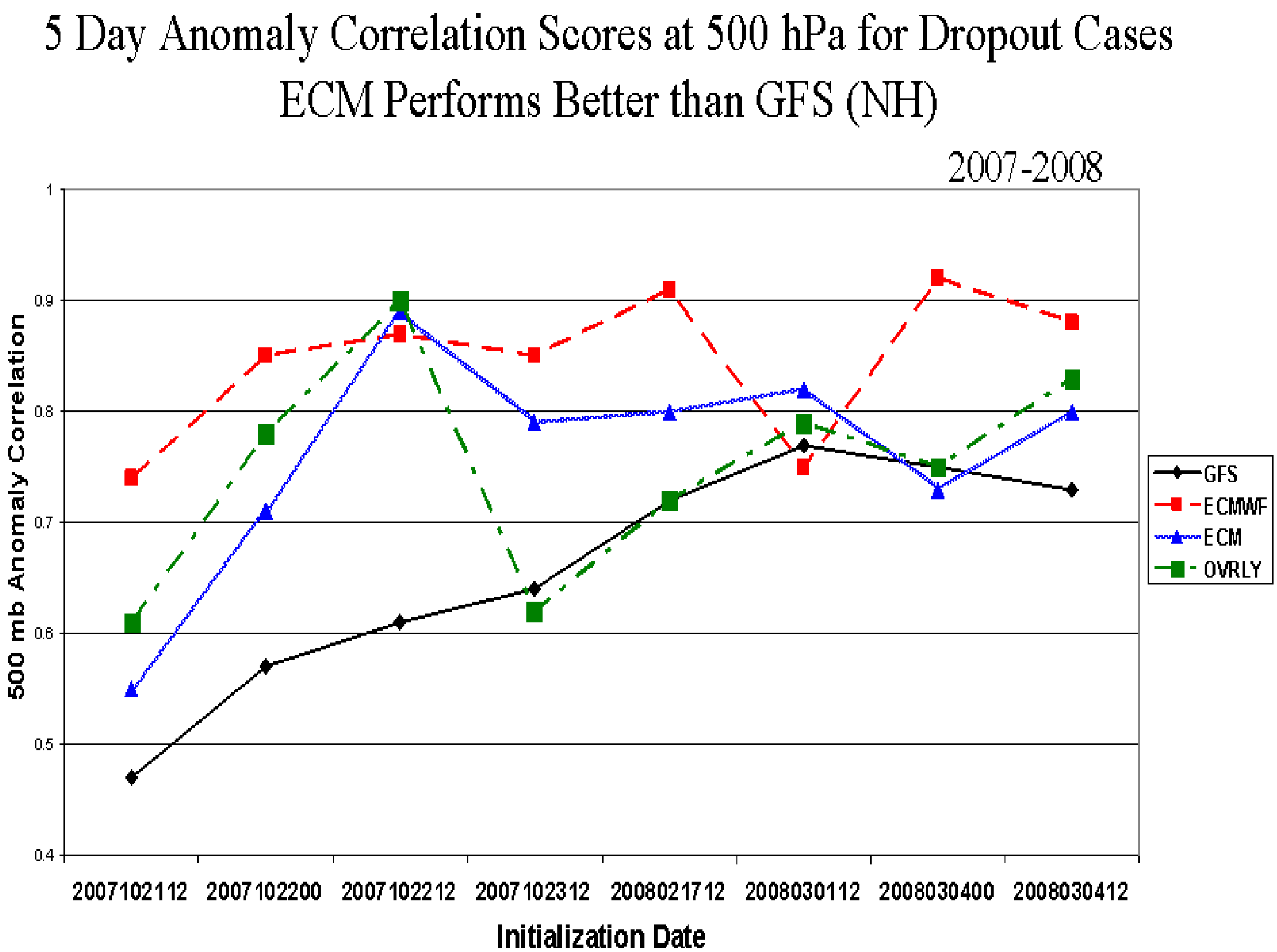

Figure 7. NH 5-day anomaly correlation skill scores at 500hPA for a number of dropout initial conditions: ECM runs (blue), OVRLY runs (green), ECMWF operations (Red) and GFS operations (black).

