

Dear Dr Unterstrasser,

Thank you for inviting me to revise my manuscript.

Please find in this PDF my responses to the reviewers (including those to a short comment from a named commentator), and how I have responded. Also in this PDF is the revised manuscript where the changes made are highlighted with blue text.

I hope that you will find the revised manuscript an improvement and will find it suitable for publication in GMD.

Many thanks.

Yours sincerely,

Ross Bannister

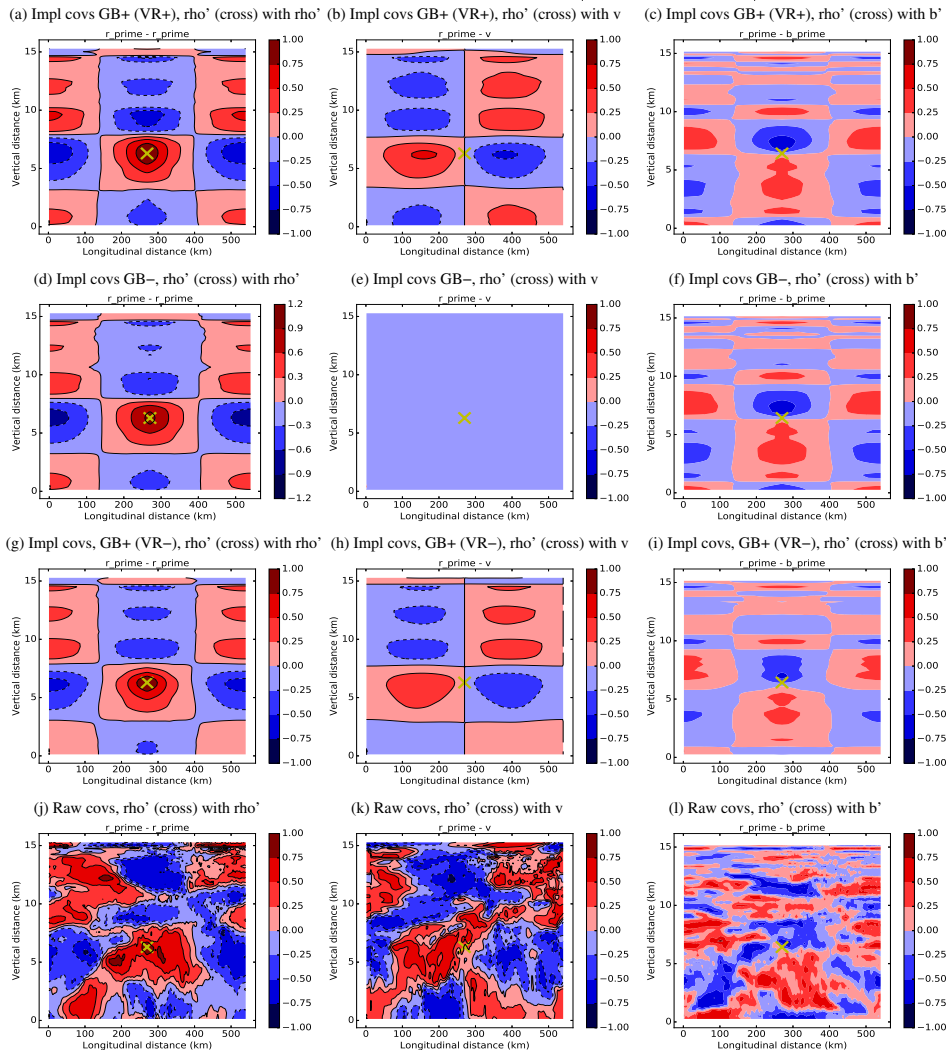
# Author response to anonymous referee #1

Thank you to referee #1 for reading the manuscript and for his/her valuable comments. In the following, the referee's comments are reproduced, my responses are in blue, and my actions to the paper are in red. This reply is identical to the posted reply to the reviewer on the discussions site except that references are made to the changes now made to the manuscript for this revision.

This paper describes a DA system that has been built for the ABC model of Petrie et al. (2017). The entire system, ABC-DA, is described as flexible, configurable, and efficient enough to be run on a personal computer. One of the stated applications of the ABC-DA is to study convective-scale DA. This system could also clearly be used as a teaching aid for DA students. Section 4 gives a tutorial on variation data assimilation and a practical “how to” for constructing a 3DVar system. Section 4 gives a tutorial on control variable transforms (CVTs) and is also a practical “how to” for developing CVTs. These two sections are well written tutorials which, by themselves, could serve as a good teaching aids.

I would recommend the publication of this paper after the author addresses a few minor comments.

- Figure 7 might be more easily interpreted if the correlation rather covariance were plotted. It is not easy evaluate the importance of the cross-covariances (columns 2 & 3).



- I have computed the correlations (FYI as above), but a certain amount of information that I wish to show is unfortunately lost in such plots, compared to the covariances (i.e. information on the implied variances as well as the correlation patterns), so I would like to keep the covariances in the paper rather than the correlations, if the reviewer agrees.
- On the importance of the cross-correlations, I have added (to the discussion around Fig. 7) an interpretation of these in terms of their effect on the analysis increments. Essentially the cross-correlations show

how the assimilation of a  $\bar{\rho}'$  measurement at the yellow cross position in Fig. 7 affect variables like  $r'$  and  $b'$ .

2. A ensemble of forecast perturbations is used for training/developing the CVT. The author describes this raw ensemble in this way: “ We regard the raw covariances as a guide to the ‘true’ covariances that should ideally be modeled by the CVT.”. In principal, the ensemble could be made large enough to provide a very accurate covariance, from which the implied covariances (from CVT choices) could be directly evaluated. Is the model state size too large to create a full rank (or nearly full) for this type of comparison?
    - (a) Yes, indeed the model state is too large to create a full rank estimate of the B-matrix. I have slightly reworded the sentence cited above to point out the limitations of the raw covariance plot, “We regard the signals contained in the raw covariances as a rough (row-rank) guide to the covariances that should ideally be modelled by the CVT.”
  3. Following on comment #2. If the training ensemble is of low rank, then it is well known that the covariances must be localized. It is possible that the covariance used for the experiments (i.e. bottom row of Figure 7) should be localized before used for developing the CVT?
    - (a) This is true, but the raw covariances still contain a signal that is useful (see my reply above).
    - (b) Localisation is not required to develop the CVT though. I have added a new appendix (new appendix A) to show that the information contained in the calibration population is more than enough to determine the CVT. Briefly, there are about  $10^5$  pieces of information of the covariance model that need to be determined during the calibration (things like vertical modes, and spectra), but  $28 \times 10^6$  pieces of information is provided in the form of 260 super-ensemble members.
  4. There is much current research on using ensembles to represent the B matrix in variational DA. Can you comment on any plans to incorporate the ability to directly use an ensemble to perform the background covariance multiply, or possibility a hybrid approach?
    - (a) This is something that certainly could be done. I have no plans at present, but I have expanded a bit the path to this at the end of the summary of the paper.
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## Author response to anonymous referee #2

Thank you to referee #2 for reading the manuscript and for his/her valuable comments. In the following, the referee’s comments are reproduced, my responses are in blue, and my actions to the paper are in red. This reply is identical to the posted reply to the reviewer on the discussions site except that references are made to the changes now made to the manuscript for this revision.

