Hybrid Background Error Covariances for a Limited-Area Deterministic Weather Prediction System

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ABSTRACT

This study introduces an experimental regional assimilation configuration for a 4D ensemble–variational (4D-EnVar) deterministic weather prediction system. A total of 16 assimilation experiments covering July 2014 are presented to assess both experimental regional climatological background error covariances and updates in the treatment of flow-dependent error covariances. The regional climatological background error covariances are estimated using statistical correlations between variables instead of using balance operators. These error covariance estimates allow the analyses to fit more closely with the assimilated observations than when using the lower-resolution global background error covariances (due to shorter correlation scales), and the ensuing forecasts are significantly improved. The use of ensemble-based background error covariances is also improved by reducing vertical and horizontal localization length scales for the flow-dependent background error covariance component. Also, reducing the number of ensemble members employed in the deterministic analysis (from 256 to 128) reduced computational costs by half without degrading the accuracy of analyses and forecasts. The impact of the relative contributions of the climatological and flow-dependent background error covariance components is also examined. Results show that the experimental regional system benefits from giving a lower (higher) weight to climatological (flow-dependent) error covariances. When compared with the operational assimilation configuration of the continental prediction system, the proposed modifications to the background error covariances improve both surface and upper-air RMSE scores by nearly 1%. Still, the use of a higher-resolution ensemble to estimate flow-dependent background error covariances does not yet provide added value, although it is expected to allow for a better use of dense observations in the future.

1. Introduction

Environment and Climate Change Canada (ECCC) has developed a high-resolution deterministic prediction system (referred to as the “pan-Canadian” system) for convective-scale predictions over Canada (Milbrandt et al. 2016), which became operational in 2017. This downscaling system is initialized from analyses produced by the ECCC operational regional deterministic prediction system (referred to as the “continental” system). These analyses are computed using low-resolution global background error covariances (Caron et al. 2015), thus making short-term convective-scale forecasting challenging. Similarly, many of the operational

limited-area data assimilation systems presented in the survey by Gustafsson et al. (2018) use background error covariances (climatological and flow-dependent) estimated from global systems.

The resolution and the quality of background error covariances are factors limiting the assimilation of dense observations (Gustafsson et al. 2018). Also, the use of climatological background error covariances limits the propagation of the information from near-surface observation networks (Bédard et al. 2015, 2017). Most state of the art assimilation systems use a combination of climatological and flow-dependent background error covariances (so-called hybrid covariance approach) to partially alleviate sampling issues related to estimating flow-dependent background error covariances from an ensemble. Over time, as background error covariance estimates from ensembles are improved, the optimal relative contribution of the climatological component of the background error covariances is expected to decrease.

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ECCC is currently developing a limited-area data assimilation system for a future operational version of the pan-Canadian prediction system (the “experimental regional” system hereafter). In an effort to use the same methodology and FORTRAN code, the global, continental, and experimental regional prediction systems are all based on the same 4D ensemble–variational (4D-EnVar) data assimilation algorithm (Buehner et al. 2015). Still, for the experimental regional system, it should be beneficial to use higher-resolution background error covariances to facilitate assimilation of temporally and spatially dense observations in the future. For this purpose, ensembles from an experimental regional ensemble Kalman filter (EnKF) were introduced and evaluated by Bédard et al. (2018). When using the same observations, the deterministic data assimilation experiment using background error covariances estimated from the regional EnKF (R-EnKF) performs as well as the experiment using background error covariances estimated from the global EnKF (G-EnKF), except for short-range accumulated precipitation scores where the experiment using background error covariances estimated from the R-EnKF performs better. The use of higher-resolution background error covariances is however expected to result in further improvements in the future by enabling a more effective use of temporally and spatially dense observations.

While providing an overview of the experimental regional hybrid 4D-EnVar data assimilation system, the purpose of this study is threefold. First, new regional climatological background error covariances are estimated for use in limited-area deterministic data assimilation. Second, the use of hybrid background error covariances is improved by adjusting covariance localization length scales, increasing the relative weight of the flow-dependent error component, and minimizing ensemble generation costs by reducing the number of ensemble members, without degrading the quality of forecasts. Finally, the added forecast value of the proposed configuration over the existing low-resolution data assimilation system (that uses global background error covariances) is demonstrated.

The following section introduces the approaches used to estimate the climatological and flow-dependent background error covariances. Section 3 provides an overview of the limited-area data assimilation and forecast system, as well as the configurations of the numerical experiments. The characteristics and quality of the climatological background error covariance matrices are assessed through diagnostic results in section 4. Results from full assimilation experiments to improve the use of different background error covariances matrices are presented in section 5. The

proposed configuration is evaluated and compared against the existing low-resolution data assimilation used in the continental system in section 6 through assimilation experiments, where the resulting forecasts are compared with in situ observations. Conclusions and aspects of future development are presented in section 7.

2. Methods for estimating background error covariances

a. Climatological background error covariances

The full background error covariances are challenging to estimate because of their size and the lack of knowledge of their statistical properties. Homogeneity and isotropy in space and time are some of the assumptions used to simplify the problem by reducing the number of statistical parameters needed to represent the covariances. ECCC uses the so-called NMC method described by Parrish and Derber (1992) to derive climatological background error covariances from a set of differences between pairs of forecasts with different lead times, but valid at the same time (Gauthier et al. 1998; Charron et al. 2012; Buehner et al. 2013). The background error covariances are estimated and stored in spectral space as this allows representing horizontal correlations as a diagonal matrix, assuming homogeneity and isotropy. For its global and continental systems (Buehner et al. 2015; Caron et al. 2015), ECCC uses a global spherical harmonics representation. For this reason, the continental system produces increments on a global grid, even though the innovation vector is computed only over the regional domain of the model (Caron et al. 2015). On the other hand, the experimental regional system uses biFourier transforms (with an extension zone) to represent the background error covariances on a limited-area domain. The topographic elevation within the domain (color contours), along with the biFourier extension (dark red contour) are presented in Fig. 1. This method was proposed for use in data assimilation by Berre (2000) and adapted to the Canadian system by Fillion et al. (2010). Given that the biFourier transform assumes periodicity, the computational grid of the limited-area analysis must be biperiodic. To avoid the spurious spreading of the analysis increments from one domain boundaries to the opposite one (through domain periodicity) an extension zone is needed and therefore the regional analysis grid is extended by approximately 2000 km toward the east and the north (representing 196 and 184 additional grid points, respectively). The domain size of the climatological background error covariances is thus larger than that of the original forecast model (864×540 versus 668×356 grid points). For its global climatological