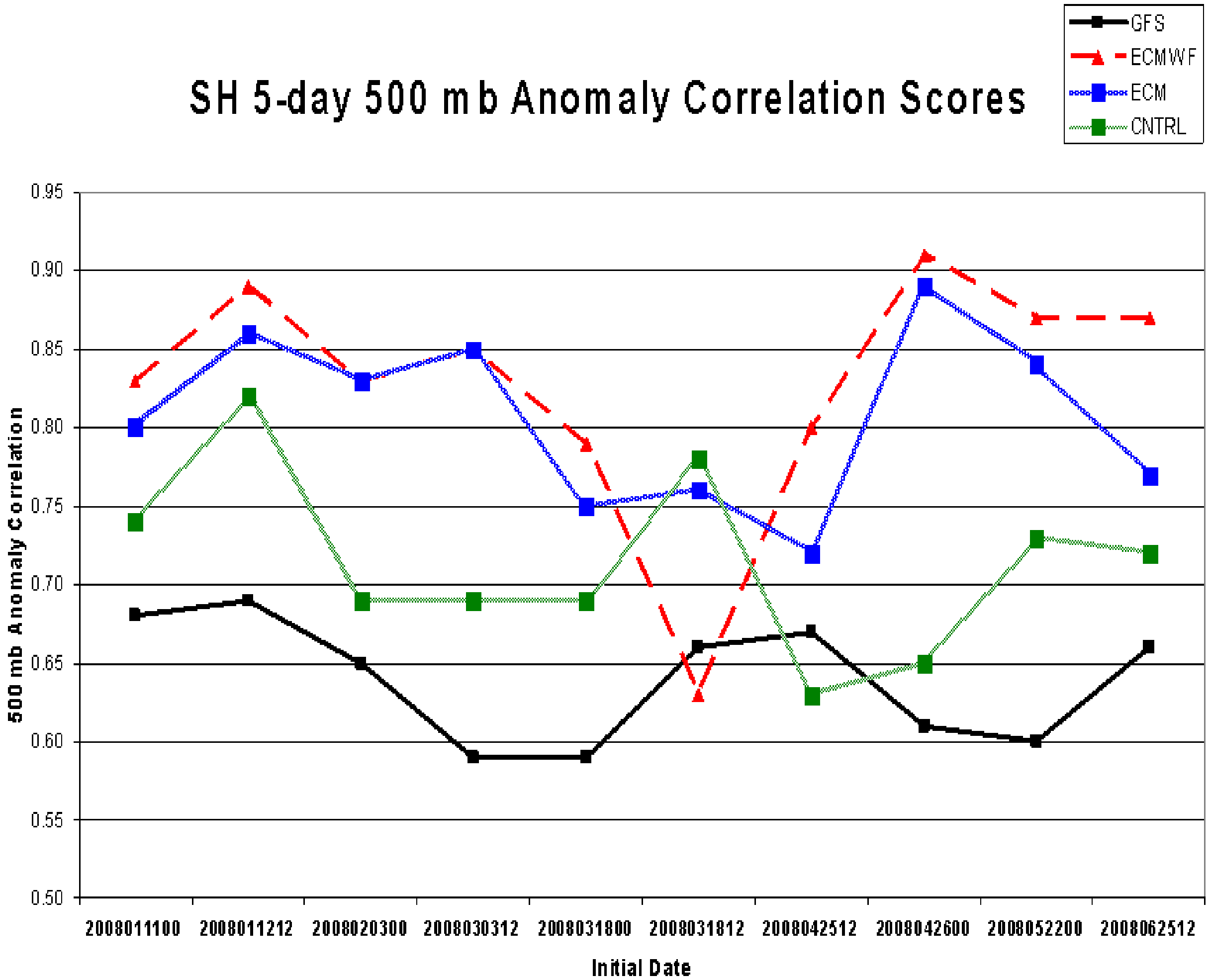

Figure 8. SH 5-day anomaly correlation skill scores at 500hPA for a number of dropout initial conditions: ECM runs (blue), CNTRL runs (green), ECMWF operations (Red) and GFS operations (black).