Review of the GMD submitted article referenced as: Title: The “ABC-DA system” (v1.4): a variational data assimilation system for convective scale assimilation research with a study of the impact of a balance constraint  
Author(s): Ross Noel Bannister MS No.: gmd-2019-318 MS Type: Model description paper Iteration: Minor Revision

The paper presents a very comprehensive technical description of a toy data assimilation system based on the previously published ABC-model formulation and codes. Its content is extremely detailed and can easily serve as useful introduction to any scientist, including young scientists and post-graduate students, interested in uploading and using the codes for research or education. The technical content is complemented by a showcase example of the scientific use of the system (the study of the impact of the ABC-associated geostrophic balance constraint in the B-matrix model).

The article is clearly written and the figures are of good quality. The presentation as a whole matches the expected goal which is to provide a scientific introduction to the ABC-DA system. As a reviewer of this article, I do not consider that my role is to evaluate or criticize whether the ABC-model and DA formulation will be a useful scientific tool per se. The present paper will however enable the scientific data assimilation community evaluate that usefulness in practice. I therefore recommend the paper for publication after very minor revisions.

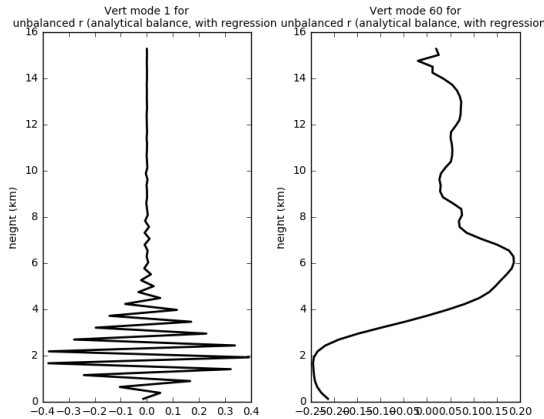
Hereafter follow my minor comments:

1. about §4.1: from what platform can a user upload UM data for initializing the very first steps? Or are such data available with the ABC system packages?

Ensembles play an important role in many cases of the toy applications. Can you say a few words about how the size of the super-ensemble is set, and what would be a "reasonable" limit of size?

- (a) The size of the sample UM data is unfortunately too large for the GitHub repository. I have though added the sample UM data (and also some pre-prepared ABC ensemble initial conditions) to the web site of the Data Assimilation Research Centre at Reading and provided a link to there from the GitHub repository. Users downloading the ABC-DA system from GitHub now see a URL to the data.
  - (b) The second point overlaps with a comment from another reviewer. A new appendix (appendix A) has been added which deals with the amount of information needed to determine aspects of the covariance model (CVT). Essentially there are about  $10^5$  pieces of information of the covariance model that need to be determined during the calibration (things like vertical modes, and spectra), but  $28 \times 10^6$  pieces of information is provided in the form of 260 super-ensemble members. This is more than adequate.
2. About Fig 6b: this particular plot is actually little discussed in the core text. My question is, noting that the vertical lengthscale increases with increasing vertical mode (i.e. the more nodes on the vertical, the deeper the penetration scale of the mode), is this behaviour due to the fact that the plot holds for the unbalanced part of the scaled density? i.e. one expects the opposite property for the balanced part of scaled density (low-order vertical modes of balanced scaled density would have the largest vertical lengthscales?). Is this correct? I suggest a short comment about Fig 6b could be added in §4.3 or §4.4.

- (a) I actually find that, for the vertical modes, the more nodes there are, the shorter the penetration scale. For info, a low mode of unbalanced scaled density is shown on the left below (short vertical scale) and a high mode is shown on the right (long vertical scale). They appear in this order because the eigensolver evidently outputs modes in ascending eigenvalue order. Such a correspondence between mode and vertical lengthscale is in fact found to be shared with vertical modes of streamfunction (which also share their vertical modes with the balanced component of scaled density). A comment has been added to the penultimate paragraph of Sect. 4.3.5 to state the above correspondence between the number of nodes and the vertical scale, and that the same (not the opposite) property exists for the balanced part of scaled density.



3. about §4.7: it is stated that the ABC-DA system is flexible enough to host a variety of DA methods, like 4D-VAR or Ensemble-Variational formulations. It seems indeed clear from the article that methods based on variational formulations, including iterative steps such as a minimisation and the computation of a gradient, are allowed. However, what about methods like Extended or Ensemble Kalman filters, or versions of Optimal Interpolation, i.e. methods where the Gain Matrix (G) would be somehow explicitly computed, and a direct inversion step involving G would be implied? Similarly, what about methods involving a number of computational steps in observation space as for LETKF (Local Ensemble Transform Kalman filters)? Can the author elaborate in only a few lines on these algorithms, in order to provide an insider view about how easy/how difficult/how different the implementation of such methods in ABC-DA would be?

- (a) As I see it, the extended or ensemble Kalman filters (of whatever flavour), or any of the methods that compute an explicit gain matrix would not follow from such a variational method presented. Some further

comments about possible developments have been added at the end of the summary section concerning the possible extension of the system to ensemble-variational or hybrid systems, including the hybrid gain system of [1].

4. §6, line 776: typo "... that that ..." => "... that the ..."

(a) This has been corrected.

5. line 774-780: in the discussion of the "control-ability" of the v-component of the wind fields. Is this weak control-ability due to the specific formulation of the ABC toy model? (my guess is "yes"). Can you comment this more in the discussion?

(a) I think that I was wrong to suggest that  $v$  is not controllable in the DA experiments. Instead I need to say that  $v$  is updated in the wrong way. I have added more in the summary (and removed the idea that it is due to low controlability). I suggest the use of observations not at the analysis time (and hence the approximations due to 3DFGAT) might be a reason why the results for  $v$  are not good, although this is not proven.

6. §4.2-4.3-4.4 & §5: One general question I have is whether the ABC-DA system can allow the use of a full, total field, B-matrix (that is, one without any balance modeling)? If a total-field B-matrix would be feasible, then the corresponding ABC-DA system could be a valuable reference system for impact studies on specific B-modeling. Can you comment on this?

