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GSI-BASED HYBRID 3DVAR DATA ASSIMILATION FOR THE BAM-CPTEC/INPE: SINGLE LOW RESOLUTION EXPERIMENTS

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Abstract:	<p>This paper aims to present the first results obtained with a GSI-based Hybrid Ensemble-Variational system applied to the Brazilian Atmospheric Model from Center for Weather Forecasts and Climate Studies at the National Institute for Space Research (BAM-CPTEC/INPE). The hybrid data assimilation system implemented is a hybrid 3DVar, using the Ensemble Kalman Filter (EnKF) and the Gridpoint Statistical Interpolation (GSI) 3DVar analysis system. This is an upgrade to the previous GSI 3DVar system being used at CPTec operations. The implementation was made using a previous established model and assimilation framework. A new background error covariance matrix was calculated, in order to properly account the ensemble covariance contribution to the static climatological part. An analysis and an evaluation of the updated system is presented and the first results for analyses and 5-day forecasts at TQ0062L028 model resolution are presented as well. The tested hybrid 3DVar system at CPTec shows an improvement for the BAM-CPTEC/INPE skill mainly over South America and Tropical region and endorses the use of ensemble covariances as a complement to the static part of the covariances as a way to reduce the misrepresentation of the background error covariances. Precipitation has been also evaluated in a comparison with observed data. Exercising with the hybrid system have shown an improvement over the pure 3DVar system in both the intensity and the distribution of the precipitation over the time mean. The results obtained with the implementation are encouraging and further improvements must be made in order to fully access the analysis and forecast skill, specially under higher resolutions.</p>
Suggested Reviewers:	<p>Jeffrey Whitaker jeffrey.s.whitaker@noaa.gov Jeffrey Whitaker work refers to ensemble Kalman filters and hybrid methods in data assimilation.</p> <p>Daryl Kleist daryl.kleist@noaa.gov Daryl Kleist work refers to the Gridpoint Statistical Interpolation system and hybrid methods in data assimilation.</p>

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We wish to submit a new manuscript entitled “**GSI-BASED HYBRID 3DVAR DATA ASSIMILATION FOR THE BAM-CPTEC/INPE: SINGLE LOW RESOLUTION EXPERIMENTS**” for consideration by the Journal of Applied Meteorology and Climatology.

This research is related to the application of a GSI-based hybrid 3DVar data assimilation coupled to the CPTEC/INPE general circulation model. The objective of this research is to verify the impacts of the use of ensemble Kalman filter covariances combined with static covariances. This static covariance matrix was calculated using 730 pairs of 48/24 hours forecasts. The hybrid 3DVar system, is exercised with 40 members and a real non linear model. The results are encouraging and shows that when using the hybrid covariances with a greater contribution from the ensemble part, the forecasts skill are improved for various model state variables. We also show that hybrid covariances can also help the model to improve the distribution of the 24 hour precipitation, in both space and time. As we have evaluated the system performance for different regions of the globe, we found that the ensemble covariances helped the model to improve its skill in regions that are known to have a lower conventional observation coverage (eg. South Hemisphere/South America). We believe that this results whould be of the interest of the journal readers because it endorses the use of hybrid covariances in data assimilation applications, specially over the southern hemisphere.

We confirm that this work is original and has not been published elsewhere nor is it currently under consideration for publication elsewhere. All authors have approved the manuscript and agree with its submission to the Journal of Applied Meteorology and Climatology.

Please address all correspondence concerning this manuscript to me at carlos.frederico@cptec.inpe.br.

Thank you for your consideration of this manuscript.

Sincerely,



Carlos Frederico Bastarz on behalf of the authors

GSI-BASED HYBRID 3DVAR DATA ASSIMILATION FOR THE BAM-CPTEC/INPE: SINGLE LOW RESOLUTION EXPERIMENTS

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ABSTRACT

9 This paper aims to present the first results obtained with a GSI-based Hybrid
10 Ensemble-Variational system applied to the Brazilian Atmospheric Model
11 from Center for Weather Forecasts and Climate Studies at the National In-
12 stitute for Space Research (BAM-CPTEC/INPE). The hybrid data assimila-
13 tion system implemented is a hybrid 3DVar, using the Ensemble Kalman Fil-
14 ter (EnKF) and the Gridpoint Statistical Interpolation (GSI) 3DVar analysis
15 system. This is an upgrade to the previous GSI 3DVar system being used
16 at CPTEC operations. The implementation was made using a previous es-
17 tablished model and assimilation framework. A new background error co-
18 variance matrix was calculated, in order to properly account the ensemble
19 covariance contribution to the static climatological part. An analysis and an
20 evaluation of the updated system is presented and the first results for anal-
21 yses and 5-day forecasts at TQ0062L028 model resolution are presented as
22 well. The tested hybrid 3DVar system at CPTEC shows an improvement for
23 the BAM-CPTEC/INPE skill mainly over South America and Tropical re-
24 gion and endorses the use of ensemble covariances as a complement to the
25 static part of the covariances as a way to reduce the misrepresentation of the
26 background error covariances. Precipitation has been also evaluated in a com-
27 parison with observed data. Exercising with the hybrid system have shown an
28 improvement over the pure 3DVar system in both the intensity and the dis-
29 tribution of the precipitation over the time mean. The results obtained with
30 the implementation are encouraging and further improvements must be made
31 in order to fully access the analysis and forecast skill, specially under higher
32 resolutions.

33 1. Introduction

34 Hybrid data assimilation systems using an ensemble Kalman Filter and a variational technique
35 have been developed (e.g., Hamill and Snyder 2000; Lorenc 2003; Zupanski 2005) and applied
36 focusing the sampling and the representation of the spatial-temporal variations of background
37 error covariances, introducing the day-to-day statistics variations of the background flow (the so
38 called “errors of the day” - Corazza et al. 2003) to the static part of the variational covariances.
39 The representation of background error covariances is one of the main issues of the operational
40 data assimilation and its specification for deterministic systems (e.g., variational systems) is of a
41 primordial importance.

42 Variational systems such as 3DVar uses a static background error covariance matrix, which
43 means that its covariances are stationary in time and does not vary, thus the same error statistics
44 are used for the whole assimilation process. A similar situation happens to a 4DVar system, which
45 - in general, uses a pre-computed covariance background error matrix at the beginning of each
46 assimilation window, which is at least propagated in time during the assimilation of observations
47 using the tangent linear version of the forecast model. Differences in the way that background
48 error statistics varies with time due to the variations in the background flow, leads to what we call
49 flow-dependence.

50 Flow-dependent covariances are a key feature of modern data assimilation systems, and its spec-
51 ification either at the beginning or during the assimilation window, allows the analysis to correct
52 account for the time and spatial dependency of the observation innovations being used into the
53 analysis increments, in both horizontal and vertical directions. Furthermore, desirable features of
54 the background error covariances also include anisotropy and inhomogeneity (non-uniform statis-
55 tics - Rabier 2005).

56 Several efforts have been made in order to add some degree of flow-dependence and anisotropy
57 to static covariances. The development of the variational techniques for operational use during the
58 1990's, include some sort of implicit modifications to the data assimilation framework. Desroziers
59 (1997) introduced a coordinate transformation to allow the data assimilation system to better ac-
60 count for structures of frontal systems. This led to an improved analysis with flow dependent
61 covariances and anisotropic correlations.

62 The gradients represented in the background flow, also include important information that could
63 be used to allow anisotropy. Riishøjgaard (1998) showed how to use the humidity field to model
64 correlation functions that can be stretched to accommodate the covariances according to the gradi-
65 ents represented in the background flow. Other approaches to model correlation functions that lead
66 to flow-dependent background error statistics, involve the use of wavelets with spectral methods
67 (e.g., Fisher 2003), but difficulties arise with the specification of these wavelets on the sphere. Re-
68 cursive filters are also another know method to derive quasi-Gaussian shapes to use in background
69 error covariance modeling. This approach have been used successfully in several applications;
70 e.g., Hayden and Purser (1995) applied isotropic recursive filters to the processing of the Na-
71 tional Environmental Satellite and Data Information Service (NESDIS); more recently, recursive
72 filters have been applied to the Gridpoint Statistical Interpolation (GSI) to model the application
73 of background error covariances (Wu et al. 2002).

74 Within these efforts, other approaches have been developed and are more related to the represen-
75 tation of nonlinearities of the background flow into the background error statistics. The 4DVar (Th-
76 paut and Courtier 1991) was developed as an extension of 3DVar (Lorenc 1986) and can implicit
77 evolve covariances inside the assimilation window. Corazza et al. (2003) added flow-dependence
78 to covariances by accounting for the “errors of the day”, using bred-vectors. Hybrid methods (e.g.,
79 Hamill and Snyder 2000) were introduced taking advantage of the ensemble Kalman Filter meth-

ods. This new approach has several advantages including the fact that operational centers have already experienced the variational technique and have some experience with ensemble Kalman Filters. Each of these methods can be taken as a compliment to ameliorate the deficiencies of the other (Wang et al. 2007, 2009). Recently, hybrid methods with real applications have been deployed (e.g., Wang et al. 2013; Clayton et al. 2013) where covariances estimated from an ensemble Kalman Filter, are linearly combined to a 3DVar static covariances matrix.

Most recent developments at CPTEC have focused on its independence on observations pre-processing, quality control and analysis. In the past few years, some analysis systems have been tested at CPTEC, including the GSI. GSI have been used in several operational NWP centers and is the data assimilation chosen for regional and global applications at the center.

With the objective of provide the BAM-CPTEC/INPE model (Figueroa et al. 2016) with its own analysis in a data assimilation cycle, in this paper are described the details of the implemented system and the first results obtained with the GSI-based hybrid 3DVar system.