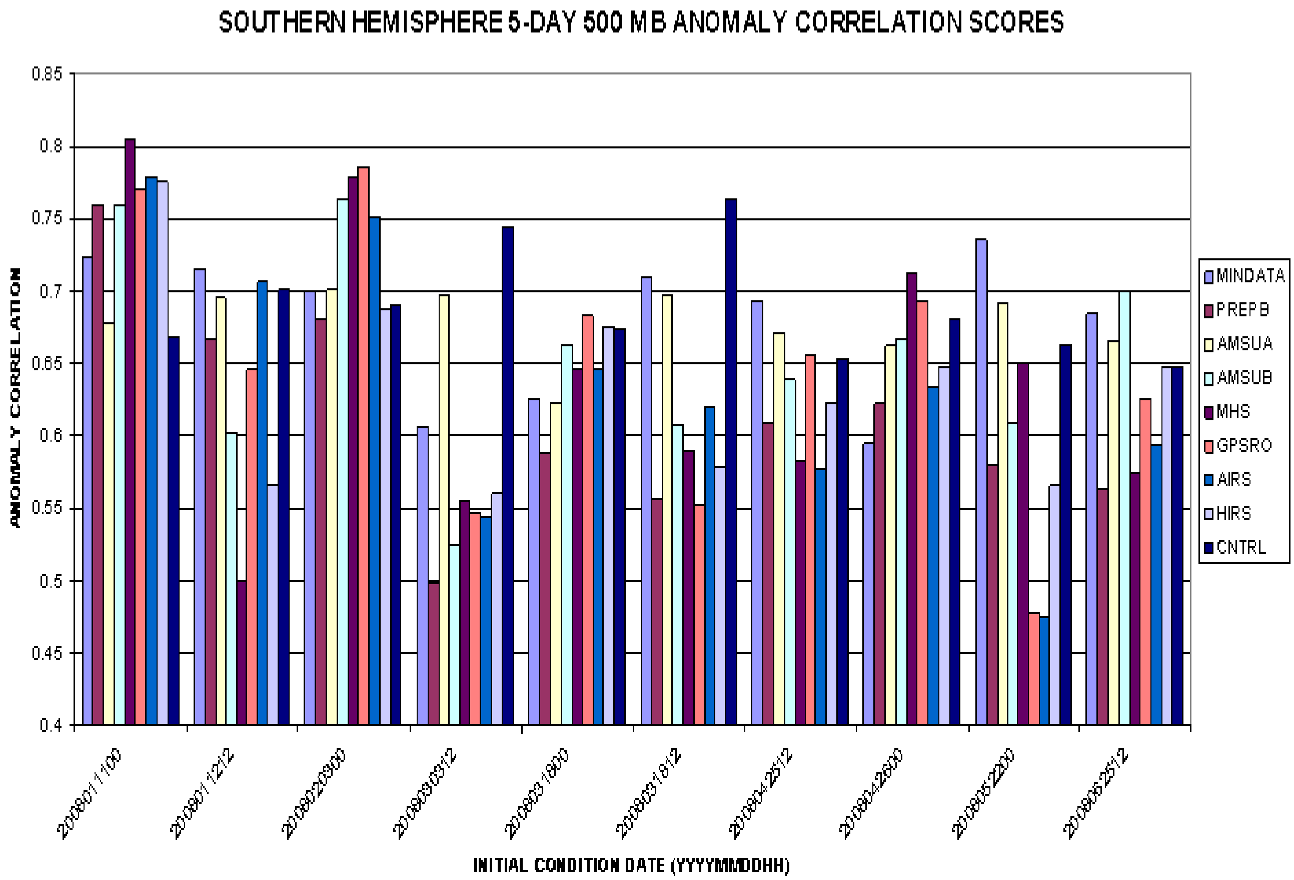

Figure 9. Impact of satellite radiance data on Southern Hemisphere dropouts. 5-day anomaly correlation scores shown for 10 cases. MINDATA is the GFS/GSI run with only TRMM and SSMI data present, PREPB is the GFS/GSI run with only conventional observations (i.e. RAOB, satellite winds, profiler, etc..), AMSUA is the GFS/GSI run with conventional observations and amsua satellite radiance data, AMSUB is the GFS/GSI run with conventional observations and amsub satellite radiance data, MHS is the GFS/GSI run with conventional observations and mhs satellite radiance data, GPSRO is the GFS/GSI run with conventional observations and gpsro satellite radiance data, AIRS is the GFS/GSI run with conventional observations and airs satellite radiance data, HIRS is the GFS/GSI run with conventional observations and hirs satellite radiance data, and CNTRL is the GFS/GSI run with conventional observations and all satellite radiance data present with a 6-hr data ingest window.