(a) I discuss in the new appendix (appendix A) that the number of pieces of information needed to determine a full B-matrix empirically is not really feasible.

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## Author response to short comment from named referee

Thank you to Pierre Gauthier for reading the manuscript and for his valuable comments. In the following, the referee's comments are reproduced, my responses are in blue, and my actions to the paper are in red. This reply is identical to the posted reply to the reviewer on the discussions site except that references are made to the changes now made to the manuscript for this revision.

Review of paper The ABC-DA system (version 1.4) : a variational data assimilation system for convective scale assimilation research with a study of the impact of a balance constraint By Ross Noël Bannister Submitted to Geoscientific Model Development Date:

### 1. MAIN COMMENTS

The resolution of operational NWP models increases and is reaching the convective scale. This raises new issues associated with the inclusion of ever increasing and complex processes. Moreover, this raises new questions regarding data assimilation methods to be used. Petrie et al. (2017) introduced a simple non-hydrostatic model that could even represent explicitly acoustic waves for data assimilation studies. This paper presents a companion variational data assimilation for this model. The paper is well written and focuses for the most part on the modeling of background error covariance. The emphasis is mostly on 3D-var including the so called FGAT (first-guess at appropriate time) which is also used in many operational systems.

In research, one would like to be able to explore different approaches to assess what could be the best one for the assimilation at the convective scale. I was expecting then that the 4D assimilation would have been more prominent, including 4D-Var in strong and weak constraint for example. In the EnVar, the control variable is the complete model trajectory including temporal correlations for the treatment of background error, which is also used in the weak constraint 4D-Var.

How does this approach compares to using the OOPS/JEDI paradigm which can be used with either a "toy" model or an operational one? I think that it would be important for a "community" model that the advantages of ABC-DA be presented from that perspective. Little is said about observation operators which can easily be the dominant component of a DA system. Assimilating large volumes of Doppler radar data is one example. The point I am making is the paper should make an effort to emphasize aspects of the ABC-DA that could entice researchers to use it.

- As I understand it, the JEDI programme is meant to be a resource to share components of data assimilation systems using an object orientated software approach. The ABC-DA system is not generic, nor object orientated as I understand it, but is suited specifically to the ABC model.
- The possible use of observation operators for Doppler has been added to the abstract and to the introduction.
- The possible development of 4DVar has been mentioned in the summary. For this paper though the focus is on background error covariances (as the reviewer mentions below), for which 3DVar is an adequate tool.

As stated line 143, “much of the design of ABC-DA is concerned with how B is modelled”. The emphasis is mostly on multivariate 3D-var including the so called FGAT (first-guess at appropriate time) which is also used in most operational system. Bouttier et al. (1997) introduced balance operators obtained from multilinear regression for a covariance model based on homogenous and isotropic correlations for the analysis variables deemed to have uncorrelated error. This corresponds to some extent to what the paper presents in too much details in my view. I do not see the point of explicitly describing how to use the code: this is important but very likely to change with time. This should be included in a user manual or website for users. On the other hand, it would be more important to explain the scientific justifications. Balance appropriate for the convective scale should be discussed: geostrophic balance does not seem to be the most relevant.

- I have provided what I believe to be enough detail for the paper to be in the spirit of the journal. A separate user guide for the code itself exists via GitHub and is referenced frequently in the paper. I hope the reviewer thinks that this is reasonable.
- Geostrophic balance is still present at the larger scales in the system, which are still analysed here. Geostrophic balance is also used, for instance, in the Met Office’s variational DA system for their 1.5km grid size model called UKV, so its relevance is worth studying in this paper. Alternative balance relationships are possible, such as the diagnostic relationship given in Sect. 4.3 of [2], which will be explored in future work.
- These scientific justification points (and details about alternative balances) have been made at the end of Sect. 4.2.1 and in the summary.

The paper ends by presenting the results of experiments to illustrate the impact of the different components representing the balance for this particular model. Is the paper about presenting the ABC-DA emphasizing the advantages of the design to study different aspects of DA that may be important for the assimilation at the convective scale? As it is, most of it is to describe what has been implemented for this particular model of B with some results indicating the impact this may have on the analysis.

I recommend that the author reviews his paper to either present ABC-DA as a polyvalent system for research on DA at the convective scale. Or that it is about a multivariate model for B and its impact on the analysis and forecast. Given the large body of literature on this topic, the latter would be rather thin.

- The ABC model and DA system have been developed over the years specifically to explore B-matrix modelling options. I guess this has had an unconscious influence on the emphasis of this paper. I have though mentioned other possible uses of the system in the introduction (e.g. to explore Doppler observation networks).

The next section presents some specific comments on some, but not all, issues with the paper.

## 2. SPECIFIC COMMENTS

### 2.1 Modelling B

- sections 3.4, 4.2, 4.3, 4.4 (~14 pages) As stated line 143, “much of the design of ABC-DA is concerned with how B is modelled”. Sections The emphasis is mostly on 3D-var including the so called FGAT (first-guess at appropriate time) which is also used in most operational system. Early on, it has been recognized that multivariate covariances should embed dynamical constraints such as an approximate geostrophic balance (e.g., see Daley ,1991). Modeling of a “static” B has been the object of many papers that should be referred to Parrish and Derber (1992) presented the first implementation of 3D-Var and introduced a new approach in which the error was divided into balanced and unbalanced components. They used an ensemble of lagged forecasts at 24 and 48-h to represent averaged background error covariances. Bouttier et al. (1997) introduced balance operators obtained from multilinear regression for a covariance model based on homogenous and isotropic correlations for the analysis variables deemed to have uncorrelated error. This is pretty much what

is presented in section 4.2. I do not see why the author presents this with so much detail given that this is at best, an example of what could be used in the ABC-DA. Buehner (2005) presents a B based on a EOF representation for stationary covariances that can capture some local effects (e.g., presence of orography).

- Parrish and Derber has been referenced towards the end of Sect. 3.4. Derber and Bouttier (1999) has been referenced towards the end of Sect. 4.2.1 (I understand that this is the peer reviewed version of Bouttier et al (1997) that the reviewer cites).
- I have tried to provide as much detail as is necessary to adequately describe the DA system.