FIG. 1. Topographic elevation (color contours) and biFourier extension (dark red contour) of the regional domain.

background error covariances (Glb-NMC), ECCC employs linear balance operators to account for intervariable correlations (so-called cross correlations) due to balance relationships such as geostrophy and hydrostaticity, as well as the Ekman relationship (Gauthier et al. 1998; Derber and Bouttier 1999; Wu et al. 2002; Bannister 2008). However, in the context of limited-area models on a small horizontal domain, Fillion et al. (2010) showed that it is possible to obtain similar forecast results by representing the cross correlations directly with the statistical background error correlations. To do so, the basic analysis control variables (streamfunction, velocity potential, temperature, natural logarithm of humidity, and surface pressure) are used directly in the regional climatological background error covariances (Reg-NMC), instead of splitting the variables into balanced and unbalanced components as in the global climatological error covariances. Using this methodology, all cross correlations between wind and mass fields must be fully accounted for to ensure a valid positive definite background error covariance matrix.

As in Berre (2000), the nonseparable nature of the vertical and horizontal correlations is considered in both the global and regional error covariances, such that vertical correlations can vary with horizontal scale. In the regional background error covariance matrix, every wavenumber has its own nonseparable correlation matrix (including intervariable cross correlations), whereas in the global matrix, the balance operators are independent of wavenumber.

The global climatological background error covariances used at ECCC were originally computed using lagged forecast differences from a global model using a grid spacing of 50 km. To achieve higher-resolution analysis increments, regional climatological background error covariances for the experimental regional system are estimated using 2 months (July and August 2014) of lagged forecast differences (120 samples) from the operational continental system, with a grid spacing of

10 km, interpolated onto the experimental regional domain, also with a 10-km grid spacing. Although the period used to compute the lagged forecast differences overlaps with the evaluation period, the datasets are partially independent because the operational continental system is only used to compute the regional climatological background error covariances and is not used in the evaluation provided. The experimental regional data assimilation system is intended for eventual use with a higher-resolution model, with a 2.5-km horizontal grid spacing. However, the incremental approach allows computing the innovations with respect to the high-resolution background state, while computing the analysis increments at a coarser-resolution (corresponding to the scales resolved by the background error covariances) without loss of information (Laroche et al. 1999). The resulting climatological background error covariances (for both global and regional systems) adopt a truncation in spectral space such that the resolved scales remain close to the original resolution of the lagged forecast differences (50 and 10 km, respectively).

While the global climatological background error covariances are computed using differences between 24- and 48-h forecasts valid at the same time, different training data and forecast lead times were tested to estimate the regional climatological background error covariances. Forecasts differences were tested with lead times of both 48 minus 24 h and 24 minus 12 h. As an alternative to using lagged forecast differences, tests were also performed using climatological background error covariances estimated using 120 (total) 6-h ensemble forecast perturbations from the R-EnKF (either from a single date, or collected from over one month). As the NMC error statistics often require error variance adjustments (Bannister 2008), preliminary tests inflating the background error variance (by a factor of 0.5 and 2.0) were performed. Although variance inflation affects the analysis fit to assimilated observations in a statistically significant way, forecast differences evaluated against radiosonde wind, geopotential height, temperature, and humidity observations were not statistically significant. This lack of sensitivity is likely due to the fact that the relatively small domain is well observed, and the analysis increment is constrained using smooth background error correlations (broad correlations at lower resolution than the background state). Therefore no variance inflation is applied to the background error variances in this study. All tests used 120 samples with no rescaling factor for comparison purposes. In the end, samples from 48-minus-24-h forecast differences resulted in the best forecasts (not shown), as in the global system, and therefore only results using these forecast differences will be presented.

Variances only vary with vertical level in the regional climatological error covariances, while they also vary with latitude in the global covariances. More specifically, the global variances are averaged over large horizontal regions and then interpolated to the desired latitude (Buehner et al. 2005). Also the balance operators vary with latitude to establish the cross correlations within the global climatological error covariances. Traditionally, humidity was analyzed in a univariate way in ECCO global and continental systems because its globally homogeneous cross correlations are considered to not be representative of the tropics, the midlatitudes or the polar regions. As shown in Berre (2000), a significant relationship can exist between humidity forecast errors and those from mass and wind fields within a smaller limited-area domain. Therefore, humidity cross correlations with wind and mass variables are included in the regional climatological error covariances.

b. Flow-dependent background error covariances

Homogeneity and isotropy assumptions in a variational data assimilation algorithm can be relaxed by using ensemble-based approaches (e.g., Buehner 2005). In this study, flow-dependent background error covariances are sampled using short-term ensemble forecasts from two EnKFs: a G-EnKF and a R-EnKF. Their resulting ensemble forecasts are available every hour within the subsequent 6-h assimilation window to estimate the 4D background error covariances for use in deterministic data assimilation systems. A complete description of the EnKFs employed in this study is available in Bédard et al. (2018; see their sections 2a and 3b).