This paper is organized as follows: Section 2 describes the strategy and the details of the implemented hybrid 3DVar system and the static part of the background error covariance matrix; Section 3 presents a description of the idealized experiments to test the hybrid system. Results from the experiments carried out are represented in Section 4 and finally, Section 5 presents the discussion regarding the results and future plans.

2. CPTEC Global Hybrid 3DVar System

In the past years, hybrid data assimilation systems have shown an increasing amount of development and several centers have been made efforts to take advantage of its benefits. Hybrids systems using the 3DVar and an ensemble Kalman Filter (EnKF) appears to be a common choice to start with. The GSI system comprises a collection of routines that are already prepared to run such

103 a hybrid 3DVar system using the EnKF to provide the ensemble covariances to compliment the
104 static covariances used in 3DVar.

105 Since 2012 CPTEC have been experimenting the GSI 3DVar analysis with its global General
106 Circulation Model (GCM) for NWP until 7 days at a TQ0299L064 spectral model resolution
107 (roughly, 45 km at the Equator, with a corresponding grid of 450 X 900 X 64 points, *lat X lon*
108 *X lev*). This version of the system was performed with a GSI's example global background error
109 covariance matrix (with a grid of 386 X 768 X 64 points, *lat X lon X lev*). Although this config-
110 uration seems to be not the ideal, it was a first attempt to run a global analysis with radiance data
111 assimilation at a higher resolution at CPTEC.

112 With the public release of the hybrid version of GSI in 2015, CPTEC started to plan a revamped
113 version of its global data assimilation system. A new version of the BAM-CPTEC/INPE model
114 was released in the summer of 2015 and was planned a test of running the BAM-CPTEC/INPE
115 with its own analysis, but using a proper background error covariance matrix and also testing with
116 the new hybrid system structure of GSI.

117 Exercise with the hybrid 3DVar assimilation technique with the BAM-CPTEC/INPE, was made
118 using the Ensemble Square Root Filter (EnSRF - Whitaker and Hammill 2002). Two experiments
119 were carried out: one experiment using 50% of ensemble contribution to the static covariance and
120 a second experiment with 75% of ensemble contribution, were designed to test the hybrid 3DVar
121 system. Another experiment with a pure 3DVar using the BAM-CPTEC/INPE in a cycled data
122 assimilation and the realization of the BAM-CPTEC/INPE with the National Centers for Environ-
123 mental Predictions (NCEP) analysis were also performed. For the three experiments using data
124 assimilation, the new static version of the background error covariance matrix were used. As we
125 have made a new background error covariance matrix for use in the experiments with the tradi-
126 tional 3DVar and the hybrid data assimilation, Subsection 2a shows the details and main aspects

127 the the new static matrix. Subsections 2b and 2c are dedicated to present the BAM-CPTEC/INPE
128 model information and the main setup for the hybrid 3DVar system, respectively. A detailed de-
129 scription of the experiments is given in Section 3.

130 *a. Static Background Error Covariance Matrix*

131 The background error covariance matrix (**B**) has the role to filter and propagate spatially the
132 observation information (Berre et al. 2013), contributing to transform part of the observations
133 innovations into analysis increments.

134 The calculation of the background error covariance matrix for the GSI system used in this work,
135 involved the use of 730 pairs of 48 and 24 hours forecasts, valid for the 0000 and 1200UTC,
136 distributed evenly over 1 year (2013). The resolution of the forecasts matches the resolution of
137 the forecast model used in the experiments, i.e., TQ0062L028 (with 192 x 96 x 28 - *lat X lon*
138 *X lev* grid points). The forecasts pairs were organized as follows: considering 2014010100, the
139 first valid forecast pair was generated with the analysis from 2013123100 (valid for a 24 hours
140 forecast) and 2013123000 (valid for a 48 hours forecast). The methodology used to calculate the
141 amplitudes (i.e., the variances and covariances) is based on the NMC method (Parrish and Derber
142 1992). This method claims that spatial correlations of the model errors are similar to the spatial
143 correlations of the differences between the 48 and 24 hours forecasts. The NMC method was cho-
144 sen for the background error covariance calculations due to the convenience of having previously
145 analyses from operations. These analyses were used to integrate the BAM-CPTEC/INPE model
146 at TQ0062L028 resolution for one year. Within the algorithm involved in the calculations, there is
147 also a procedure to remove the bias in the vertical model column, which were also used. Covari-
148 ances were calculated for the standard GSI control variables, i.e., streamfunction (ψ), unbalanced
149 velocity potential (χ), unbalanced temperature (T), unbalanced surface pressure (ps) and the nor-

malized relative humidity (*rh*). The sea surface temperature (*sst*) is the same as the one used on the GFS-NCEP background error covariance matrix (i.e., the Real-Time, Global, Sea Surface Temperature - RTG_SST analysis, from which the variances and length scales were interpolated to the target grid).

In practice, although GSI doesn't explicit construct \mathbf{B} , it applies the covariances of \mathbf{B} using recursive filters (Purser et al. 2003a,b):

$$\mathbf{B} = \mathbf{B}_z(V^1 \mathbf{B}_x^1 \mathbf{B}_y^1 \mathbf{B}_y^1 \mathbf{B}_x^1 V^1 + V^2 \mathbf{B}_x^2 \mathbf{B}_y^2 \mathbf{B}_y^2 \mathbf{B}_x^2 V^2) \mathbf{B}_z \quad (1)$$

where,

- V^1 and V^2 are the standard deviations of each control variable (from the \mathbf{B} file);
- \mathbf{B}_x , \mathbf{B}_y and \mathbf{B}_z are the recursive filter applications in the directions of x (west-east), y (south-north) and z (vertical);
- \mathbf{B}^1 and \mathbf{B}^2 represents the application of the recursive filter in the horizontal scales (x and y).

An important property of the recursive filters in the GSI framework, is the adjustment of the amplitudes and the length scales in order to make the aspect of the covariances anisotropic, letting them to adjust to the background flow. These parameters and scales used in the application of the recursive filters are sort of empirical and a discussion of it can be found in Wu et al. (2002). The resulting amplitudes of the calculated \mathbf{B} are presented in Section 4a.

b. The Brazilian Atmospheric Model (BAM)

CPTEC has been made efforts to continuously develop and improve its own GCM for operational use at the center. As a result of this efforts, the BAM-CPTEC/INPE (Figueroa et al. 2016) brings

169 the most recent advances in both model dynamics and physics. Although the version of the BAM-
170 CPTEC/INPE model used in this work is not exactly the same version used in Figueroa et al.
171 (2016), the version used in the experiments will be referred as “BAM v0.0”, which includes the
172 same dynamical core and a simplified physics package (mostly described in Cavalcanti et al. 2002).
173 This simplified physics package is based on a large scale condensation due to the chosen model
174 resolution (TQ0062L028, roughly 200 km at the Equator) and the ensemble size (40 plus 1 of
175 the hybrid analysis). Furthermore, microphysics was avoided due to the intense computational
176 requirements (Silvio N. Figueroa, personal communication).

177 The BAM-CPTEC/INPE is a spectral model representing mass and winds in terms of vorticity
178 and divergence, with a pure sigma vertical coordinate, used at the center for operational NWP
179 (current resolution is TQ0666L064, roughly 20 km at the Equator) up to 5 days, and - at a coarse
180 resolution (TQ0126L028, roughly 100 km near the Equator) for extended NWP up to 15 days,
181 using an ensemble prediction system based on Empirical Orthogonal Functions (EOF) for the
182 perturbation of the initial condition. Seasonal and climate simulations are made as well. For these
183 applications analysis are still taken from GFS-NCEP.

184 *c. Hybrid Ensemble-Variational Analysis Cycle*

185 The hybrid 3DVar is the variational system with hybrid covariances intended to be the next
186 generation of atmospheric analysis at CPTEC. This system was exercised in an experimental basis
187 at CPTEC for weather forecasts only (up to 5 days at TQ0062L028 model resolution). Plans
188 include to use the ensemble of analysis from the hybrid system to replace or to augment the
189 current size (15 members) and consequently the spread of the center’s global Ensemble Prediction
190 System (EPS, described in Mendonça and Bonatti 2009; Cunningham et al. 2015), for extended
191 atmospheric forecasts (up to 15 days). The hybrid system used in this work is coupled with the

192 BAMv0 model through an interface that reads the spectral forecasts from the BAMv0 model and
 193 rewrites the spectral coefficients for use as a background for the GSI system.

194 The current hybrid setup requires the realization of the GSI observer using the mean ensemble as
 195 a background. No analysis is made at this point and this step is only necessary to write the diagnos-
 196 tics files from the departures. The next step is the realization of the observer using the departures
 197 related to the ensemble mean, but using every ensemble member as a background. In the setup
 198 tested, an ensemble of 40 members was used. This number represents a reasonable ensemble size,
 199 which fits all the computational requirements, regarding the allowed computational time and disk
 200 space without compromise the efficiency. Once the observer ensemble of departures is computed
 201 within GSI, the EnSRF is applied to update the ensemble of backgrounds. The final determin-
 202 istic hybrid 3DVar analysis is then achieved using the covariances from the updated ensemble of
 203 backgrounds, which are blended with the static pre-computed background error covariance matrix.
 204 Figure 1 shows a schematic diagram of the analysis cycle.