## 2.2 Other comments

- p.7: section 3.3. devotes 7 lines to observations. Later, section 5 gives 8 more lines to the observation operators. This is a bit short in my view.
  - Additionally Sect. 4.5 is dedicated to observation operators. I do believe that an adequate discussion of the observation specifications has been made for this particular paper. More technical aspects of the observation network specifications is provided in the technical documentation, which is cited throughout the paper, and available on GitHub. Further mentions of how the system can be extended to include Doppler wind observations have been made (e.g. in the abstract) to help interest readers who may wish to use the ABC system to investigate observation strategies.
- p.6, line 173: The propagator is said to be difficult to derive so it is replaced by the identity. It has been theoretically defined (LeDimet and Talagrand, 1988) and developed for operational model. Even more, the “transpose” of it has also been developed, the “adjoint model”. In the context of the incremental form of 4D-Var, some simplifications to the model can be made regarding resolution or the used of a simplified physics. It would be important to know whether it should be possible to expand the ABC-DA to make it possible to do 4D-Var.
  - Reference to LeDimet and Talagrand (1986) has been added to Sect. 3.1 of the paper.
- p.7, line 200: using the analysis variables  $\delta(x - x_b) = U$  with  $B = UU^T$  means that we need to get the square root of B but we do not have to invert it. The flip side to this is that if B is singular the increment is built based on the singular vectors of B. For an ensemble like the ETKF, for instance, the increment could only be a linear combination of the members of the ensemble that define B. p.8, lines 207-213: I think this needs to be revised. What is said here only applies to a particular B model with isotropic and homogenous correlations which happens to yield a diagonal matrix when expressed in terms of spectral components (e.g., Fourier, Bessel or spherical harmonics).
  - I have added a short comment here that a singular B-matrix can be modelled using the CVT approach (end of Sect. 3.4). I don’t agree with the reviewer that the text applies only to isotropic and homogenous correlations, e.g. if the variances of the spectral components are not just a function of total wavenumber, but of the individual x and y wavenumber components separately, then the covariances can be anisotropic. I have added another short comment (also at the end of Sect. 3.4) that the approach allows more complicated forms of the CVT than  $U_s = \Sigma U_v U_h$ .
- p.8, line 224: in the incremental form, there is no need to invert U, insofar as the initial point of the minimization is the background state, in which case, initially,  $\chi = 0$ .
  - This is true for the first outer loop where  $x^r = x^b$ , but strictly speaking  $U^{-1}$  is needed for later outer loops when  $x^r \neq x^b$ . This is now mentioned in the text.
- p.8, line 235: the description of the algorithm does not indicate how  $\lambda$  is updated.
  - This is given in step 2(f)v.
- p.9, line 245: I agree that the test of transpose is useful to test specific part of the code. But the gradient test (based on a Taylor expansion) should also be mentioned. It is simpler and is routinely used to validate complex operational variational DA systems when all components are active. It should be mentioned.
  - A comment has been added to Sect. 3.6. The gradient test is now coded and included as part of ABC-DA.

- p.10, line 280: I do not think U-1 is needed.
  - It is needed for the calibration. A comment has been added.
- p.10, line 290: the Helmholtz theorem states that there both a potential component and a rotational one (the streamfunction).
  - Equation (13) is for the rotational part and Eq. (14) is for the irrotational part. These equations (and (23) and (24)) are all derived from the Helmholtz theorem,  $(\delta \mathbf{u}, \delta \mathbf{v}) = \nabla_h \delta \chi_{vp} + \mathbf{k} \times \nabla_h \delta \psi$  ( $\nabla_h$  is the horizontal gradient operator and  $\mathbf{k}$  is the vertical unit vector), but simplifications arise due to the lack of latitude dependence in this system. The reader is now reminded of this after Eq. (14).
- p.11, line 296: defining the balance operators is a separate exercise that needs more explanation. Using linear regression has been proposed by Bouttier et al. (1997) and used by others. This requires some insight into the type of balance that could exist. At synoptic scales, geostrophic and Ekman balance have been used to guide the linear regression. What kind of stationary balance can we expect at convective scales. Reference should be made to Parrish and Derber (1992) and Bouttier et al. (1997).
  - Reference to Parrish and Derber has been made at the end of Sect. 3.4 (and Gauthier et al, 1999). The peer-reviewed version of Bouttier et al. (1997) (which is Derber and Bouttier (1999)) has been added at the end of Sect. 4.2.1 which discusses the validity of geostrophic (and hydrostatic) balance. Further possibilities for convective-scales have been discussed in the summary.
- p.12, eq.(23): I think the winds cannot be represented as irrotational and this impacts the very formulation of U. Please revise. This impact the form of B as presented in eq.(22). p.14, line 366: I do not think we can represent B as a finite expansion of its eigenvectors, in general. It is a composition of operators that reflect the general form of the balance operators. In the univariate case for example, with homogeneous and isotropic correlations, this would require a large number of eigenvectors to properly represent it particularly if the characteristic scale is small.
  - The wind does have a rotational part: Eq. (23) is for the irrotational part and Eq. (24) is for the rotational part in this toy model (see also two points above).
  - Only the spatial transforms (vertical and horizontal) are represented as expansions of (approximate) eigenvectors. In the vertical, all 60 eigenvectors are represented (there are 60 levels), and in the horizontal, all 360 wavenumbers are represented (there are 360 longitude points). Hence all scales represented in the model are represented in the DA.
- p.15: section 4.3: one diagnostic used to calibrate the error statistics is to verify if the a priori statistics used in the assimilation are consistent with what is measured from the innovation covariances when real observations are compared to the forecast of a model.
  - A comment that this diagnostic is possible has been added to Sect. 3.6.
- p.15, section 4.3.1: as I understand it, an ensemble of forecasts obtained from the UM is used to define the balance operators. To what extent can we expect those to reflect the balance of ABC forecasts?
  - The UM data are processed to make them consistent with the ABC system, and are then spun-up with an ABC model forecast. I agree that the degree of memory of the UM system has not been tested. A comment has been added to Sect. 4.3.1.
- p.23, eq.(33): given that only a wind potential is used, the multivariate B of eq.(33) needs some explaining.
  - The rotational part of the wind couples to the scaled density field via Eq. (15), which is reflected in (33) (all terms with the  $\alpha$  factor).

### 3. REFERENCES

- Bouttier, F., J. Derber and M. Fisher, 1997: The 1997 revision of the Jb term in 3D/4D Var. ECMWF Tech Memorandum No. 238, 54 pages.
- Buehner, M., 2005: Ensemble-derived stationary and flow-dependent background-error covariances: evaluation in a quasi-operational setting. Quart. J.R. Meteor. Soc., 131, 1013-1043.
- Gauthier, P., M. Buehner and L. Fillion, 1998: Background-error statistics modeling in a 3D variational data assimilation scheme: estimation of the impact on analyses. In Proceedings of ECMWF workshop on diagnosis of data assimilation systems, Reading UK, 2 to 4 November 1998.



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## References

- [1] Stephen G Penny. The hybrid local ensemble transform Kalman filter. *Monthly Weather Review*, 142(6):2139–2149, 2014.
- [2] R.A. Pielke. *Mesoscale Meteorological Modeling*. Academic Press, San Diego, California, 2002.