1) GLOBAL ENSEMBLE KALMAN FILTER

The G-EnKF used in this study is based on the methodology presented by Houtekamer et al. (2014a,b). In brief, it is a stochastic sequential ensemble Kalman filter (Houtekamer and Mitchell 2001; Houtekamer et al. 2005, 2014a,b) using different physical parameterizations among the ensemble members and additive covariance inflation to cope with insufficient ensemble spread. Also, spatial background-error covariance localization is applied to reduce the effects of sampling errors from the limited ensemble size (Houtekamer and Mitchell 2001).

More specifically, ECCO's G-EnKF has 256 ensemble members with ~ 50 -km horizontal grid spacing (800×400 global grid) and is cycled four times per day (at 0000, 0600, 1200, and 1800 UTC). Differences with respect to the configuration described by Houtekamer et al. (2014a,b) include: the G-EnKF model has 80 vertical levels with the top level at 0.1 hPa, the initialization is based on the (3D) incremental analysis update approach (IAU;

Bloom et al. 1996), and brightness temperature observations from a relatively small number of hyperspectral infrared sounder (AIRS, CRIS, and IASI) channels are assimilated. Localization length scales are set in a way that forces the background-error covariance to zero at a horizontal distance ranging from 2100 km at the surface to 3000 km at the model top, and at a natural logarithm of atmospheric pressure difference of 2.0 in the vertical. In both the EnKF and 4D-EnVar, covariance localization is applied to the following analysis variables: surface pressure, temperature, wind components and specific humidity (for 4D-EnVar, the natural logarithm of specific humidity is used). In addition, the intervariable and temporal correlations present in the ensemble are fully kept. Surface pressure is treated in our EnKF and 4D-EnVar systems like other surface variables, and unlike the approach proposed by Wu et al. (2017) where cross covariances between surface pressure and other variables are allowed to extend higher in the atmosphere. The additive inflation is based on the global climatological background-error covariances with a scaling factor of $(0.33)^2$.

2) REGIONAL ENSEMBLE KALMAN FILTER

The R-EnKF is an experimental limited-area version of the G-EnKF algorithm, with the exception that all its ensemble members have identical forecast model configuration. The R-EnKF configuration is similar to that of the G-EnKF employed in this study. Its 256 ensemble members are matched to those from its global counterpart, which also provides the lateral boundary conditions (LBCs). The R-EnKF domain and model configuration are the same as those from the experimental regional deterministic prediction system with 10-km horizontal grid spacing. The additive inflation is also based on the global climatological background-error covariances, but with a reduced scaling factor of $(0.25)^2$ because the higher-resolution model produces a more rapid increase of the ensemble spread in the short-range forecasts (an error growth assessment is provided in Bédard et al. 2018).

3. Experimental framework

a. An experimental regional numerical weather prediction system

The numerical weather prediction system employed in this study is based on the limited-area version of the Global Environmental Multiscale (GEM) model version 4 (Girard et al. 2014; Zadra et al. 2014) using 80 staggered vertical levels with the model top at 0.1 hPa. The horizontal domain covers most of Canada and the northern United States (including part of Alaska). As opposed to the configuration described by Milbrandt

TABLE 1. Deterministic data assimilation system configurations of the 3D-Var experiments performed to compare the regional climatological background error covariances against the global covariances.

Experiment	Method		Training data		
	Spectral-space representation	Statistical balance operators	Horizontal grid spacing	Forecast lead time	Sample size
3D-Glb	Spherical harmonics	Yes	50 km	24 and 48 h	120
3D-Reg	Bi-Fourier	No	10 km	24 and 48 h	120

et al. (2016), the gridpoint spacing of the experimental regional system is 10 km (instead of 2.5 km) due to computational resource restrictions.

The data assimilation procedure and model configuration used in this study are the same as presented in Bédard et al. (2018). Briefly, the experimental system employs a continuous data assimilation cycle and the model is initialized using the four-dimension incremental analysis update scheme (4D-IAU: Bloom et al. 1996; Buehner et al. 2015) every 6 h (0000, 0600, 1200, and 1800 UTC). All observations assimilated in the global and continental systems are used provided they are located within the model domain. The assimilated observations include those from radiosondes, aircraft, ground-based global positioning system (GB-GPS) instruments (zenith total delay), land stations, ships, buoys, scatterometers, atmospheric motion vectors, satellite-based radio occultation, and brightness temperature from microwave and infrared satellite sounders/imagers. Forecasts up to 48-h lead time are launched twice per day (at 0000 and 1200 UTC) and the LBCs are provided by the operational global deterministic prediction system (Buehner et al. 2015; Qaddouri et al. 2015) and are smoothly updated to account for nonzero analysis increments at the boundaries.

In addition to using hybrid background-error covariances, the assimilation system has the capability to use only climatological or ensemble-based flow-dependent background-error covariances. This feature is convenient to assess the quality of the different background error covariance matrices. The specific covariances evaluated in this study, along with the data assimilation system configuration of the experiments, are listed in Tables 1–5.¹ The 16 deterministic data assimilation experiments presented are carried out over July 2014, all using the same limited-area model configuration.