205 The hybrid 3DVar system minimizes a 3D variational cost function in the same fashion as 3DVar.
 206 The main difference is regarded to the way the background error covariance matrix is defined and
 207 applied. Equation 2 (presented here in a more general way) represents the hybrid 3DVar cost
 208 function, where x' is the new analysis increment.

$$J(x') = \frac{1}{2}(x')^T(\alpha_1\mathbf{B} + \alpha_2\mathbf{P}^b)^{-1}(x') + \frac{1}{2}[y_o - \mathbf{H}(x')]^T\mathbf{R}^{-1}[y_o - \mathbf{H}(x')] \quad (2)$$

209 Note that the term $(\alpha_1\mathbf{B} + \alpha_2\mathbf{P}^b)$ represents the linear combination between the pre-computed
 210 static \mathbf{B} and the ensemble flow-dependend ensemble covariances \mathbf{P}^b . The coefficients α_1 and α_2
 211 are the weights assigned to each parcel of the linear combination, trough which we control the
 212 amount of contribution of the ensemble covariances to the static part.

213 In Equation 2, x' is defined as:

$$x' = x + \sum_{k=1}^K (a_k \circ x_k^e) \quad (3)$$

214 This analysis increment is defined as the sum between the standard analysis increment (x) due
 215 to the static background error covariance contribution and the summing between the extension of
 216 the control variable (a_k , to account for the ensemble localization) and the ensemble perturbation
 217 of each member ($x_k^e = \frac{(x_k^b - \bar{x}^b)}{\sqrt{K-1}}$). A more detailed explanation of the GSI methodology to extend
 218 the variational framework to accommodate the ensemble covariances can be found in Wang et al.
 219 (2007, 2008a,b); Wang (2010); Wang et al. (2013).

220 Despite the fact that the hybrid 3DVar analysis cycle have been established for the BAMv0
 221 model, some caveats have been found and will demand attention on future revisions of this sys-
 222 tem. The system works in a single resolution, i.e., both the control and the ensemble of back-
 223 ground/analysis are run at the same model resolution (currently TQ0062L028). As a consequence,
 224 a recentering of the ensemble mean around the hybrid analysis, is not made. Another point to
 225 mention is the fact that the bias mass and angle of the radiance channels and instruments were not
 226 being updated. This decision was taken because, as a testing system, no compromise was made
 227 to keep the radiance information error updated. Also, there is no vertical localization within the
 228 EnSRF, so a fixed value is used for the entire vertical column.

229 3. Experimental design

230 To test the hybrid 3DVar system, a set of experiments were idealized in order to verify the
 231 analysis and forecasts skill (in terms of the Root Mean Square Error - RMSE and the Anomaly
 232 Correlation - AC), by comparing them with a pure (control) 3DVar analysis. The pure 3DVar
 233 analysis, in turn, was compared to an offline analysis experiment by integrating the BAMv0 model

with an independent analysis. The next subsection are dedicated to explain the design of each experiment.

a. Control Experiment

The control experiment is intended to be a 3DVar experiment run with the new background error covariance matrix. This experiment is the control run and is compared to the hybrid 3DVar experiments. The control was ran using the variational analysis in TQ0062L028 resolution and the model configuration (both the dynamics and the physics) is the same among every experiment. The analysis cycle is setup in the following manner. A set of three background forecasts of 3, 6 and 9 hours (where the central analysis is always at 6 hours) are used by GSI for the update with the observations in a First Guess at Appropriate Time (FGAT) approach. Observations include conventional data (u , v , T , q and ps) from several sources (e.g., the Global Telecommunication System - GTS) and unconventional data, like radiance, retrievals and Global Positioning System - Radio Occultation (GPS-RO).

Table 2 in Section 3c summarizes the types of observations included in the experiments. The same set of observations are used for the hybrid 3DVar experiments as well.

The analysis cycles continues when GSI writes the analysis file for the atmosphere and the surface. It is worth to note that only the atmospheric part of the analysis was used to initialize the BAMv0, although the model restart files were used to initialize the surface fields, as well clouds and radiation. This same approach is taken for the hybrid experiments.

Another idealized experiment is the offline analysis (i.e., without an analysis cycle). In this experiment the BAMv0 where integrated in time with a hi-resolution NCEP spectral operational analysis which was chopped at each analysis time (i.e., 00, 06, 12 and 18UTC). From this experiment, 120 hours forecasts are generated, in the same fashion as the pure 3DVar run. This

257 offline experiment is intended to serve as a control for the pure 3DVar experiment, whereas the
258 pure 3DVar analysis experiment serves as a control for the hybrid 3DVar experiments.

259 *b. Hybrid 3DVar Experiments*

260 Exercising with the hybrid 3DVar was made cycling the system with the BAMv0 model be-
261 tween December 2012 and January 2013. A spin up time was considered and the first month of
262 the simulations was taken apart from the results. One of the reasons for this practice is the fact
263 that the initial ensemble of analysis was generated by running the BAMv0 model from a single
264 deterministic analysis and forecasts made up to 30 days at each 12 hours (i.e., twice a day). From
265 this, a time series of 60 forecasts ranging from 12 hours up to 720 hours from the analysis time
266 was assembled. The first 40 forecasts were kept and carefully modified to reflect the background
267 time for the first analysis to be generated in all hybrid 3DVar experiments.

268 To assess the behaviour of the hybrid 3DVar system using the BAMv0 model as a background
269 and its new background error covariance matrix, two cycled data assimilation experiments were
270 ran. The experiment called 3DVar represents the variational GSI/3DVar experiment with the new **B**
271 (considering $\alpha_1 = 1$, i.e., no ensemble covariance contribution). The experiment called EnSRF50
272 (EnSRF75) represent the same data assimilation cycle ran using the hybrid **B** through the use of
273 the EnSRF (considering $\alpha_2 = 0.5$ and $\alpha_2 = 0.25$, i.e., considering 50% and 75% of contribution
274 of the ensemble covariances, respectively).

275 Table 1 summarizes the experiments designed to exercise the hybrid 3DVar system, ranking the
276 ensemble covariance contribution for each experiment.

277 *c. Observational Data*

278 The observational data used for the experiments with a cycled analysis using the 3DVar GSI and
279 the EnSRF algorithm, are the same. Table 2 shows a summary of the observational data used.

280 *d. Model Setup*

281 In all experiments, regardless the analysis used, the same model configuration had been taken.
282 Table 3 summarizes the main options adjusted within the dynamical core and physics options. It
283 is worth to note that in the data assimilation cycle (regardless the hybrid or the pure variational
284 option), the atmospheric model was restarted at every cycle (00, 06, 12 and 18UTC). The BAMv0
285 restart files comprises the previous states of the land-surface, clouds and radiation. Sea surface
286 temperature, snow cover and soil moisture are read from separated files and the dynamical state
287 (i.e., momentum) are provided by the atmospheric analysis. These conditions are valid for the
288 generation of the background files (3h, 6 and 9 hours forecasts) used by the GSI.

289 *e. GSI Setup*

290 This subsection is intended to give an overview of the basic and main GSI options that was
291 chosen to complete the experimental design. GSI has many different option that can be adjusted
292 in order to allow the system run with specific procedures or to tune the system through the use
293 of knobs that must be adjusted empirically. All of these option can be found on the official GSI
294 manual, available at the Development Testbed Center (DTC) website.

295 Two of these general options worth to mention here (the choice for humidity control variable
296 and the moisture constraint), as they were kept the same among all experiments using GSI.

297 HUMIDITY CONTROL VARIABLE

298 GSI has two options to treat the humidity control variable. They are the pseudo relative-humidity
299 and the normalized relative humidity. As we were testing a new background error covariance
300 matrix, we decided to choose the normalized relative humidity as the humidity control variable in
301 all experiments. The normalized relative humidity allows the relative humidity to change in the
302 inner loops in accordance to changes in the surface pressure, temperature or specific humidity.

303 MOISTURE CONSTRAINT

304 Supersaturated and negative moisture are non-physical solutions that arises from computation
305 modes. In GSI, there is an option that can be tuned in order to control the supersaturated and
306 negative moisture. Several tests were made in order to achieve reasonable values to allow the
307 stability of the system. The values found are 5.0 for the supersaturated moisture constraint and
308 0.005 for the negative moisture constraint.

309 4. Results

310 This section shows the results obtained with the application of a hybrid background error co-
311 variance matrix through the use of a hybrid 3DVar system for the BAMv0 model. Along with the
312 experimental results, the main characteristics of the calculated background error covariance matrix
313 are shown. Results from the experiments with the hybrid 3DVar are divided into three categories:
314 1) the ensemble innovation statistics; 2) forecasts skill (up to 120 hours, taken in terms of AC along
315 with t-Student tests) and 3) precipitation assessment (taken in term of a comparison with the GPCP
316 data). The evaluations are made to the regions Global (GL), North Hemisphere (NH - lons:0°-
317 360°; lats:20°N-80°N), Tropics (TR - lons:0°-360°; lats:20°S-20°N), South Hemisphere (SH -
318 lons:0°-360°; lats:80°S-20°S) and South America (SA - lons:0°-360°; lats:49.875°S-11.375°N).

319 *a. Standard Deviations of the Static \mathbf{B}*

320 Experiments with a cycled data assimilation (analysis from 3DVar and hybrid 3DVar experi-
321 ments) were made using the same version of the static background error covariance matrix. In
322 Section 2a, it was showed how the static part of the hybrid background error covariance matrix
323 was calculated and how its application within GSI is made. Following the results in Wu et al.
324 (2002), the main features of the static \mathbf{B} are presented here in a similar manner.

325 In order to make an quantitative and a qualitative description of the amplitudes represented by
326 the computed covariance matrix, Figure 2 depicts the standard deviations of the variance error for
327 the ψ , χ , T , rh , oz and ps . As a reference, Table 4 presents the maxima and minima values for the
328 amplitudes shown in Figure 2 along with the values for the horizontal and vertical length-scales.