# The “ABC-DA system” (v1.4): a variational data assimilation system for convective scale assimilation research with a study of the impact of a balance constraint

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**Abstract.** Following the development of the simplified atmospheric convective-scale ‘toy’ model (the ABC model, named after its three key parameters: the pure gravity wave frequency,  $A$ , the controller of the acoustic wave speed,  $B$ , and the constant of proportionality between pressure and density perturbations,  $C$ ), this paper introduces its associated variational data assimilation system, ABC-DA. The purpose of ABC-DA is to permit quick and efficient research into data assimilation methods suitable for convective scale systems. The system can also be used as an aid to teach and demonstrate data assimilation principles.

ABC-DA is flexible and configurable, and is efficient enough to be run on a personal computer. The system can run a number of assimilation methods (currently 3DVar and 3DFGAT have been implemented), with user configurable observation networks. Observation operators for direct observations and wind speeds are part of the current system, and these can be expanded relatively easily to include operators for Doppler winds for example. A key feature of any data assimilation system is how it specifies the background error covariance matrix. ABC-DA uses a control variable transform method to allow this to be done efficiently. This version of ABC-DA mirrors many operational configurations, by modelling multivariate error covariances with uncorrelated control parameters, each with special uncorrelated spatial patterns.

The software developed does (amongst other things) model runs, calibration tasks associated with the background error covariance matrix, testing and diagnostic tasks, single data assimilation runs, multi-cycle assimilation/forecast experiments, and has associated visualisation software.

As a demonstration, the system is used to tackle a scientific question concerning the role of geostrophic balance (GB) to model background error covariances between mass and wind fields. This question arises because, although GB is a very useful mechanism that is successfully exploited in larger scale assimilation systems, its use is questionable at convective scales due to the typically larger Rossby numbers where GB is not so relevant. A series of identical twin experiments is done in cycled assimilation configurations. One experiment exploits GB to represent mass-wind covariances in a mirror of an operational set-up (with use of an additional vertical regression (VR) step, as used operationally). This experiment performs badly where error accumulates over time. Two further experiments are done: one that does not use GB, and another that does but without the VR step. Turning off GB impairs the performance, and turning off VR improves the performance in general. It is concluded that there is scope to further improve the way that the background error covariance matrices are represented at convective-scale.

Ideas for further possible developments of ABC-DA are discussed.

## 1 Introduction

The grid sizes of limited area models for operational weather forecasting have become small enough to allow some convective processes to be resolved explicitly (Clark et al., 2016; Yano et al., 2018). Some leading operational models include the COSMO (Consortium for Small scale MOdelling) model (Baldauf et al., 2011), used at MeteoSwiss (1.1 km grid size) and at DWD (2.8 km grid size); the AROME (Application of Research to Operations at Mesoscale) model (Brousseau et al., 2016), used at Météo-France (1.3 km grid size); the UKV (UK Variable resolution) model (Tang et al., 2013) (1.5 km grid size); and the WRF (US Weather Research and Forecasting) model (Schwartz and Liu, 2014) (3 km grid size). Each of these systems is invaluable in the forecasting of fine-scale weather, including that associated with convective storms, and has its own data assimilation (DA) system to estimate its initial conditions from new observations and a background state.

Apart from the capability to assimilate new high-resolution observation types, such as radar reflectivity and Doppler radial wind, the DA systems are still based on those designed for use with synoptic- and planetary-scale phenomena in mind. The convective-scale DA problem needs to account for effects that can often be safely ignored or treated approximately when dealing with large scales. These include certain dynamical properties of background state errors (namely non-hydrostatic and non-geostrophic contributions, vertical motion, multiple phases of water, strong inhomogeneity and flow-dependence, and non-Gaussianity), certain properties of observation errors (namely cross-correlations), and other features associated with a small grid size (e.g. feature misalignment). There are also challenges associated with assimilating new observation types (as mentioned above, including the large volumes of data needed), the short DA time window (often 1 hour or less), the compatibility of lateral boundary conditions from a coarser parent model, and questions concerning the appropriateness of allowing DA to simultaneously modify the larger scale flows present in the convective-scale problem.

The properties of background state errors is of particular concern to this paper, although the DA system to be described can be equally applied to study [other aspects of convective-scale DA, such as the exploration of strategies for high-resolution observation networks \(such as those from Doppler wind instruments\), or indeed some of the advanced DA methods mentioned below](#). In DA, the background state is traditionally assumed to be subject to random error which is distributed according to a Gaussian distribution described by a multivariate error covariance matrix (the ‘**B**-matrix’, e.g. Bannister (2008a)). Given that **B** is too large to store explicitly, in variational DA (Var) it is represented in the form of a ‘model’ (Bannister, 2008b). One important means of representing **B** in a way that naturally adapts to the flow conditions is to derive a matrix implicitly from an ensemble of forecasts, which are often produced anyway for probabilistic forecasting purposes. This is the basis of the ensemble Kalman filter (e.g. Houtekamer and Zhang (2016)), and EnVar (pure ensemble-variational) formulations (e.g. Liu et al. (2008)). Although information from an ensemble in principle follows the dynamical properties of the model to be reflected in the **B**-matrix used at the analysis time, the result is often corrupted by sampling error due to the small ensemble sizes (usually a few tens of members). For this reason, the **B**-matrix used operationally is often still modelled according to physical insight. That insight though is based on traditional assumptions of (for instance) geophysical balance whose applicability are questionable at convective-scales.

Studying convective-scale DA in operational systems is burdened severely by the cost and complexity of these systems. The DA system described in this paper has been designed in the same spirit as that of the convective-scale ‘toy’ model (the ‘ABC model’, Petrie et al. (2017)), i.e. with an emphasis on low cost and simplicity. This DA system (together with the model code is hereafter called ‘ABC-DA’) is a multi-featured Var system suited to the ABC model. ABC-DA is actually a suite of software used not only to perform DA itself (in cycling mode if required), but also to calibrate the  $\mathbf{B}$ -matrix from sets of forecast data, to flexibly generate randomly perturbed data such as synthetic observations from a ‘truth’ run (which can then be assimilated), to compute a sample of covariances implied from a chosen  $\mathbf{B}$ -matrix model, and to perform a set of validation tests. The suite also includes sample plotting codes to help visualise and monitor the outputs, a script to build the executables, sample run scripts, and detailed user documentation. The ABC-DA numerical codes are written in Fortran-90, scripts are written in Linux Bash, and the plotting code is written in Python-2. Certain open-source software libraries are also required to compile the code.