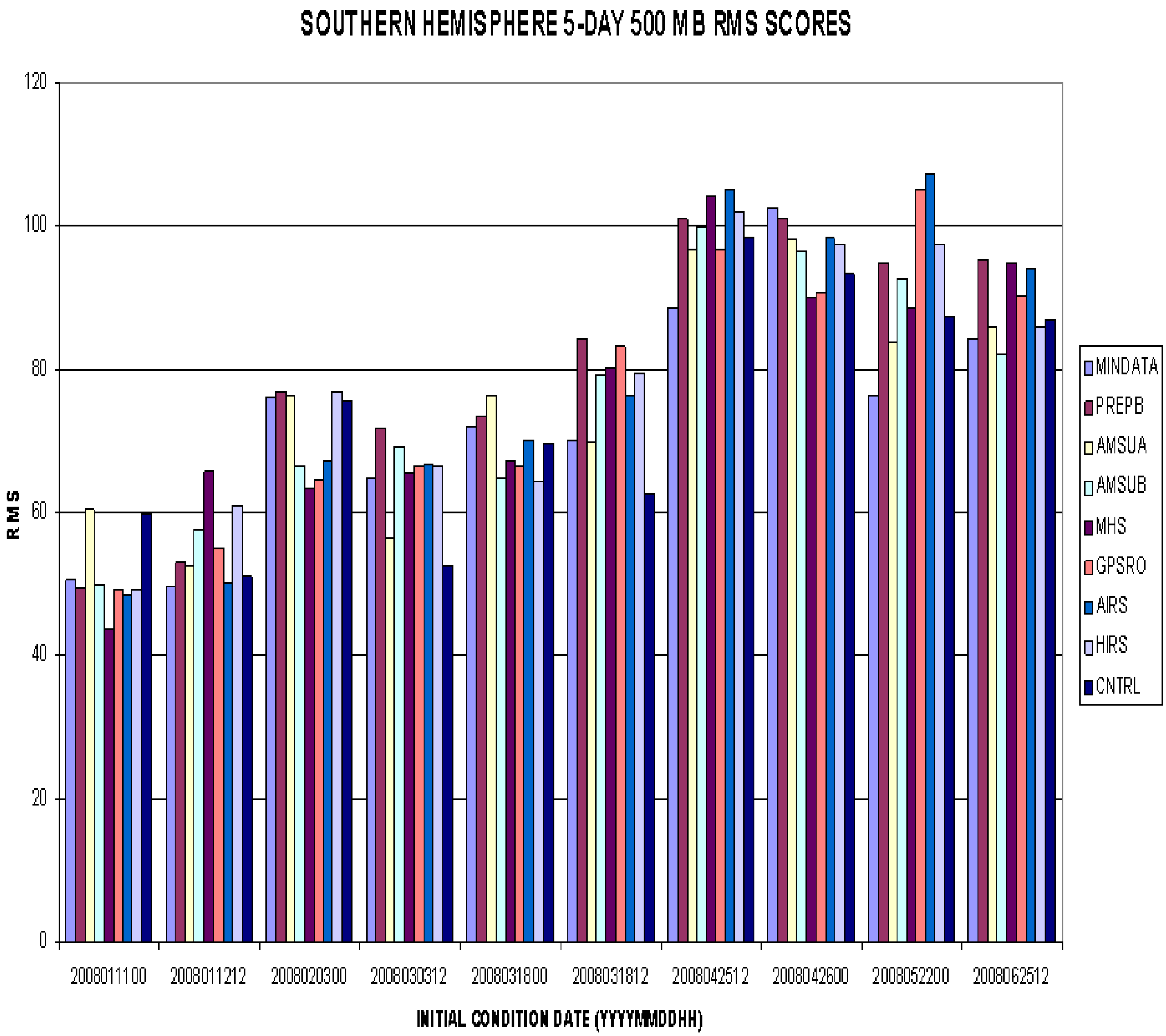

Figure 10. Impact of satellite radiance data on Southern Hemisphere dropouts. 5-day root-mean-error scores shown for 10 cases. The experiments are named the same as Fig. 9.