Three-dimensional variational (3D-Var) data assimilation experiments are first performed to assess the regional climatological background error covariances and to compare them against the global covariances (see

Table 1). Different 4D-EnVar experiments are also carried out using the ensemble from the R-EnKF to determine the parameters that will provide the best forecast results (see Tables 2 and 3). These experiments test the regional climatological and flow-dependent background error covariance ratio, and the length scale of the localization function, which is based on the fifth-order piecewise rational function defined by Gaspari and Cohn (1999). The horizontal and vertical scales are, respectively, defined as the radial distance and as the difference in the natural logarithm of atmospheric pressure, where the localization function reaches zero. Although Ménétrier and Auligné (2015) proposed a straightforward tool to estimate the optimal localization length scale, early attempts at applying it to ECCO systems resulted in unrealistically large length scales due to the multimodel nature of the G-EnKF. Also, as the assimilation system is not sensitive to background error variance inflation, all of the hybrid weight experiments presented assume that the sum of the weights is equal to one. Experiments varying the number of ensemble members used in the deterministic analysis to specify the flow-dependent covariances are also carried out to explore the trade-off between computational cost and forecast quality (Table 4). Because of the dependency between these three parameters, it is not possible to explore all the possible combinations and thus, only a subset of the possible combinations is presented. Once the best configuration is determined, the accumulated impact from the different proposed modifications are evaluated by comparing the forecast quality of the proposed configurations against that of the assimilation scheme used in the currently operational continental system that is based on using global error covariances (see Table 5).

b. Evaluation methodology

Analyses and forecasts are compared against upper-air and surface observations to evaluate the performance of each experiment carried out. Observations from aircrafts (wind components and temperature) and radiosondes (wind components, temperature and humidity), as well as zenith total delay (related to precipitable water) from GB-GPS instruments, are employed for the upper-air evaluation. Wind components, temperature,

¹ Although 19 experiments are listed, only 16 were carried out as the following 4 experiments are identical: 4D-Reg-R87.5 (Table 2), 4D-Reg-H1400V1 (Table 3), 4D-Reg-M128 (Table 4), and 4D-Reg-opt (Table 5).

TABLE 2. Deterministic data assimilation system configurations of the 4D-EnVar experiments performed to test the regional climatological and flow-dependent background error covariance ratio.

Experiment	Climatological B matrix		Flow-dependent B matrix		
	Source	Weight	Source	Weight	Horizontal and vertical localizations
4D-Reg-R50	Reg-NMC	50%	128 R-EnKF members	50%	1400 km and 1.0
4D-Reg-R75	Reg-NMC	25%	128 R-EnKF members	75%	1400 km and 1.0
4D-Reg-R87.5	Reg-NMC	12.5%	128 R-EnKF members	87%	1400 km and 1.0
4D-Reg-R100	—	0%	128 R-EnKF members	100%	1400 km and 1.0

humidity (dewpoint depression) and surface pressure observations from surface stations' synoptic (SYNOP) reports are used for the performance evaluation near the surface. The bias, standard deviation (STD), and root-mean-square error (RMSE) scores against aircraft, GB-GPS, and surface observations are computed every 6 h, while the scores against radiosonde observations are computed every 12 h. Statistical significance is assessed using Student's *t* test (for bias) and Fisher's exact test (for STD).

Because this study contains a large number of experiments, only statistically significant RMSE results are discussed in detail. The effect of the error covariance matrices on biases is generally not statistically significant (not shown), such that the RMSE differences presented in this study are mostly attributable to a reduction in analysis fit to assimilated observations and forecast error STD. Also, scorecards are employed as a diagnostic tool to compare the overall performance of an experiment against that of a reference or control experiment. The relative change in RMSE defines the improvement score used throughout this study, where positive (negative) values represent improved (degraded) forecasts with respect to the reference experiment. The scorecards combine upper-air forecast RMSE improvement scores from aircraft and GB-GPS observations. The vertically averaged improvement scores are presented alongside those from surface observations for each observed variable every 6 h from 6- to 48-h lead times. As a synthesis, the scorecards also present average RMSE improvement scores for each lead time and each variable, along with the overall averages that include all upper-air and surface RMSE improvement scores. Such aggregated

scores are used to determine the parameters that provide the best forecast results. The scorecards do not include scores against radiosonde observations as they are mostly available only every 12 h. Nevertheless, detailed upper-air evaluations have been performed using all three data sources. The evaluations against radiosonde and aircraft observations generally provide similar results (not shown). As radiosondes are the standard observations used for forecasts verification at ECCC, the detailed upper-air evaluations used to compare the forecast quality of the proposed configuration against that of the currently operational continental system focus on scores against radiosonde observations.

4. Results with climatological background error covariances

The global and regional climatological background error covariances are represented with different variables because the global climatological error covariances split temperature, surface pressure and velocity potential into balanced and unbalanced components. Thus, in order to compare both directly, the global climatological background error covariances are resampled. First, 1000 homogeneous and isotropic perturbations are drawn randomly using the global climatological background error covariances. Then, they are interpolated onto the 10-km experimental regional domain and the covariances are recomputed with the proposed methodology to estimate equivalent regional climatological background error covariances. This procedure is not ideal as it is expected to introduce noise in the resampled

TABLE 3. Deterministic data assimilation system configurations of the 4D-EnVar experiments performed to test the localization length scales.

Experiment	Climatological B matrix		Flow-dependent B matrix		
	Weight	Source	Weight	Horizontal and vertical localizations	
4D-Reg-H2800V2	0%	128 R-EnKF members	100%	2800 km and 2.0	
4D-Reg-H2000V1.4	0%	128 R-EnKF members	100%	2000 km and 1.4	
4D-Reg-H1400V1	0%	128 R-EnKF members	100%	1400 km and 1.0	
4D-Reg-H1000V0.7	0%	128 R-EnKF members	100%	1000 km and 0.7	
4D-Reg-H700V0.5	0%	128 R-EnKF members	100%	700 km and 0.5	

TABLE 4. Deterministic data assimilation system configurations of the 4D-EnVar experiments performed varying the number of ensemble members used in the deterministic analysis to minimize the computational costs.