329 The distribution of the variances of stream function (ψ) and velocity potential (χ) are presented
330 in a vertical cross-section, as shown in Figure 2. These distribution shows some of the features of
331 the non-divergent and divergent part of the wind for the BAMv0 model. The ψ variances distribu-
332 tion are sort of symmetric with respect to the Equator line. They are more elongated throughout
333 the vertical column and are concentrated at the model top. Higher values of the streamfunction
334 variances are located over the poles, between sigma levels of 0.6 (~ 614.4 hPa) and 0.2 (~ 204.8
335 hPa). In the tropical regional, these values are more confined between 0.3 (~ 307.2 hPa) and 0.1
336 (~ 102.4 hPa) sigma levels. The distribution of the variances of the velocity potential also shows a
337 symmetric pattern with respect to the Equator line and are mostly concentrated with higher values
338 over the tropical region, between sigma levels of 0.3 (~ 307.2 hPa) and 0.1 (~ 102.4 hPa).

339 Temperature (T) variances are distribute from the Equator line towards the pole, in both hemi-
340 spheres. At 30°N large values extend onwards with a maximum peak between 0.9 (~ 921.6 hPa)
341 and 0.8 (~ 819.2 hPa) sigma layers. At 60°S , a symmetric pattern is represented, as can be seen

342 in Figure 4c in Wu et al. (2002). Variances of the humidity (rh) are distributed with a peak in
 343 approximately 60°S between 0.7 (~ 716.8 hPa) and 0.6 (~ 614.4 hPa) sigma layers. Layers above
 344 0.6 sigma, variances diminish with height until layer 0.2 (~ 204.8 hPa), whereas the opposite pat-
 345 tern seems to happen around latitude 60°N . Ozone (oz) distribution of variances are concentrated
 346 in upper layers, 0.5 (~ 512 hPa) upwards, with a peak in the tropical region. In the current setup,
 347 GSI does not analyses ozone observations. In the BAMv0 model ozone is transported throughout
 348 the grid during the forecast. The surface pressure (ps) variances are distributed with two local
 349 maxima values in the midlatitudes (higher values are located below 60°S) and minimum values
 350 in the tropical region. It is worth to note that the surface pressure variance distribution are fairly
 351 different from what can be found in Figure 4e from Wu et al. (2002).

352 Most of the characteristics in the distribution of the error amplitudes may be due to the represen-
 353 tation of the BAMv0 topography, including the choices for the model physics and the treatment of
 354 the model dynamics and resolution. At this resolution (i.e., TQ0062L028), steep topography may
 355 be not well represented (peaks in topography may be too smooth), what can lead to discrepancies
 356 in the representation of the pressure and winds. A separated study still has to be made in order
 357 to address the sensitivity of the background error covariance matrix to the BAMv0 options and
 358 the resulting variances. Furthermore, one may consider the fact that such amplitudes can be tuned
 359 within GSI by setting up specific parameters for the application of the covariances using recursive
 360 filters.

361 Table 4 summarizes the maximum and minimum values for the amplitudes of the standard de-
 362 viations and horizontal and vertical length-scales, including for the other quantities not shown in
 363 Figure 2.

364 *b. Ensemble Innovation Statistics*

365 For an evaluation of the ensemble of analyses produced in experiments using the EnSRF, an
 366 ensemble innovation assessment was made in terms of a scaled bias to diagnose deficiencies in the
 367 ensemble spread due to inflation and localization adjustment.

368 To assess how the ensemble deals with the system spread in the presence of observational error,
 369 innovations are shown as a measure of how good the ensemble spread is due to the observation
 370 innovation. In Figure 3, a comparison between the innovation statistics from EnSRF is shown for
 371 three different regions (NH; TR and SH) and only for the conventional observations. We left the
 372 same evaluation regarding unconventional observations for a separated study. In order to make
 373 it easier to understand, the y axis shows the ratio between the standard deviation of the prior
 374 innovations (i.e., $y^o - \mathbf{H}x_k^b$, where k is an ensemble member) and the square root of the ensemble
 375 total spread (i.e., $\sqrt{\mathbf{S} + \mathbf{R}}$). The ensemble innovation is given by,

$$EI = \frac{y^o - \mathbf{H}x_k^b}{\sqrt{\mathbf{S} + \mathbf{R}}} \quad (4)$$

376 where,

- 377 • y^o : is the observation vector;
- 378 • x_k^b : is the vector of the k -th ensemble member;
- 379 • \mathbf{S} : is the ensemble spread;
- 380 • \mathbf{R} : is the observation error from the observation error covariance matrix.

381 As we are normalizing the standard deviation of the priors innovations by the ensemble total
 382 spread, the lower the values, the better the ensemble innovation is. Ideally, the standard devi-

383 ation of the priors should match the value of the ensemble total spread if the ensemble is well
384 conditioned, i.e., with a good amount of spread and proper localization and inflation.

385 In Figure 3, the upper panel shows the statistics for 00UTC and the bottom panel the same
386 statistics for 12UTC. This was made with the purpose to reduce the size of the time series and to
387 separate the signal from both times, so this would make easier to analyze the results. Furthermore,
388 synoptic times of 06 and 18UTC were kept away from the evaluation due to the fact that there is
389 less meteorological observations at these synoptic times. Red lines (dashed and solid) refers to the
390 hybrid 3DVar experiment where 50% of ensemble contribution to the static part of the covariance
391 matrix, whereas the blue lines refers to the same experiment but denoting the case where 75% of
392 ensemble contribution to the static part of the covariances were drawn.

393 Figures 3d,e,f (in both panels) with the ensemble innovation statistics for T at NH, TR and SH,
394 regardless the relative amount of ensemble contribution, shows that the differences between the
395 priors and the posteriors are more noticeable at the NH, where T is closer to the zero line.

396 The standard deviation for the horizontal wind (uv) at 00UTC (Figure 3a), was very close to the
397 ensemble total spread, indicating that the ensemble fit to the observation was good and the amount
398 of ensemble spread was reasonable. At the TR region (Figure 3b), however, the opposite was
399 found. In the SH region (Figure 3c), a similar situation to NH happens and the amplitude of the
400 ensemble innovation signal increases indicating, possibly, that the lack of ensemble inflation due
401 to reduced number of conventional observation in the region. Innovation statistics for variables q
402 follows the trends figured for T , with increasing values over TR regions all along the simulations.
403 For the surface pressure, on the other hand, innovation statistics seems to decrease with time (in
404 both 00 and 12UTC), specially over SH region. This may be an indication that the ensemble spread
405 is not good there.

406 *c. Forecast Skill*

407 The forecast skill up to 5 days, was assessed in terms of the Anomaly Correlation (AC). As
408 CPTEC developments are focused in the Tropics and the the South America regions, results are
409 shown for these region along with for the whole Globe and North and South Hemispheres. To
410 assess how different the experiments are between each other, a t-Student test was also made with
411 a 95% of confidence level. For each plot of the AC, a t-Student test is presented and the lower
412 boxes shows whether or not the curves are different at the defined confidence level. When the
413 curves crosses their respective boxes, it means that the differences between the experiment (e.g.,
414 EnSRF50) and the experiment of reference (i.e., REF, the BAMv0 model integrated with the op-
415 erational NCEP analysis) are of no difference, indicating that the test for the null hypothesis fails.
416 In this case, the null hypothesis is that the mean of the hybrid experiment verified is statistically
417 indistinguishable from the mean of the experiment of reference.

418 Figure 4 shows the 5-day forecasts AC with a t-Student test for regions NH, TR and SH. Fig-
419 ure 5 shows the 5-day forecasts AC with the same t-Student test, but for the regions GL and SA.
420 Variables evaluated are the surface pressure ($psnm$), specific humidity at 925 hPa ($q925$), air tem-
421 perature at 850 hPa ($T850$), zonal wind component at 250 hPa ($u250$) and geopotential height at
422 500 hPa ($z500$). Experiments summarized in Table 1 were run with the same configuration (i.e.,
423 using the same code and options chosen through namelists).

424 Experiment EnSRF50 indicate the best analysis performance for all regions and variables eval-
425 uated. Surface pressure ($psnm$) at NH has practically no difference using either EnSRF75 or
426 EnSRF50 for the first 24 hours of forecasts.

427 In the TR region - a region specially difficult to predict for, forecast of $psnm$, $q925$ and $T850$
428 (Figures 4b,e,h) from EnSRF75 have shown a good performance with respect to experiments REF

429 and 3DVar. The improvements with respect to REF for *psnm* (Figure 4b), are of almost 24 hours
 430 (considering 80% of the AC). Figure 4e, shows improvements of the experiment EnSRF75 with re-
 431 spect to experiment 3DVar, in the order of almost 4 days in advance (considering 85% of the AC).
 432 A similar improvement was found for the forecast of the *T850* (Figure 4h), with respect to experi-
 433 ment to experiment 3DVar were experiment EnSRF75 still holds 80% of AC for 72 hours forecast,
 434 whereas experiment 3DVar limits its forecast skill for this variable up to 36 hours. The zonal com-
 435 ponent of the horizontal wind at 850 hPa (*u850* - Figures 4n), showed an slightly improvement over
 436 the TR region. It is worth to note in Figures 4b,h,q the spin up time that the BAMv0 model took
 437 to initialize with the GFS-NCEP analysis. However, this effect was not noticed for every evalu-
 438 ated variable. Figure 4g, for example, indicates that there is no practical difference between the
 439 experiments whose AC scores are very similar. The t-Student test, however, reveals that the 3DVar
 440 experiment did not fail the null hypothesis test for the 120 hours forecasts, while the remaining of
 441 the experiments holds the test up to 36 hours (EnSRF50) and 72 hours (EnSRF75). On the other
 442 hand, however, experiment EnSRF75 was statistically different from the REF up to 72 hours.