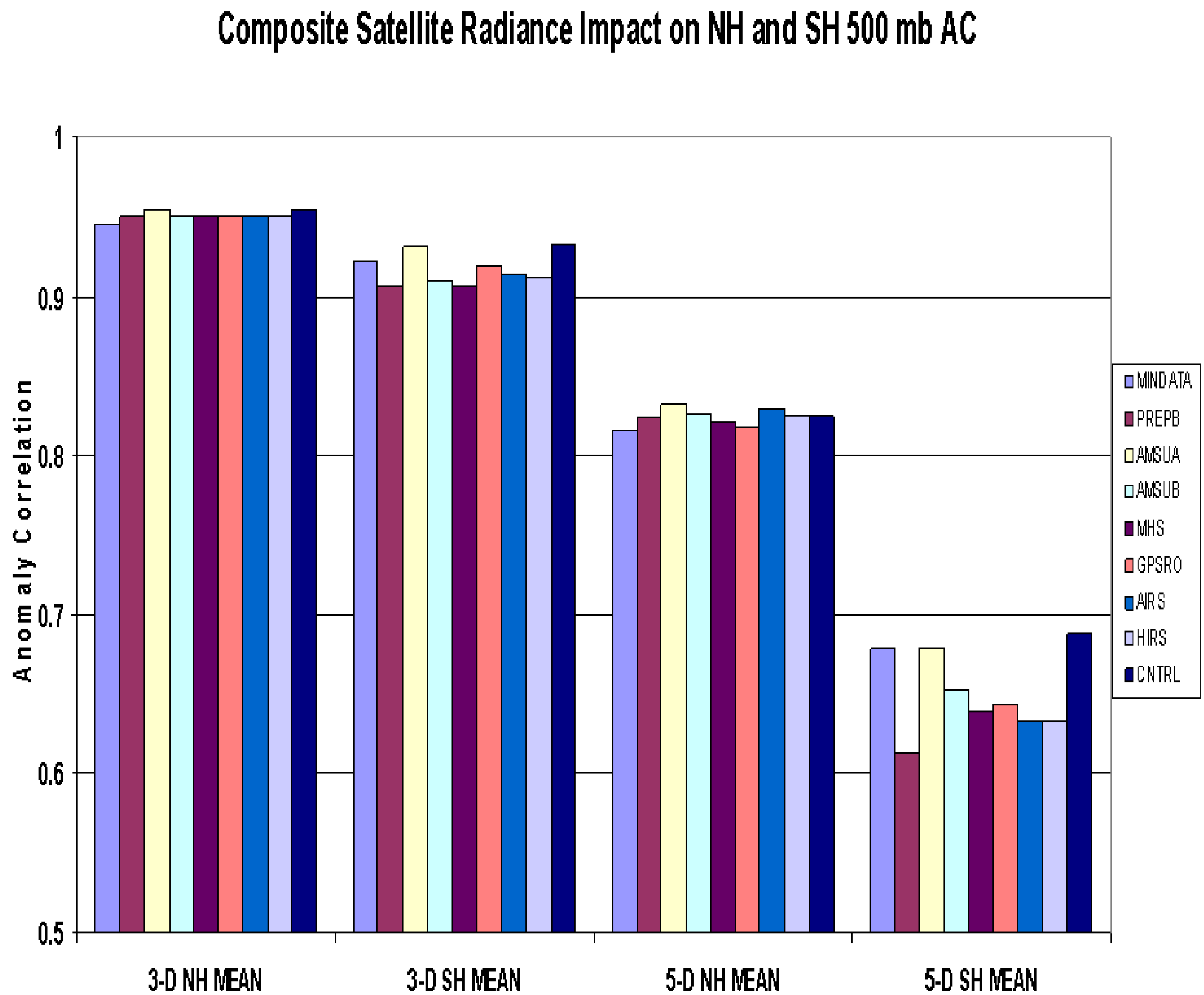

Figure 11. Impact of satellite radiance data on Southern Hemisphere dropouts for the composite 3-day and 5-day anomaly correlation scores of 10 cases. Also, Northern Hemisphere scores are shown for these cases. The experiments are named the same as Fig. 9.

Satellite Data Counts on March 4, 2009 12Z

	Received		Selected		Assimilated	
amsua	14,971,259	3.42%	672,912	7.28%	487,741	22.69%
amsub	10,939,849	2.50%	69,468	0.75%	48,559	2.26%
airs	194,014,483	44.38%	2,068,232	22.37%	420,579	19.56%
sndr	7,911,144	1.81%	69,282	0.75%	27,099	1.26%
gpsro	137,548	0.03%	127,458	1.38%	34,649	1.61%
hirs3	6,822,395	1.56%	313,766	3.39%	34,576	1.61%
hirs4	6,711,471	1.54%	311,906	3.37%	36,841	1.71%
mhs	6,936,840	1.59%	47,200	0.51%	38,693	1.80%
ssmi	21,584	0.00%	21,584	0.23%	3,784	0.18%
trmm	10,628	0.00%	10,628	0.11%	1,526	0.07%
sbuv	22,220	0.01%	21,670	0.23%	6,996	0.33%
iasi	188,385,736	43.10%	4,750,523	51.38%	727,367	33.83%
satwnd	244,210	0.06%	244,210	2.64%	244,210	11.36%
quikscat	0	0.00%	516,763	5.59%	37,439	1.74%
TOTAL	437,129,367	100.00%	9,245,602	100.00%	2,150,059	100.00%

Figure 12. Satellite radiance data counts for 2009030412.