This paper presents the scientific documentation for the system, with examples and pointers to how a user can access the software. Finally a short study of ABC-DA is presented to investigate the impact of balance constraints in the formulation of the convective-scale  $\mathbf{B}$ -matrix. The paper is structured as follows. In Sect. 2 the ABC model is described, in Sect. 3 the ABC-DA system is outlined, in Sect. 4, the ABC-DA system is described in detail, in Section 5 a brief study of the role of geostrophic balance is presented, and in Sect. 6 the paper is summarised.

## 2 The ‘ABC’ model

### 2.1 The model equations

The ABC model comprises a set of simplified partial differential equations for a two-dimensional spatial grid ( $x$  and  $z$ ), plus time ( $t$ ), which are based on the Euler equations. This section summarises the ABC model, and the reader is directed to Petrie et al. (2017) for the details. The model equations are as follows:

$$\frac{\partial u}{\partial t} + B\mathbf{u} \cdot \nabla u + C \frac{\partial \tilde{\rho}'}{\partial x} - fv = 0, \quad (1a)$$

$$\frac{\partial v}{\partial t} + B\mathbf{u} \cdot \nabla v + fu = 0, \quad (1b)$$

$$\frac{\partial w}{\partial t} + B\mathbf{u} \cdot \nabla w + C \frac{\partial \tilde{\rho}'}{\partial z} - b' = 0, \quad (1c)$$

$$\frac{\partial \tilde{\rho}'}{\partial t} + B\nabla \cdot (\tilde{\rho}\mathbf{u}) = 0, \quad (1d)$$

$$\frac{\partial b'}{\partial t} + B\mathbf{u} \cdot \nabla b' + A^2 w = 0, \quad (1e)$$

where  $\mathbf{u} = \begin{pmatrix} u & v & w \end{pmatrix}$  is the wind vector (comprising zonal, meridional, and vertical wind components respectively),  $\tilde{\rho}$  is the scaled density variable (akin to pressure),  $b$  is the buoyancy variable (akin to temperature),  $f$  is the Coriolis parameter,  $g$  is the acceleration due to gravity, and  $A$ ,  $B$ , and  $C$  are tunable parameters (see below). Primed variables indicate perturbations from a reference state defined as  $b(x, z, t) = g + b_0(z) + b'(x, z, t)$  and  $\tilde{\rho}(x, z, t) = 1 + \tilde{\rho}'(x, z, t)$ . The model supports a range of motions, namely balanced (Rossby-like) modes, and unbalanced (gravity and acoustic) modes, which have been studied in

detail in Petrie et al. (2017). There are three tunable parameters:  $A$  is the pure gravity wave frequency, controlling the gravity wave speeds in the model;  $B$  modulates the advective and divergent terms in the equations, controlling the acoustic wave speeds; and  $C$  specifies the equation of state that relates pressure and density perturbations,  $p' = C\rho_0\tilde{\rho}'$ , where  $\rho_0$  is a density scaling constant. In the linearised equations, only the product  $BC$  (and not  $B$  and  $C$  individually) affects the characteristics of the flow, so  $C$  also controls the acoustic wave speeds. In numerical integrations of the non-linear equations Eq. (1), the effect of scaling  $C$  is found to be virtually indistinguishable from scaling  $B$  in terms of the patterns of forecast perturbations.

## 95 2.2 Properties of the ABC model equations

Equations Eq. (1) conserve total mass and energy, although this exact property is lost when the equations are discretised for numerical integration. The equations approximate to geostrophic and hydrostatic balance (GB and HB respectively) when the Rossby number,  $Ro = \mathcal{U}/f\mathcal{L}$  is small (where  $\mathcal{U}$  is the characteristic zonal wind speed and  $\mathcal{L}$  is the characteristic horizontal length-scale of the motion). The GB relations are

$$100 \quad -fv + C\frac{\partial\tilde{\rho}'}{\partial x} = 0, \quad (2a)$$

$$u = 0, \quad (2b)$$

and the HB relation is

$$-b' + C\frac{\partial\tilde{\rho}'}{\partial z} = 0. \quad (3)$$

These balance relations are well satisfied for motion at the large scales where  $Ro$  is small and are used in traditional Var  
110 schemes to model the covariances between mass, wind, and temperature perturbations in background errors. We will revisit these later in the paper.

## 2.3 Discretisation and integration

As reported in Petrie et al. (2017) the continuous equations Eq. (1) have been discretised in time and space (the current implementation uses a  $360 \times 60$  (horizontal  $\times$  vertical) element grid with a gridbox size of  $1500 \times 250$  m. Variables are stored  
110 on an Arakawa C grid in the horizontal and Charney-Phillips in the vertical (see Fig. 1 of Petrie et al. (2017)), and periodic boundary conditions are imposed in the horizontal to avoid the need for a driving model to provide lateral boundary conditions. The integration scheme used is the split-explicit, forward-backward scheme of Cullen and Davies (1991) with a main timestep of  $\Delta t = 4$  s.

## 2.4 Future developments of the model

115 The current version of the ABC model does not include moist processes. There is much that can be learned about convective-scale DA from a dry model, but assimilating and forecasting moisture fields is a major reason for convective-scale forecasting (Sun et al., 2014; Bannister et al., 2020). It is planned to upgrade the model to permit the advection of one or more water

variables and allow condensation and evaporation processes to affect the flow. The assimilation of moisture is a complex task and so a moist ABC-DA system is expected to be very useful in that line of research.

## 120 3 Overview of the ABC-DA system

Like the ABC model, the DA system is intended to be low cost and easy to run when compared to a operational-scale system, yet mirror many of the features and options available in operational systems. In this section we review the principles on which ABC-DA is based, which includes a definition of the mathematical notation, but we leave it to Sect. 4 to describe the details.

### 3.1 Variational data assimilation

125 Var systems construct a scalar functional (called a cost function,  $J$ ) that is minimised with respect to the state  $\mathbf{x}$  by considering observations made over a time window (indicated by an integer time index)  $t \in [0, T]$ :

$$J[\mathbf{x}] = \frac{1}{2}(\mathbf{x} - \mathbf{x}^b)\mathbf{B}^{-1}(\mathbf{x} - \mathbf{x}^b) + \frac{1}{2} \sum_{t=0}^T [\mathbf{y}(t) - \mathbf{y}^m(t)]^T \mathbf{R}_t^{-1} [\mathbf{y}(t) - \mathbf{y}^m(t)]. \quad (4)$$