443 Figure 5 shows the same evaluation as Figure 4, but for regions GL and SA. The SA region is
 444 of great interest for CPTEC because it is Brazil's target forecast region. The same response from
 445 experiments EnSRF75 and EnSRF50 were found, indicating that for the SA region, the ensemble
 446 covariances can also play an important role in the determination of the forecasts skill. For the
 447 GL region, AC scores are similar to what we have found on NH region. Besides that, the AC
 448 for *q925* at GL region (Figure 5c), shows that the forecasts drawn from the EnSRF75 experiment
 449 was good up to 120 hours. Remaining variables (i.e., *psnm*, *T850*, *u250* and *z500* - Figures
 450 5a,e,g,i, respectively) showed similar AC scores in comparison with the NH region. For the SA
 451 region, good results were found *psnm* (Figure 5b), for up to 84 hours forecasts; *q925* (Figure 5d),
 452 with AC greater than 85% for 120 hours and *T850* (Figure 5f) with AC of 80% from experiment

453 EnSRF75 for up 72 hours forecasts. Zonal wind at 250 hPa (u_{250}) and, specially, z_{500} , did not
454 drawn good AC scores. The z_{500} (Figures 5k,l) from experiment EnSRF75 did not performed well
455 as for others variables. From 84 hours forecast ahead, its was the worse and experiment EnSRF50
456 - and even experiment 3DVar, were better.

457 A comparison between the analysis schemes used in the experiments, shows that the humidity
458 analysis drawn from the EnSRF50 experiment, was improved over the pure 3DVar analysis. For
459 these hybrid 3DVar experiments, background error covariance matrix is the same static covariance
460 matrix used within the 3DVar experiment. This is an indication that the ensemble covariance plays
461 an important role on defining how the analysis increments are applied.

462 PRECIPITATION ASSESSMENT

463 Precipitation forecasts drawn from the REF experiment and from the pure 3DVar and the hy-
464 brid 3DVar analysis has been also evaluated. Figure 6a shows the observed Global Precipitation
465 Climatology Project v2.2 (GPCPv2.2) 2.5° (Adler et al. 2003) global monthly mean precipitation
466 and the forecasted precipitation - represented as a monthly mean, drawn from the REF (Figure
467 6b), 3DVar (Figure 6c), hybrid 3DVar analyses with EnSRF50 (Figure 6d) and EnSRF75 (Figure
468 6e). The comparison between the 24 hour monthly mean forecasts and the GPCP 2.5 is valid
469 for January 2013 (12UTC) and the gridded data has been interpolated to a 2.5° grid resolution to
470 match GPCPv2.2. GPCP 24 hour monthly mean precipitation for January 2013 depicts the main
471 features of the tropical precipitation (from 8 mm above) and the subtropical precipitation (until 8
472 mm), with most of the convective precipitation being distributed over the tropical region.

473 The precipitation fields being compared in Figure 6a represents the monthly mean at 12UTC
474 beginning at 1st January 2013, until 31rd January 2013. All experiments shows the spatial features
475 of the large scale precipitation and the convective precipitation as well. Figure 6a is used as a

reference and the evaluation is made by comparing the precipitation intensity, distribution and the spatial average of the monthly mean, annotated below each picture.

The precipitation forecasts from the experiments, shows a reasonable spatial distribution in comparison with GPCPv2.2 monthly mean precipitation. It is worth to note that the model configuration for large scale condensation, cumulus convection and horizontal and vertical diffusion were kept the same, so the differences are supposed to be due to the initial condition only. Main differences between precipitation forecasts from experiments are mostly related to the intensity of the precipitation, once the spatial distribution between them are fairly similar. Figure 6b, shows the resulting monthly mean 24 hour precipitation from the BAMv0 model initialized with the REF analysis. In comparison with any other experiment (including the GPCPv2.2 reference), the BAMv0 model tended to produce more convective precipitation in the Tropical region. The spatial average of the time mean amounts to 2.9718 mm/month, yielding the highest value among the experiments, even higher than GPCPv2.2 (2.7197 mm/month). All experiments with data assimilation cycle, on the other hand, have produced precipitation with less concentrated distribution and a more reasonable spatial average. The spatial average in experiment EnSRF50 (Figure 6d) is the one which more approximates GPCPv2.2, although the rest of the data assimilation experiments has concentrated the convective precipitation in a more conformable way.

The exaggerated amount of precipitation produced by experiment REF must be due to fact that this experiment was made by just running the BAMv0 model with the GFS-NCEP analysis, although a topography smoothing and a initialization with normal modes has been made for every analysis used in this specific experiment. The choices for the cumulus parametrization and the diffusion parameters may also play an important role in the precipitation production. The experiments with the data assimilation cycle, with the exception of experiment EnSRF75 (Figure 6e) -

499 which is the experiment that yielded the lower monthly mean, seems to be well conditioned with
500 the option chosen for the forecasts.

501 In order to better understand and to identify the regions where the experiments have accumulated
502 more or less the precipitation, Figure 7 shows the time series of the spatial averages for each
503 experiment, including the GPCP. In this figure, the GPCPv1.2 1DD (1 Degree Daily - Huffman
504 et al. 2001) was used and the observed data has been interpolated to the analysis grid (with 1.875°).
505 Accompanying Figure 7, Tables 5 and 6 shows the spatial averages (μ) and the standard deviations
506 (σ) for each experiment (including the interpolated GPCP1DD) at the regions evaluated (GL, NH,
507 TR, SH and SA).

508 In contrast to what we have found by analyzing the spatial distribution of the precipitation fore-
509 casts in Figure 6, the time series for the spatial averages showed in Figure 7, shows us that - with
510 the exception of region NH (Figure 7b), all experiments have some difficulties to reproduce the ob-
511 served precipitation in 24 hour forecasts. Deficiencies can be noted with respect to the amplitude
512 (maxima and minima) and to the average. In some specific cases, forecasted precipitation nearly
513 matched observed values - e.g., experiment EnSRF75 in TR region (Figure 7c) which matched the
514 GPCPv1.2 during some periods of the month. This results is with accordance to what we found
515 when analyzing the forecast skill (Figures 4 and 5), showing that among the hybrid 3DVar exper-
516 iments, the 75% of the EnSRF ensemble contribution to the static part of the background error
517 covariance was beneficial in most cases. On the other hand, experiment REF have exaggerated the
518 precipitation over time mainly for the GL and TR regions (Figures 7a and 7c). This is an expected
519 result, since this experiment have used an independent analysis and the model was not configured
520 to give the best result from it. For the TR and SA regions (Figures 7c,e), precipitation forecasts
521 were mostly above the observed values indicated by GPCPv1.2. In these regions, the convective
522 precipitation plays an important role and models tend to exaggerate the precipitation there. If we

523 consider the SH region (Figure 7d) - which contains more oceanic parts (in opposition to the NH
524 region), models tends to produce more large-scale precipitation whereas the convective precipita-
525 tion tends to be less important in the results. Consequently, the precipitation forecasts tends to be
526 below the observed values.

527 All experiments with the hybrid background error covariance matrix showed reasonable results
528 if compared to experiments 3DVar and REF. It appears, however, that the precipitation - specially
529 the convective precipitation, to be not so sensitive to changes in the covariance matrix, although
530 the experiment with greater ensemble contributions (EnSRF75) do perform better than the rest of
531 the experiments made.

532 **5. Summary and discussion**

533 In this work we have tested an implementation of the hybrid 3D variational (hybrid 3DVar)
534 data assimilation technique with the BAMv0 model. For this implementation, we carried out the
535 calculation of a static background error covariance matrix used in the linear combination with
536 the covariances from the ensemble part. To test the implementation, experiments were made in a
537 TQ0062L028 model and analysis resolution using an ensemble of analysis of 40 members, testing
538 the EnSRF algorithm. Results shows an general improvement of the winds, temperature, moisture
539 and surface pressure, mainly over South America and the Tropical region, which is a target region
540 for CPTEC operations. The moist part of the BAMv0 model (e.g., Specific Moisture, Precipitable
541 Water and Precipitation) resulted in a slight difference from the control run (the BAMv0 model
542 initialized with the GFS-NCEP analysis) and the from the BAMv0 model simulation initialized
543 with the pure 3DVar analysis.

544 In this work it is clear that the ensemble contributions to the static part of the covariance matrix
545 plays an important role in determining the skill of the analysis, and consequently the skill of the

546 forecasts. In some cases, we found improvements of more than 3 days, which we consider a great
547 step towards a robust analysis to use in daily operations. Furthermore, with this implementation,
548 we could not only show that our implementation is in the right way, but also that we could improve
549 the pure 3DVar analysis (despite some practical issues that have to be properly addressed). Our
550 results corroborates and contribute to the understanding of the application of hybrid background
551 error covariances matrices.

552 Further improvements to this work shall include the treatment of the caveats pointed out in
553 Section 2c. The realization of the hybrid 3DVar system at CPTEC operations will also depends
554 on the CPTEC capacity to keep the system at a higher resolution without compromise the system
555 performance and to afford the computational cost involved. A study regarding the dual resolution
556 feature for the hybrid system must be considered as the resolution of the ensemble limits the
557 system performance, and the use of the re-centering and ensemble inflation.

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TABLE 1. Hybrid 3DVar experiments and covariance matrix setup.

Experiment	Hybrid Setup	Description
REF	–	based on GFS-NCEP
3DVar	–	based on BAMv0-CPTEC
EnSRF50	50% Static/Ens. (40 mem.)	based on BAMv0-CPTEC
EnSRF75	75% Ens. (40 mem.)	based on BAMv0-CPTEC

TABLE 2. Observational data used in the experiments with a cycled analysis.