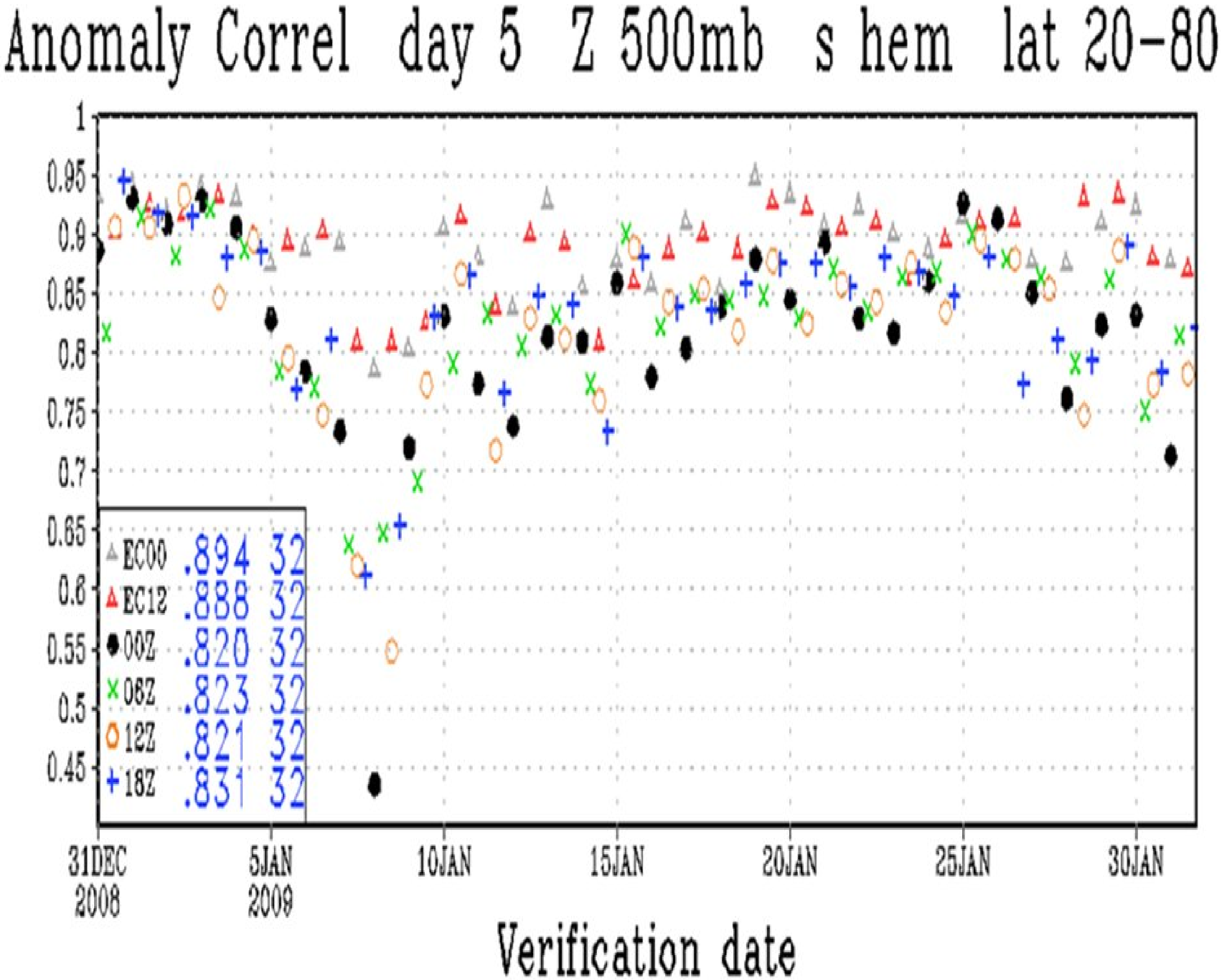

Figure 13. 5-day forecast 500 hPa anomaly correlation skill score for 20-80 North for the production GFS at 00, 06, 12 and 18 Z cycles and ECMWF 00 and 12 Z cycles during January 2009.