Experiment	Climatological B matrix		Flow-dependent B matrix	
	Weight	Source	Weight	Horizontal and vertical localizations
4D-Reg-M256	0%	256 R-EnKF members	100%	1400 km and 1.0
4D-Reg-M128	0%	128 R-EnKF members	100%	1400 km and 1.0
4D-Reg-M96	0%	96 R-EnKF members	100%	1400 km and 1.0
4D-Reg-M64	0%	64 R-EnKF members	100%	1400 km and 1.0

error structures. However, this step is necessary to allow a direct comparison of the global and regional climatological background error correlations. The resulting multivariate vertical correlations, horizontal correlation length scales and variances are presented in Figs. 2–4.

a. Multivariate vertical correlations

Figure 2 presents the multivariate vertical correlation of streamfunction, velocity potential, temperature and natural logarithm of humidity for both the global and regional climatological background error covariances (left and right panels, respectively). Comparing the multivariate vertical correlations, one can see that the autocorrelations for each variable as well as the cross correlations between streamfunction and temperature are similar. By construction, the humidity cross correlations should be absent in the global climatological error covariances (some correlations are present due to resampling noise), while it is correlated with all variables in the regional climatological error covariances. Although humidity cross correlations are expected to be most significant in the atmospheric boundary layer (ABL), Fig. 2 (right panel) shows that, in the regional case, humidity is correlated with temperature and streamfunction throughout the troposphere up to ~ 200 hPa.

By construction, the original global climatological error covariances also neglect correlations between velocity potential and temperature, as well as those between velocity potential and streamfunction, except for the Ekman relationship in the ABL, which is represented by a balance operator. Interestingly, the global climatological error correlations presented in Fig. 2 exhibit velocity potential cross correlations with streamfunction

and temperature well above the ABL, which should be zero by construction. These small correlations are likely artifacts from transforming the zonal and meridional wind perturbations to streamfunction and velocity potential perturbations over a biperiodic limited-area domain (Lynch 1989). In the regional climatological error covariances, cross correlations between all variables are allowed. Because both methods account for the Ekman relationship (explicitly or implicitly), the cross correlations between velocity potential and streamfunction should share some similarities near the surface where cyclonic (anticyclonic) flow is associated with convergence (divergence). However, the velocity potential cross correlations with streamfunction and temperature are different in the regional and global climatological error covariances. In the stratosphere, the regional climatological error covariances show positive correlations between velocity potential and temperature, showing that convergence is likely associated with local warming (cooling) through subsidence (updraft). Velocity potential is also correlated with streamfunction as a result of temperature correlations with both streamfunction and velocity potential in the regional climatological error covariances. Other studies have also found cross covariances between velocity potential (or divergence) and both streamfunction (or vorticity) and temperature through the use of balance operators [e.g., Brousseau et al. (2011), their Eqs. (2) and (3)]. They show that the balanced mass field (related to vorticity) can explain some of the divergence variance (their Fig. 8c), and divergence can explain a substantial amount of the temperature variance (their Fig. 8e). In both cases, the cross covariances are largest near and above the tropopause

TABLE 5. Deterministic data assimilation system configurations of the 4D-EnVar experiments performed to evaluate the accumulated impact from the different modifications proposed.

Experiment	Climatological B matrix		Flow-dependent B matrix	
	Source	Weight	Source	Horizontal and vertical localizations
4D-Glb-orig	Glb-NMC	50%	256 G-EnKF members	2800 km and 2.0
4D-Glb-opt	Glb-NMC	12.5%	256 G-EnKF members	1400 km and 1.0
4D-Mix-opt	Reg-NMC	12.5%	256 G-EnKF members	1400 km and 1.0
4D-Reg-opt	Reg-NMC	12.5%	128 R-EnKF members	1400 km and 1.0

FIG. 2. Multivariate vertical correlation of streamfunction, velocity potential, temperature, and natural logarithm of humidity for both the (left) resampled global and (right) original regional climatological background error covariances. The light gray line represents the model vertical level near 200 hPa.

and close to the surface, consistent with those from our regional cross covariances presented in Fig. 2.

b. Horizontal correlation length scales

Figure 3 presents the horizontal correlation length scale of streamfunction, velocity potential, temperature, and

and natural logarithm of humidity at every vertical level for both the global and regional climatological background error covariances. This characteristic horizontal length scale is defined in terms of the local curvature in the horizontal correlations of zero separation distance (Daley 1991; Gauthier et al. 1998). Figure 3 shows that

FIG. 3. Horizontal correlation length scale of streamfunction, velocity potential, temperature, and natural logarithm of humidity at every vertical level for both the global (Glb-NMC: blue) and regional (Reg-NMC: red) climatological background error covariances.

FIG. 4. Variances of streamfunction, velocity potential, temperature, and natural logarithm of humidity at every vertical level for both the global (Glb-NMC: blue) and regional (Reg-NMC: red) climatological background error covariances.

the regional climatological background error covariances generally have shorter horizontal correlations than the global covariances for all vertical levels. This difference is more pronounced for temperature and humidity than for the wind-related variables. The shorter horizontal correlations from the regional climatological error covariances may result from a multitude of factors, including the fact that a higher-resolution model is expected to produce errors with a shorter correlation length scale in the horizontal because of the additional small scales represented. Also, the global correlations are horizontally averaged over the globe, including many large areas (e.g., tropical regions) where the forecast errors are characterized by larger-scale horizontal correlations (e.g., see Fig. 10 of Pannekoucke et al. 2008). On the other hand, the regional climatological error correlations are computed using forecasts only over a well-observed portion of the northern extratropical mid-latitudes that is generally characterized by shorter-scale horizontal correlations (Pannekoucke et al. 2008).

c. Variances

Variances of streamfunction, velocity potential, temperature, and natural logarithm of humidity at every vertical level for both the global and regional climatological

background error covariances are presented in Fig. 4. Results show that the regional variances are higher than the global variances in the upper troposphere (above ~ 400 hPa), while the opposite is true in the stratosphere. In the lower troposphere however, the regional and global variances are comparable for all the variables, except for temperature near the surface where the regional variances are higher. The global humidity variance profile was set empirically many years ago (following a bell shape peaking near 500 hPa), while the regional variances are computed directly from the set of lagged forecast differences. As a result, the global variances are smaller in the troposphere and larger near the surface and in the stratosphere, thus potentially giving less (more) weight to humidity observations in the troposphere (in the ABL and the stratosphere).

d. 3D-Var data assimilation experiments

The quality of the climatological background error covariance matrices is assessed by comparing results from 3D-Var data assimilation experiments using either the global (3D-Glb) or the regional (3D-Reg) climatological error covariances. Figure 5 presents the scorecard comparing the 3D-Glb with the 3D-Reg experiments.