Mnemonic	Type	Description
airsbufr	Unconventional	AMSU-A/AIRS radiances from AQUA
amsuabufr	Unconventional	AMSU-A 1b radiances (brightness temperature) from NOAA-15, 16, 17, 18, 19 and METOP-A
hirs4bufr	Unconventional	HIRS4 1b radiances from NOAA 18, 19 and METOP-A
mhsbufr	Unconventional	MHS moisture sounders MHS from NOAA 18, 19 and METOP-A
iasibufr	Unconventional	IASI sounders from METOP-A
gpsrobufr	Conventional	GPS radio occultation refractivities
prepbufr	Conventional	ps , T , q , pw , uv , spd , dw and sst observations

TABLE 3. BAMv0 model setup (main options) used within the data assimilation cycles.

Option	Setup
Resolution	TQ0062L028
Integration timestep	1200 seconds
Wind transport	Eulerian
Mass transport	Semi-Lagrangean
Initialization	Diabatic
Restart	Surface
Mass conservation	$\ln(p)$
LW radiation	Harshvardhan et al. (1987)
SW radiation	CLiRAD (Chou 1999)
Cumulus convection	Grell (1993)
Shallow convection	Tiedtke (1983)
Top of PBL	Holtslag and Boville (1993)
Bottom of PBL	Mellor and Yamada (1974)
Surface model	SSiB (Sellers et al. 1996)

721 TABLE 4. Maximum and minimum values of Amplitudes, Horizontal and Vertical Length-Scales of the Static
722 TQ0062L028 background error covariance matrix.

	Amplitudes		Horizontal L-S		Vertical L-S	
	Min	Max	Min	Max	Min	Max
ψ	7.60×10^5	6.83×10^6	4.59×10^5	1.31×10^6	1.00×10^{-2}	1.48×10^0
χ	0	5.05×10^6	0	1.95×10^6	0	1.60×10^0
t	0	2.43×10^0	0	7.49×10^5	0	1.77×10^0
q	0	6.92×10^{-1}	0	7.29×10^{-1}	0	6.61×10^5
oz	0	1.76×10^6	0	5.90×10^5	0	5.30×10^0
cw	0	1.95×10^6	0	5.00×10^5	0	4.91×10^0
ps	6.84×10^{-2}	2.29×10^{-1}	3.56×10^5	5.26×10^5	–	–
ssr	2.00×10^{-2}	4.32×10^{-1}	5.07×10^2	8.00×10^2	–	–

723 TABLE 5. Area average of 24 hour (12UTC) precipitation (in mm/month) for the Globe (GL) and South
724 America (SA).

	GL		SA	
	μ	σ	μ	σ
GPCP	2.8635	0.1123	3.1321	0.7743
REF	3.0478	0.1036	5.2812	0.7786
3DVar	2.7601	0.1118	5.0152	0.8779
EnSRF50	2.8103	0.0935	4.6480	0.7768
EnSRF75	2.5745	0.1089	3.8128	0.6702

725 TABLE 6. Area average of 24 hour (12UTC) precipitation (in mm/month) for the North Hemisphere (NH),
726 Tropics (TR) and South Hemisphere (SH).

	NH		TR		SH	
	μ	σ	μ	σ	μ	σ
GPCP	1.7228	0.2653	4.2820	0.2694	2.6068	0.2053
REF	1.5547	0.2842	5.4655	0.3733	2.0758	0.2685
3DVar	1.4344	0.2438	4.7657	0.3420	2.0499	0.2512
EnSRF50	1.5605	0.2779	4.8385	0.2990	1.9999	0.2546
EnSRF75	1.4566	0.2520	4.2710	0.2209	1.9756	0.2619

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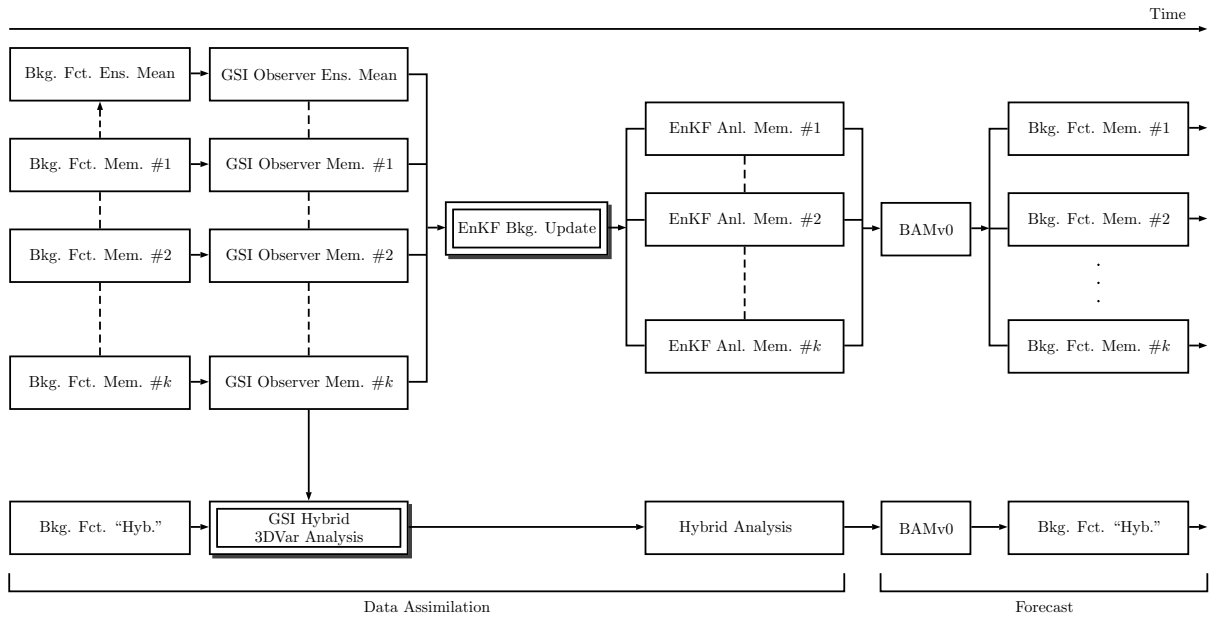


FIG. 1. Schematic diagram depicting the hybrid 3DVar analysis cycle for the BAMv0 model.

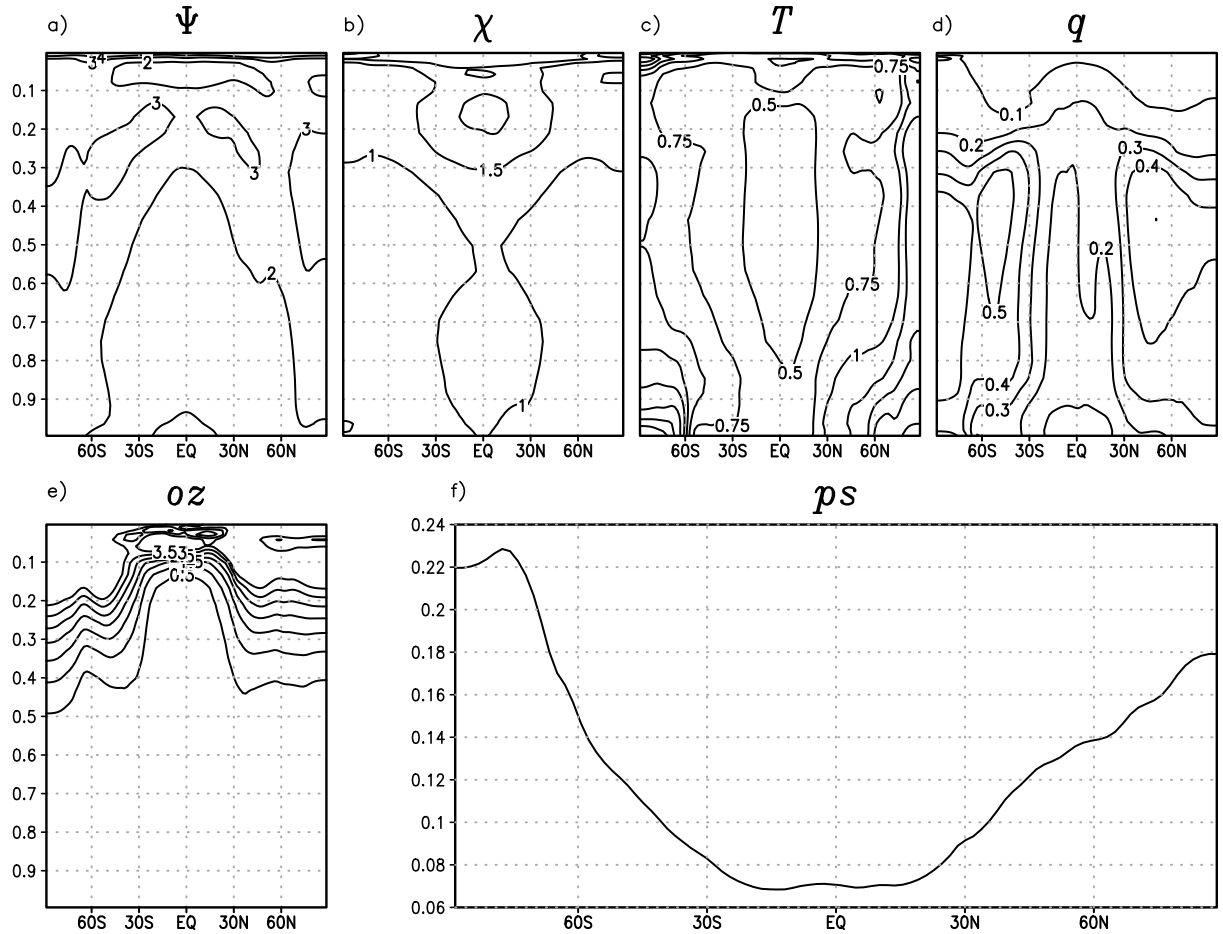


FIG. 2. Standard deviations of the variance errors distribution for ψ [$10^6 m^2 s^{-1}$], χ [$10^6 m^2 s^{-1}$], T [K], q , oz and ps [$\ln(hPa)$] throughout latitudes and vertical sigma levels.