In Eq. (4),  $\mathbf{x}$  represents all variables of the model state at  $t = 0$  (here  $u, v, w, \tilde{\rho}'$ , and  $b'$ ) at each location in the domain,  $\mathbf{x}^b$  is a special state at  $t = 0$  called the background state (normally a short forecast from the previous DA),  $\mathbf{y}(t)$  is the collection  
 130 of observations at time  $t$ , and  $\mathbf{y}^m(t)$  is the model's version of the observations computed from  $\mathbf{x}$ . Let there be  $n$  elements in  $\mathbf{x}$  and  $p_t$  elements in  $\mathbf{y}(t)$ . Here we use the convention that quantities like  $\mathbf{x}$  without a time argument imply the value at  $t = 0$ . The model's observations are found in two steps: firstly the state is found at time  $t$  using the model propagator:  $\mathbf{x}(t) = \mathcal{M}_{0 \rightarrow t}(\mathbf{x})$ , which is the result of integrating Eq. (1) from times 0 to  $t$ , and then the model's observations are found using the observation operator at this time:  $\mathbf{y}^m = \mathcal{H}_t(\mathbf{x}(t))$ . [This DA method is known as 4DVar \(Dimet and Talagrand, 1986\).](#)  
 135  $\mathbf{B}$  and  $\mathbf{R}_t$  are covariance matrices (e.g. Kalnay (2002)) pertaining to errors in the background state, and in the observations at time  $t$  respectively. Mathematically  $\mathbf{B}$  (an  $n \times n$  matrix) and  $\mathbf{R}_t$  (a  $p_t \times p_t$  matrix) may be thought as the metrics in which deviations are measured in the cost function (i.e. measures of the precision to which the background and observations are known). The analysis,  $\mathbf{x}^a$  is the special state that minimises  $J$ .

The  $\mathbf{B}$  and  $\mathbf{R}_t$  matrices are important as they can have a profound effect on the way that observations combine with the  
 140 background to yield the analysis. It is a particular challenge to use a  $\mathbf{B}$ -matrix that is relevant to the uncertainties in convective-scale forecasts. As  $\mathbf{B}$  is usually a much larger matrix than  $\mathbf{R}_t$  (operationally by orders of magnitude), it cannot practically be stored explicitly. Instead the  $\mathbf{B}$ -matrix is modelled, which is usually done via the technique of control variable transforms (CVTs) – see Sect. 3.4. As this modelling process is a major component of any DA system, and may require new thinking for convective-scale systems, much of the design of ABC-DA is concerned with how  $\mathbf{B}$  is modelled. [As a starting point for](#)  
 145 [ABC-DA, the approach that is currently implemented is a conventional one \(to mirror typical current operational configurations that were designed around global systems, Sect. 4.2, but still applied for convective-scale systems\). This approach though can be adapted to accommodate new convective-scale strategies that are discussed at the end of the paper.](#)

### 3.2 The incremental formulation of the problem

If  $\mathcal{M}_{0 \rightarrow t}$  and  $\mathcal{H}_t$  are linear functions, then Eq. (4) is a quadratic function of  $\mathbf{x}$  and may be minimised using efficient algorithms such as a conjugate gradient-based method (Golub and Van Loan, 1996; Lewis et al., 2006). The model  $\mathcal{M}_{0 \rightarrow t}$  though is a non-linear operator, and many observations require non-linear observation operators (such as measurements of wind speed, top-of-atmosphere radiance, etc.). This leads to a non-quadratic function, which may have multiple minima. Furthermore there are no general efficient minimising algorithms for such problems. In order to simplify the problem, the cost function is minimised by breaking it down into a sequence of quadratic problems by iteratively linearising  $\mathcal{M}_{0 \rightarrow t}$  and  $\mathcal{H}_t$ . This is incremental Var (Courtier et al., 1994).

Suppose that  $\mathbf{x}^r(t)$  is a reference trajectory satisfying  $\mathbf{x}^r(t) = \mathcal{M}_{t-1 \rightarrow t}(\mathbf{x}^r(t-1))$ ,  $1 \leq t \leq T$ . A perturbation to this trajectory ( $\delta$  prefix) at  $t$  is approximately related to a perturbation at  $t-1$  via the linear operation  $\delta \mathbf{x}(t) \approx \mathbf{M}_{t-1 \rightarrow t} \delta \mathbf{x}(t-1)$ , where the full states are  $\mathbf{x}(t) \approx \mathbf{x}^r(t) + \delta \mathbf{x}(t)$  and  $\mathbf{x}(t-1) \approx \mathbf{x}^r(t-1) + \delta \mathbf{x}(t-1)$ .  $\mathbf{M}_{t-1 \rightarrow t}$  is the tangent linear (or Jacobian) of  $\mathcal{M}_{t-1 \rightarrow t}$  and is mathematically representable by an  $n \times n$  matrix. We assume that  $\mathbf{x}^r(t) + \delta \mathbf{x}(t)$  is close to  $\mathcal{M}_{t-1 \rightarrow t}(\mathbf{x}^r(t-1) + \delta \mathbf{x}(t-1))$  providing  $\delta \mathbf{x}(t-1)$  is sufficiently small. Similarly, suppose that the observation values computed from  $\mathbf{x}^r(t)$  satisfy  $\mathbf{y}^{\text{mr}}(t) = \mathcal{H}_t(\mathbf{x}^r(t))$ . A perturbation to these reference observations is approximately related to a perturbation in  $\mathbf{x}^r(t)$  via the linear operation  $\delta \mathbf{y}(t) = \mathbf{H}_t \delta \mathbf{x}(t)$ .  $\mathbf{H}_t$  is the tangent linear (or Jacobian) of  $\mathcal{H}_t$  and is mathematically representable by a  $p_t \times n$  matrix. These approximations may be summarised as the following:

$$\mathbf{x} \approx \mathbf{x}^r + \delta \mathbf{x}, \quad (5a)$$

$$\mathbf{y}^{\text{m}}(t) \approx \mathbf{y}^{\text{mr}}(t) + \delta \mathbf{y}^{\text{m}}(t), \quad (5b)$$

$$\text{where } \delta \mathbf{y}^{\text{m}}(t) = \mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \delta \mathbf{x}. \quad (5c)$$

When Eq. (5) and the following definitions:

$$\delta \mathbf{x}^{\text{b}} = \mathbf{x}^{\text{b}} - \mathbf{x}^r, \quad (6a)$$

$$\mathbf{d}(t) = \mathbf{y}(t) - \mathcal{H}_t(\mathcal{M}_{0 \rightarrow t}(\mathbf{x}^r)) = \mathbf{y}(t) - \mathbf{y}^{\text{mr}}(t), \quad (6b)$$

are substituted into Eq. (4),  $J$  becomes a functional of the perturbation  $\delta \mathbf{x}$  instead of the full state  $\mathbf{x}$ :

$$J[\delta \mathbf{x}] = \frac{1}{2} (\delta \mathbf{x} - \delta \mathbf{x}^{\text{b}})^{\text{T}} \mathbf{B}^{-1} (\delta \mathbf{x} - \delta \mathbf{x}^{\text{b}}) + \frac{1}{2} \sum_{t=0}^T [\mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \delta \mathbf{x} - \mathbf{d}(t)]^{\text{T}} \mathbf{R}_t^{-1} [\mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \delta \mathbf{x} - \mathbf{d}(t)]. \quad (7)$$