FIG. 5. Scorecard presenting the relative change in forecast RMSE for the 3D-Glb (blue) and the 3D-Reg (red) experiments. The scores are evaluated against upper-air (aircraft temperature T and winds U, V), GB-GPS [zenith total delay (HU)] and surface (SYNOP temperature T , humidity T_d , winds U, V , and surface pressure P_s) observations. Red (blue) triangles indicate that the RMSE of the 3D-Reg (3D-Glb) experiment is lower than that of the 3D-Glb (3D-Reg) experiment. Upper-air scores are vertically averaged. The improvement scores are presented for each observed variable every 6 h from 6- to 48-h lead times. As a synthesis, the average RMSE improvement scores is presented for each lead time (right) and each variable (top), while the overall upper-air and surface RMSE improvement scores appears to the left of the scorecard.

Results show that the regional climatological error covariances generally improves near-surface (+0.28%) and upper-air (+0.36%) forecasts. An examination of the results for individual variables and vertical levels was done (not shown) to assess the statistical significance of the score differences, since it is not straightforward to assess significance for the aggregated scores presented in the scorecard. The improvements are statistically significant (at most lead times) for upper-air temperature (+0.75%) and winds (+0.79%), as well as surface pressure (+1.09%). On the other hand, score differences for upper-air humidity, as well as surface temperature, humidity and wind, are either neutral or negative in Fig. 5, but those are not statistically significant.

When looking at upper-air RMSE improvement scores against radiosondes (Fig. 6), one can see that the regional climatological error covariances provide a much closer fit to the assimilated observations (at 0 h) than the global climatological error covariances. This is partly due to the shorter horizontal correlation scales in the regional climatological error covariances. Tropospheric humidity variances being larger in the regional climatological

error covariances also contribute to the closer fit to the observations, except near the surface where the opposite is true. Figure 6 also shows that the 3D-Reg experiment provides some small but statistically significant upper-air forecast improvements (for all four variables) over the 3D-Glb experiment.

5. Results with flow-dependent and hybrid background error covariances

Results from full assimilation experiments to improve the use of different background error covariances matrices are presented in this section. Aggregated scores are used to optimize the covariances localization length scales, the number of ensemble members used to compute the flow-dependent background error covariances, and the relative weight of the climatological and flow-dependent error components that provide the best forecast results.

a. Localization length scales

The 4D-EnVar experiments are performed to test different vertical and horizontal localization length

FIG. 6. Relative change in upper-air forecast RMSE, as computed against radiosonde winds, temperature, and dewpoint depression observations comparing the 3D-Glb (blue) and 3D-Reg (red) experiments. Results are presented for both the analyses (0 h) and forecasts (12, 24, 36, and 48 h) between the surface and 100 hPa. Color shades indicate the relative change in RMSE score and superimpose numerical values indicate statistical significance above 90%. Red (blue) shades indicate that the RMSE of the 3D-Reg (3D-Glb) experiment is lower than that of the 3D-Glb (3D-Reg) experiment.

scales. Table 6 presents the overall surface and upper-air RMSE improvement score when using 128 R-EnKF members to estimate the flow-dependent background error covariances. The control experiment here (4D-Reg-H2800V2) is based on the localization length scales used in ECCO operational global and continental deterministic assimilation systems. Results indicate that the surface and upper-air RMSE scores are improved when reducing the length scales by a factor of approximately 1.4 (4D-Reg-H2000V1.4) and improved even more when reducing the length scales by a factor of 2 (4D-Reg-H1400V1). Further reducing the localization length scales (4D-Reg-H1000V0.7) improves the surface score but not the upper-air score. However, preliminary results over winter cases, where the flow is dominated by larger scale phenomena, indicated that results are degraded when reducing the length scales by more than a factor of 2 (not shown). Reducing the length scales by a factor of 4 (4D-Reg-H700V0.5), the localization length scales become shorter than the correlation length scales from the ensembles (Bédard et al. 2018) and both the upper-air and surface forecasts are significantly degraded. Similar results were obtained using more ensemble members (i.e., 256 members), or using ensemble members from the G-EnKF (not shown). The

configuration using a horizontal length scale of 1400 km and a vertical length scale of 1.0 (in the natural logarithm of pressure) provided consistent forecast results for the experimental regional system during both the summer and winter periods. These length scales are used in the experiment presented in the remainder of this study.

b. Number of members

Results showing the impact of varying the number of ensemble members used to specify the flow-dependent covariances for the 4D-EnVar algorithm are presented in Table 7. RMSE improvement scores are assessed with the goal of minimizing the computational cost of generating both the ensemble forecasts and the deterministic analyses, without degrading the quality of the forecasts. Although less ensemble members are used in these experiments, only one regional ensemble dataset has been generated such that the R-EnKF itself still uses 256 members and the quality of the ensemble mean remains unchanged. Only the estimated flow-dependent background error covariances and the computational cost of the 4D-EnVar analyses are affected in this study, although the aim is to reduce the computational cost of the R-EnKF by using the minimum number of ensemble members in future applications.

TABLE 6. Overall surface and upper-air RMSE improvement scores for the 4D-EnVar experiments performed to test the localization length scales.