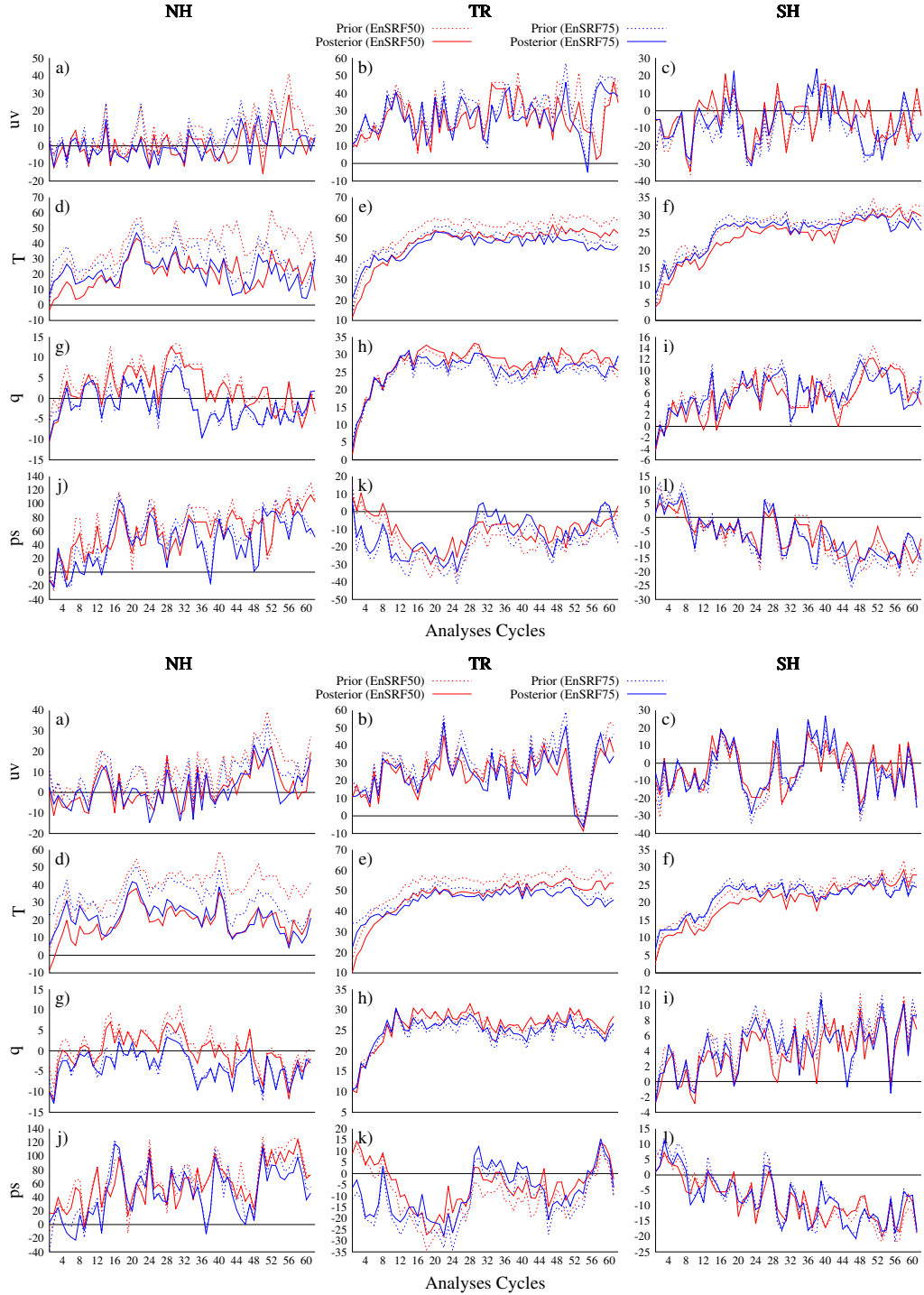


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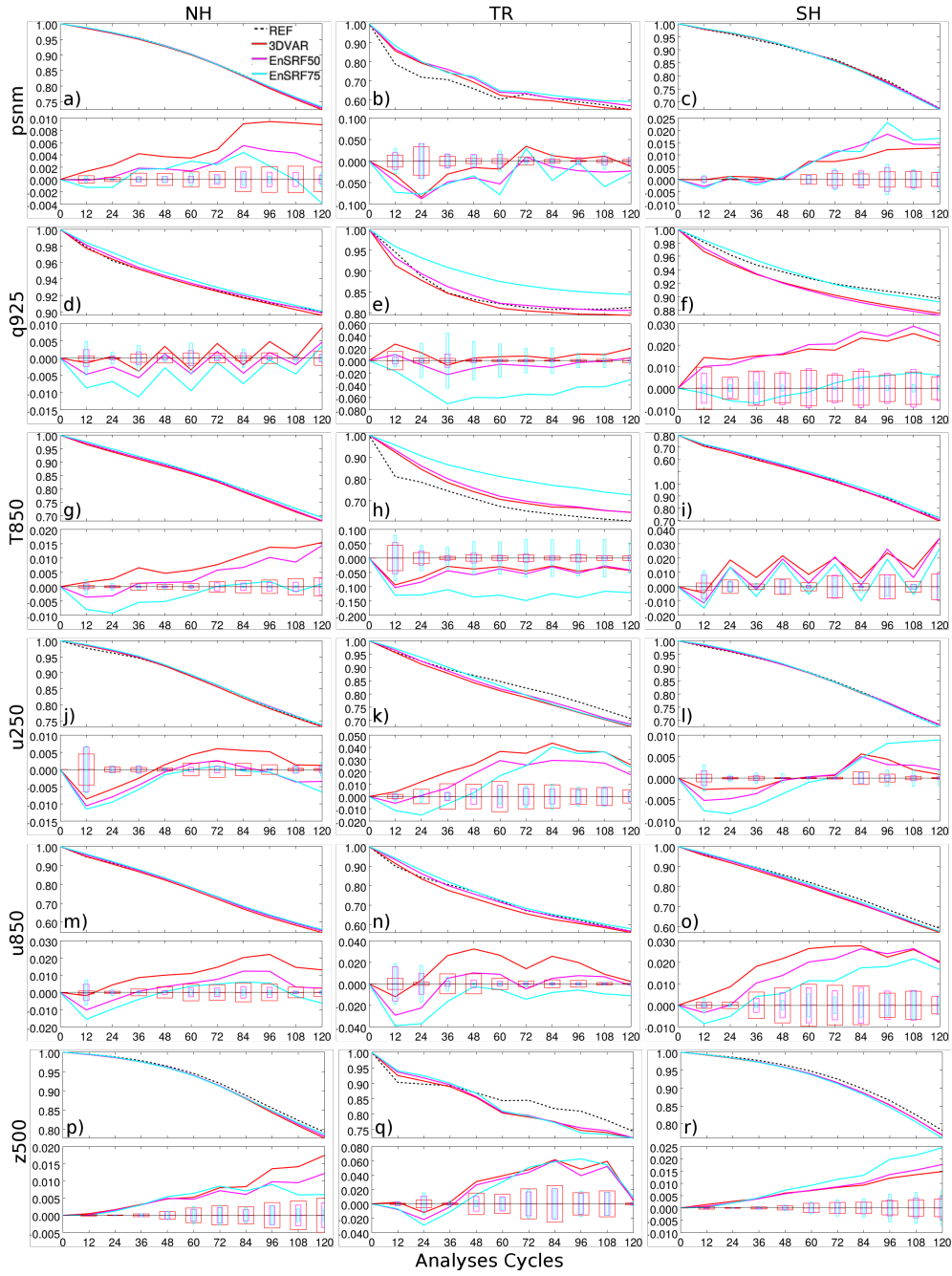


FIG. 4. 5-day forecast skill for regions NH, TR and SH. Dashed black line represents the REF experiment analyses and forecasts; solid red line, the 3DVar experiment; magenta line, the EnSRF50 and cyan line, the EnSRF75. All figures are presented with their respective t-Student significance test, where a 95% confidence interval is hold.