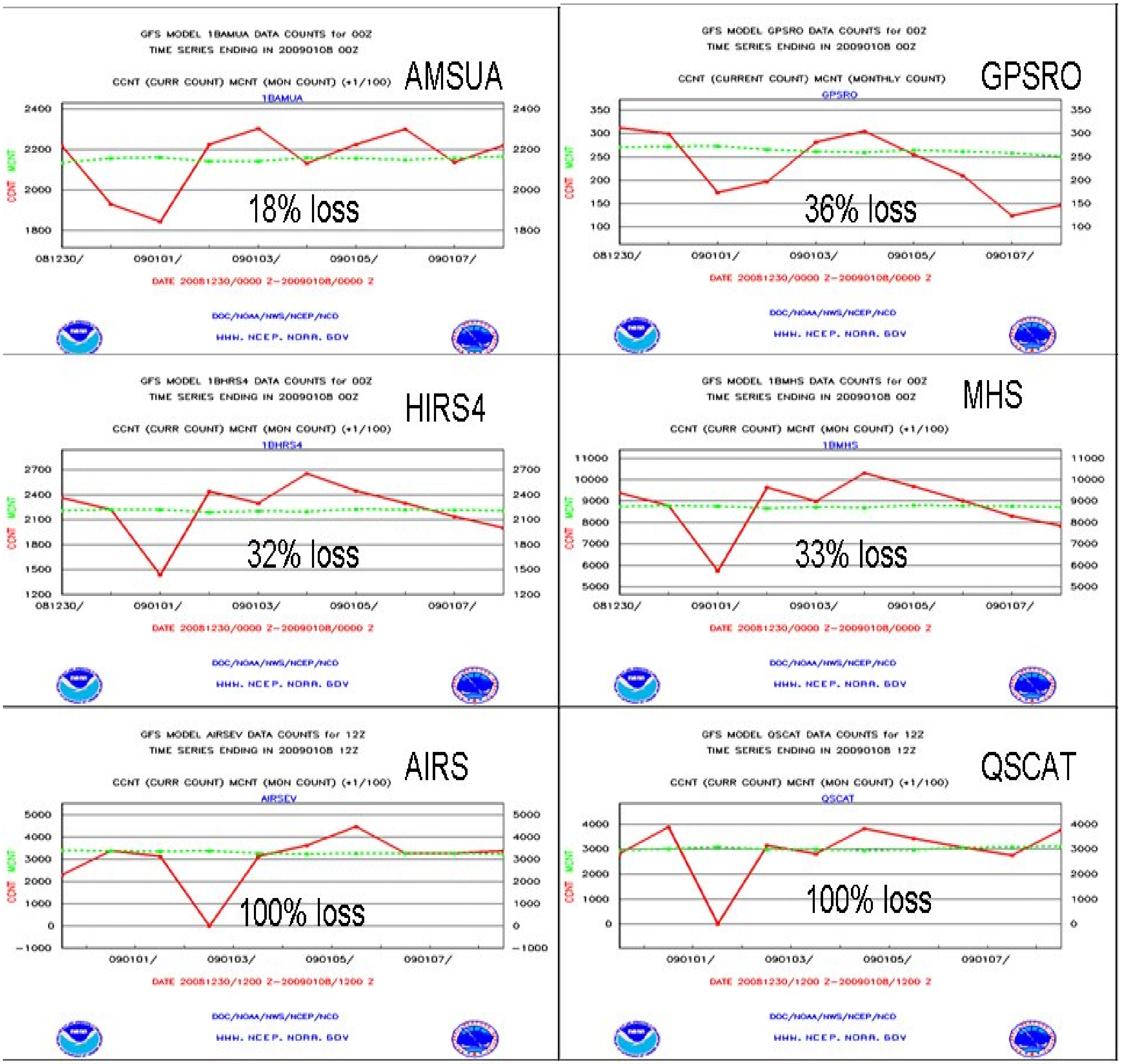

Figure 14. Satellite data counts for the period 20081230-20090107 covering the 5-day forecast dropout initializing on 2009010312.