Experiment	Surface improvement	Upper-air improvement
4D-Reg-H2800V2	(Control)	(Control)
4D-Reg-H2000V1.4	+0.45%	+0.57%
4D-Reg-H1400V1	+0.66%	+1.27%
4D-Reg-H1000V0.7	+0.91%	+1.24%
4D-Reg-H700V0.5	−0.38%	−0.24%

Using the “optimal” localization length scales determined previously, Table 7 indicates that reducing the number of ensemble members from 256 to 128 in the deterministic analysis does not affect the quality of the forecasts in a statistically significant way. Computational timings indicate that the computational cost is reduced by approximately a factor of 2 (not shown). Still, upper-air (surface) score degradation becomes statistically significant when using 96 (64) members or less. A comparable experiment was attempted using the G-EnKF ensemble members in the experimental deterministic data assimilation system and similar results were obtained (not shown). Although results suggest that the experimental regional deterministic assimilation system does not benefit from using more than 128 ensemble members, the EnKFs do benefit from using more members. Subsequently, the cost reductions associated with a reduced number of ensemble members would become more significant if the EnKF itself could use less members, without degrading the quality of the resulting ensemble covariances (e.g., by recentering the EnKF mean analyses around a deterministic analysis).

c. Relative contribution of background error components

The impact of varying the relative contributions of the climatological and flow-dependent background error covariance components is now examined. Table 8 presents the overall surface and upper-air RMSE improvement scores for the 4D-EnVar experiments performed. All of the experiments presented employ the “optimal” localization length scales and 128 R-EnKF members, although similar results are obtained when using the G-EnKF ensemble members (not shown). Table 8 shows that the experiment using only the flow-dependent error covariances (4D-Reg-R100) and the experiment with equal weight for the two error components (4D-Reg-R50) give similar results, except the 4D-Reg-R100 provide small improvements to the surface RMSE. On the other hand, hybrid experiments where the flow-dependent component has more relative weight than the climatological

TABLE 7. Overall surface and upper-air RMSE improvement scores for the 4D-EnVar experiments performed varying the number of ensemble members used in the deterministic analysis. The asterisk indicates that differences are not statistically significant.

Experiment	Surface improvement	Upper-air improvement
4D-Reg-M256	(Control)	(Control)
4D-Reg-M128	+0.26% *	−0.09% *
4D-Reg-M96	+0.20% *	−0.47%
4D-Reg-M64	−0.38%	−1.32%

component (4D-Reg-R75 and 4D-Reg-R87.5) yield better results (small differences, but statistically significant), similar to NOAA’s Rapid refresh system (Benjamin et al. 2016). The hybrid experiment giving the highest weight to the flow-dependent component gives the best results (4D-Reg-R87.5). This result is consistent with conclusions from other studies (e.g., Lorenc and Jardak 2018), and suggests that although the climatological component only has a small relative weight in the system (12.5%), its contribution is clearly important as using only the flow-dependent component degrades the forecasts compared to the best hybrid configuration. This is possibly due to the fact that climatological background error covariances benefit from a large effective sample size (from horizontally averaging to obtain homogeneous covariances) to estimate correlations that can become small at long distances. This is in contrast with ensemble-based flow-dependent error covariances that are attenuated at large distances by the localization applied to restrain the larger sampling errors resulting from the relatively small ensemble being used.

6. Results comparing the proposed configuration and the currently operational continental system

To demonstrate the cumulative added value of the proposed modifications to the background error covariances, experiments integrating those changes step-by-step are evaluated and compared against the existing assimilation configuration that uses low-resolution global background error covariances (4D-Glb-orig), as in the ECCC global and continental systems. Table 9 presents the

TABLE 8. Overall surface and upper-air RMSE improvement scores for the 4D-EnVar experiments performed to test the regional climatological and flow-dependent background error covariance ratio. The asterisk indicates that differences are not statistically significant.

Experiment	Surface improvement	Upper-air improvement
4D-Reg-R50	(Control)	(Control)
4D-Reg-R75	+0.11%	+0.23%
4D-Reg-R87.5	+0.42%	+0.32%
4D-Reg-R100	+0.18%	−0.07% *

TABLE 9. Overall surface and upper-air RMSE improvement scores for the 4D-EnVar experiments performed to evaluate the accumulated impact from the different modifications proposed.

Experiment	Surface improvement	Upper-air improvement
4D-Glb-orig	(Control)	(Control)
4D-Glb-opt	+0.76%	+0.77%
4D-Mix-opt	+0.88%	+0.89%
4D-Reg-opt	+0.73%	+1.17%

overall surface and upper-air RMSE improvement scores for the different 4D-EnVar experiments performed. More specifically, results show the overall cumulative impact from: 1) changing the localization length scales and the hybrid ratios from the operational values to the “optimal” values as defined in sections 4 and 5 (4D-Glb-opt); 2) replacing the global climatological error covariances by the regional covariances (4D-Mix-opt); and 3) replacing the flow-dependent error covariances from the G-EnKF by those from the R-EnKF (4D-Reg-opt).

Table 9 shows that both the overall surface and upper-air scores are significantly improved (+0.76% and +0.77%, respectively) when adjusting the covariance localization length scales and increasing the relative weight of the flow-dependent component. The improvements are statistically significant for all variables at most forecast lead times (not shown). Forecasts are further improved (additional increase of 0.12%) when using the regional climatological background error covariances instead of the global covariances. Improvements are statistically significant in forecasts up to 24-h lead time (not shown). Estimating the flow-dependent error component using the members from the R-EnKF rather than from the G-EnKF did not improve the forecasts in a satisfactory way: the upper-air forecasts are improved (additional increase of 0.28%), but the surface scores are degraded (decrease of 0.15%). In general, the flow-dependent error covariances from the R-EnKF provide a better analysis fit to upper-air wind observations because of the shorter correlation length and higher resolution (Bédard et al. 2018), but the ensuing forecasts are of comparable quality for both experiments. Subsequent experimental results indicate that using 256 ensemble members from the R-EnKF (instead of 128) yield a similar outcome (not shown).