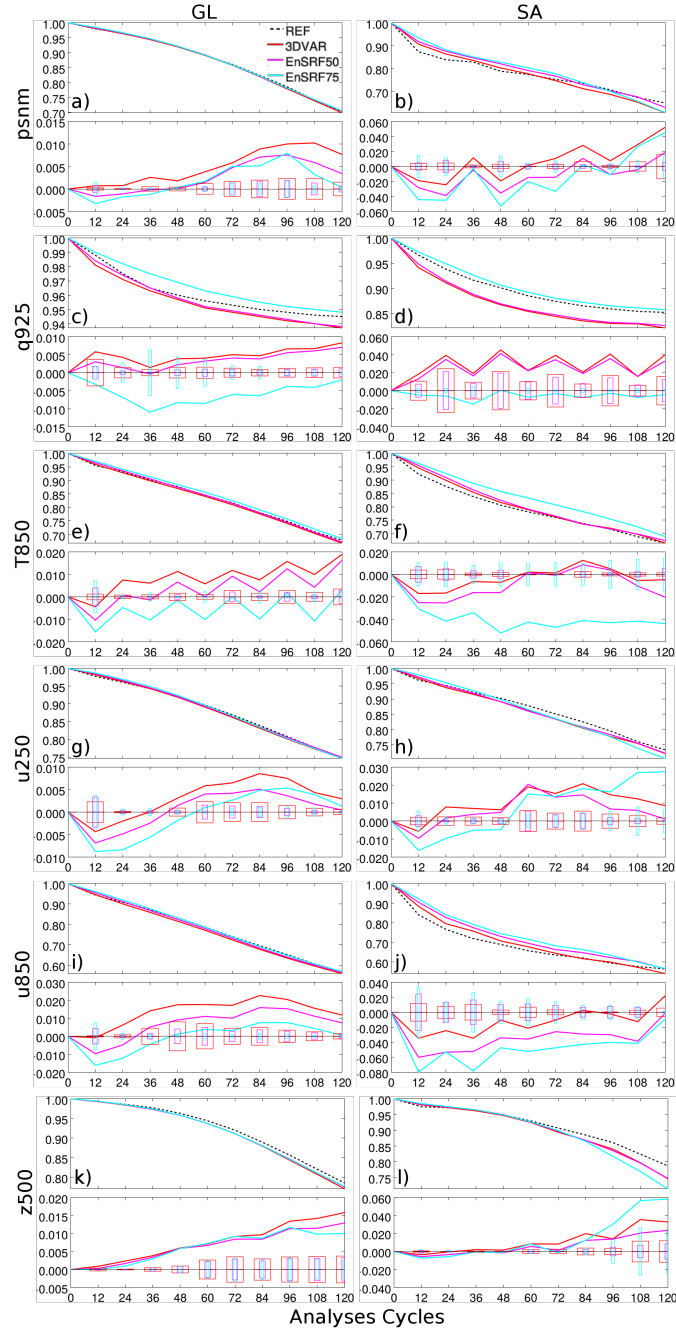


FIG. 5. Same as Figure 4, but for the GL and SA regions.

GPCP 2.5 24h Precip. Ave. (January 2013)

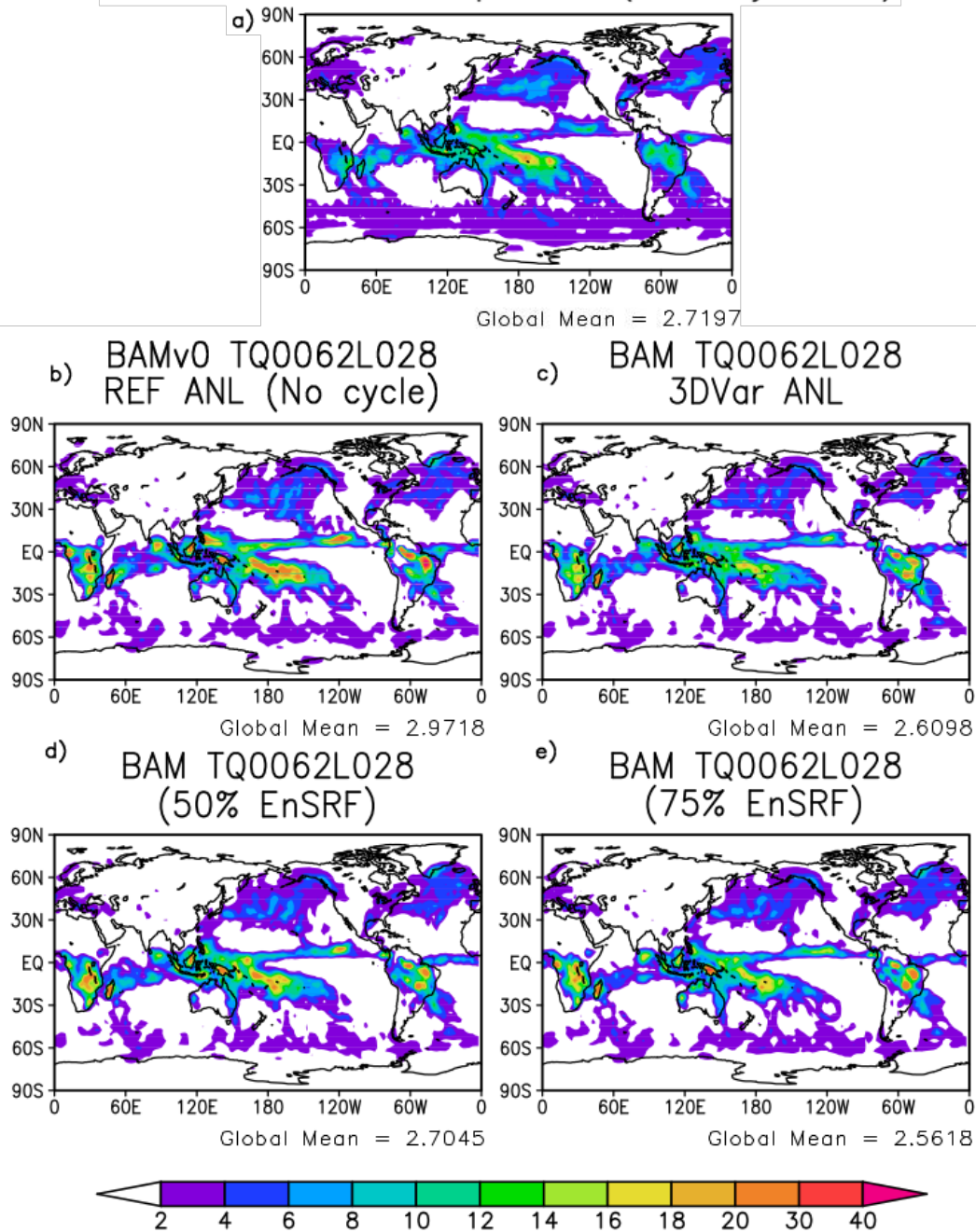


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Area Average 24 hr Precip. 12z01Jan2013 12z31Jan2013

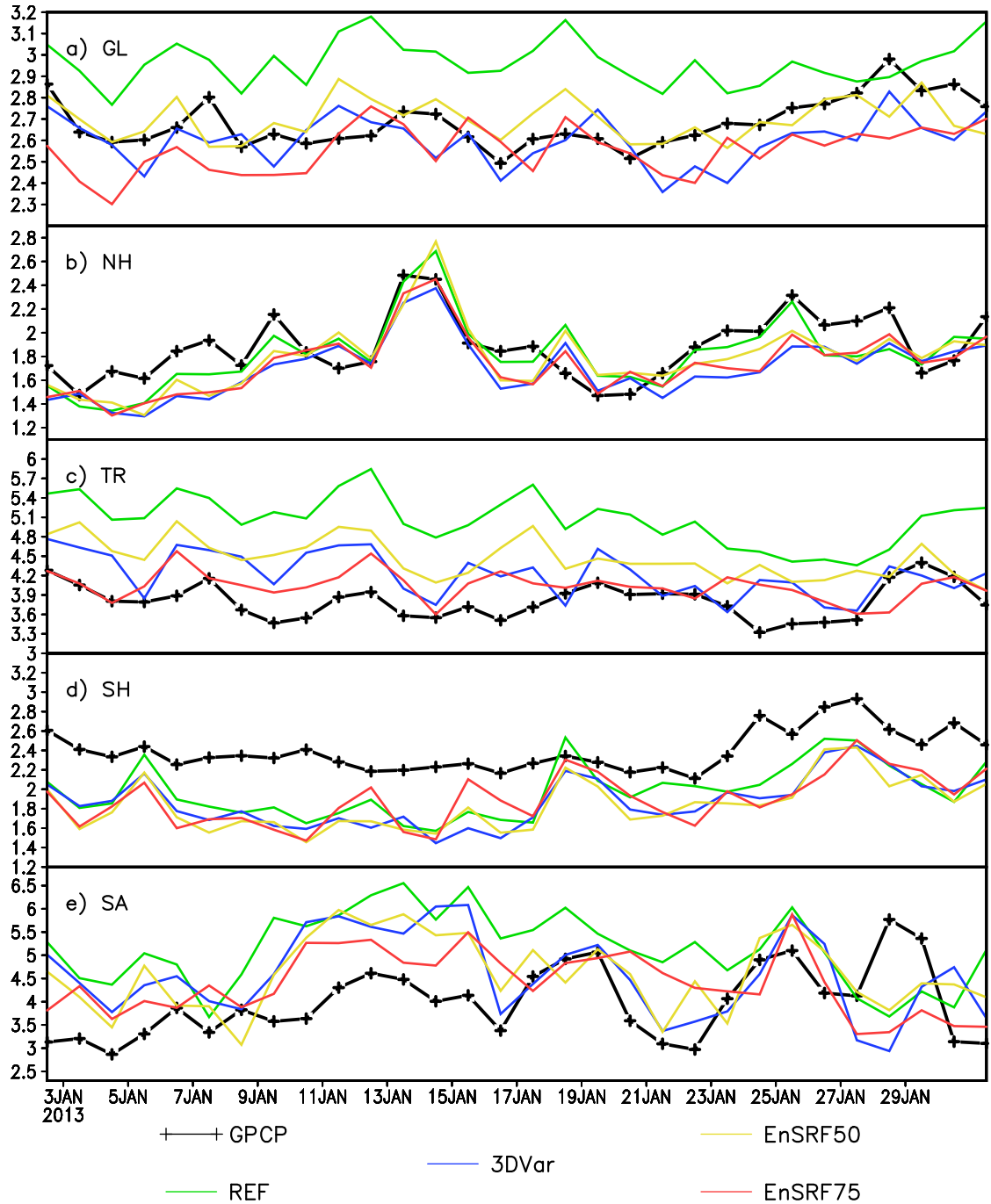


FIG. 7. Spatial averages of the 24 hour forecast precipitation (in mm/day) valid for January 2013 at 12Z. Panel a) precipitation for the whole globe (GL); b) same for the North Hemisphere (NH); c) for Tropics (TR); d) for South Hemisphere (SH) and e) for South America (SA). Precipitation from experiments are compared with the observed precipitation from GPCPv1.2.