To assess the cumulative forecast improvements in more detail, Fig. 7 presents the scorecard comparing the 4D-Glb-orig (control) with the 4D-Reg-opt experiments. Results indicate that upper-air humidity and surface pressure fields are improved by more than 2% and 1%, respectively, while the other variables are improved by less than 1%. The overall improvements are +0.73% for the surface score and +1.17% for the upper-air score. The scores presented in Fig. 7 are statistically significant for

all variables (upper-air and surface winds, temperature, and humidity, as well as surface pressure) at most vertical levels and lead times (not shown).

As a complement, Fig. 8 details the upper-air RMSE improvement scores, as evaluated against radiosondes. Results indicate that the 4D-Reg-opt experiment provides a better analysis fit to the assimilated radiosonde wind observations at all levels, and temperature (humidity) observations above 300 hPa (800 hPa). On the other hand, the 4D-Glb-orig provides a better analysis fit to humidity observations near the surface, likely due to the discrepancy between the global and regional climatological background error variances for humidity. Still, the RMSE scores against radiosonde observations show that the proposed configuration of the experimental regional system (4D-Reg-opt) provides statistically significant temperature, wind and humidity forecast improvements for most vertical levels and most lead times, although there is more variability in the scores for longer lead times because the degree of statistical significance decreases with lead time.

7. Conclusions

This study addresses background error covariances for use in an experimental limited-area hybrid 4D-EnVar data assimilation system. Climatological background error covariances for deterministic analysis are estimated using direct statistical cross correlations, instead of linear balance operators as in most global applications. Also, the use of hybrid background error covariances is tested by modifying the covariance localization length scales and the relative weight of ensemble-based flow-dependent error covariances. The number of ensemble members being used by the deterministic assimilation algorithm is also varied in order to minimize computational costs, but without degrading the quality of the ensuing forecasts.

Diagnostic results suggest that the global climatological error covariances provide limited velocity potential correlations with streamfunction and temperature because of limitations from the balance operators used to represent the multivariate correlations. The methodology employed to estimate the regional climatological background error covariances is able to provide the full vertical multivariate correlations. Results show that the regional climatological background error covariances provide a better analysis fit to assimilated observations (compared to the global climatological error covariances) because of its shorter horizontal correlation scales. The quality of the climatological background error covariance matrices is assessed through full assimilation experiments covering the month of July 2014.

FIG. 7. Scorecard presenting the relative change in forecast RMSE for the 4D-Glb-orig (blue) and the 4D-Reg-opt (red) experiments. The improvement scores are evaluated against upper-air (aircraft temperature T and winds U , V), GB-GPS [zenith total delay (HU)] and surface (SYNOP temperature T , humidity T_d , winds U , V , and surface pressure P_s) observations. Red (blue) triangles indicate that the RMSE of the 4D-Reg-opt (4D-Glb-orig) experiment is lower than that of the 4D-Glb-orig (4D-Reg-opt) experiment. Upper-air scores are vertically averaged. The improvement scores are presented for each observed variable every 6 h from 6- to 48-h lead times. As a synthesis, the average RMSE improvement scores is presented for each lead time (right) and each variable (top), while the overall upper-air and surface RMSE improvement scores appears to the left of the scorecard.

RMSE scores (as evaluated against aircraft, radiosonde, GB-GPS, and surface observations) show that the use of the regional climatological error covariances statistically significantly improves upper-air temperature and wind, as well as surface pressure forecasts.

Assimilation experiments are performed to determine a configuration of the background error covariances that results in improved forecast quality. Results show that forecasts can be significantly improved by reducing the employed horizontal and vertical localization length scales, likely because the experimental regional system covers mostly a well-observed land area, while the global domain includes the oceans and tropical areas, which tend to have larger correlations. The relative weight of climatological and flow-dependent background error components is also fine-tuned. The experimental system benefits from giving more weight to the flow-dependent error component than in the operational configuration, possibly because ensemble generation methods have improved over time. However, results suggest that including the climatological component still has a positive impact on the forecasts. Assimilation experiments were

also performed to evaluate the impact of using a reduced number of ensemble members to estimate flow-dependent background error covariances from the R-EnKF. This suggests that, in the context of the experimental regional system, it may be possible to reduce the assimilation computational costs by reducing the number of ensemble members (from 256 to 128), without degrading the quality of the ensuing forecasts.

The proposed modifications are combined together and the resulting assimilation configuration of the experimental regional system is compared against using that of the existing low-resolution continental data assimilation system. Overall, the regional climatological error covariances are used in the proposed assimilation configuration and the localization length scales for the ensemble-based error statistic component are reduced by a factor of 2. Also, the relative weight of the flow-dependent (climatological) error covariances is increased (reduced) from 50% (50%) to 87.5% (12.5%). The proposed configuration improves near-surface and upper-air forecast RMSE scores by approximately 1%. Still, the use of the higher-resolution ensemble from the R-EnKF does

FIG. 8. Relative change in upper-air forecast RMSE, as computed against radiosonde winds, temperature and dewpoint depression observations comparing the 4D-Glb-orig (blue) and 4D-Reg-opt (red) experiments. Results are presented for both the analyses (0 h) and forecasts (12, 24, 36, and 48 h) between the surface and 100 hPa. Color shades indicate the relative change in RMSE score and superimpose numerical values indicate statistical significance above 90%. Red (blue) shades indicate that the RMSE of the 4D-Reg-opt (4D-Glb-orig) experiment is lower than that of the 4D-Glb-orig (4D-Reg-opt) experiment.

not yet provide strictly positive improvements, although its shorter correlation scales are expected to allow for a better use of dense observations in the future. Future work on the experimental limited-area hybrid 4D-EnVar data assimilation system should include experiments using scale-dependent horizontal localization as explored by Caron and Buehner (2018) and Caron et al. (2019).

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