This is the incremental form of 4DVar.  $J[\delta \mathbf{x}]$  is exactly quadratic, allowing efficient algorithms to be used to minimise it to yield the special state  $\delta \mathbf{x}^{\text{a}}$ . The iterations required to minimise Eq. (7) form an *inner loop*. The full cost function Eq. (4) is minimised by updating the reference state,  $\mathbf{x}^r \rightarrow \mathbf{x}^r + \delta \mathbf{x}^{\text{a}}$ , and repeating the inner loops. These iterations form the *outer loop*. In the first outer loop,  $\mathbf{x}^r$  is typically set to  $\mathbf{x}^{\text{b}}$ . This inner/outer loop procedure though does not necessarily find the global minimum of Eq. (4), which can lead to complications in highly non-linear systems with a long DA time window (e.g. Fabry and Sun (2010)).

Because  $\mathbf{M}_{0 \rightarrow t}$  is a difficult operator to derive, the approximation that  $\mathbf{M}_{0 \rightarrow t} = \mathbf{I}$  is often made. This leads to an approximate method called 3DFGAT (3DVar First Guess at Appropriate Time, Lee et al. (2004); Lawless (2010)). For applications when it is too expensive to use  $\mathcal{M}_{0 \rightarrow t}$  in the DA loops, a further approximation is made that  $\mathbf{x}(t) = \mathbf{x}$  over the window. This is called 3DVar, although many system that specify 3DVar actually use 3DFGAT.

### 3.3 The observations, their operators, and their error statistics

The observation operator  $\mathcal{H}_t$  (and  $\mathbf{H}_t$ ) are built to suit the range observations assimilated. The components of  $\mathcal{H}_t$  and  $\mathbf{H}_t$  represent the model's version of the observations. Typical examples include simple bi-linear interpolation of grid values to an observation location, the computation of model wind speed as the root of the sum of squares of the wind components, or the evaluation of top-of-atmosphere radiance by a radiative transfer equation. The ABC-DA system currently implements observations of the first two kinds, but the system is flexible enough to support observations of any required model variable at arbitrary times and positions. The  $\mathbf{R}_t$ -matrices are taken to be diagonal, and have specified variances. The system could be adapted to extend any of these aspects to include more complicated observation operators, such as radiative transfer models, or Doppler winds, or for correlated observation errors.

### 3.4 Modelling B with control variable transforms

The B-matrix is meant to represent the covariances of errors in  $\mathbf{x}^b$ . Operational-scale DA systems all share the challenge of determining and using B given that this  $n \times n$  matrix is too large to manipulate (or even store) and is in any case unknowable. Most practical variational methods use *control variable transforms* (CVTs) to simplify this problem. Consider a vector  $\delta\chi$ , which is an alternative representation of  $\delta\mathbf{x}$  via the relation

$$\delta\mathbf{x} = \mathbf{U}\delta\chi. \quad (8)$$

$\delta\chi$  is called a *control vector*, and  $\mathbf{U}$  is the CVT. The CVT is a powerful way of accounting for cross-correlations between background errors of model variables (including spatial and multivariate components).  $\delta\mathbf{x}$  and  $\delta\chi$  have different assumed statistical properties: model space errors have covariance  $\langle \delta\mathbf{x}\delta\mathbf{x}^T \rangle_b = \mathbf{B}$ , and control variables are taken to be uncorrelated and have unit variance  $\langle \delta\chi\delta\chi^T \rangle_b = \mathbf{I}$ , where the 'b' subscript indicates expectation over hypothetical background error samples. When Eq. (8) is substituted into Eq. (7)  $J$  becomes a functional of  $\delta\chi$ :

$$J[\delta\chi] = \frac{1}{2} (\delta\chi - \delta\chi^b)^T (\delta\chi - \delta\chi^b) + \frac{1}{2} \sum_{t=0}^T [\mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \mathbf{U} \delta\chi - \mathbf{d}(t)]^T \mathbf{R}_t^{-1} [\mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \mathbf{U} \delta\chi - \mathbf{d}(t)]. \quad (9)$$

Notice that the B-matrix has effectively disappeared from this formulation, because of the assumed statistical properties of  $\delta\chi$ . This is a considerable simplification, although the problem of defining the CVT remains. The  $\delta\chi$  cost function is minimised (giving the special vector  $\delta\chi^a$ ), which then leads to  $\delta\mathbf{x}^a$  via Eq. (8). This is equivalent to minimising Eq. (7) with a background error covariance matrix equal to

$$\mathbf{B}^{\text{ic}} = \mathbf{U}\mathbf{U}^T, \quad (10)$$



which is known as the *implied background error covariance matrix*. Apart from not needing to know the  $\mathbf{B}$ -matrix explicitly, the minimisation problem Eq. (9) is found to be numerically better conditioned than Eq. (7), leading to a more efficient and  
210 accurate minimisation.

It is common to work backwards here: first a CVT is proposed (based on physical principles such as those discussed in Bannister (2008b) and later in this paper), and then its ability to generate reasonable background error covariance structures is studied by looking at the implied covariances. This can be done by studying either  $\mathbf{U}\mathbf{U}^T$ , or the analysis increments of single-observation DA experiments. Constructing  $\mathbf{U}$  is one way of doing *background error covariance modelling*. We do this  
215 by defining new parameters and their spatial covariances via a proposed form like  $\mathbf{U} = \mathbf{U}_p \mathbf{U}_s$  (Bannister, 2008b). Here  $\mathbf{U}_p$  is the *parameter transform* (where  $\mathbf{U}_p^{-1}$  transforms model variables to alternative parameters that are assumed uncorrelated using sets of balance operators as in Parrish and Derber (1992); Gauthier et al. (1999)), and  $\mathbf{U}_s$  is the *spatial transform* (which transforms each parameter's field to modes that are assumed to be uncorrelated, such as Fourier modes).  $\mathbf{U}_s$  can itself be decomposed into separate horizontal, vertical parts, and scaling parts, e.g.  $\mathbf{U}_s = \mathbf{\Sigma} \mathbf{U}_v \mathbf{U}_h$  (see Sect. 4.2.3). More complicated  
220 sequences of transforms are also possible, e.g. based on wavelets (Deckmyn and Berre, 2005). A property of the CVT approach is that  $\mathbf{B}$  can be modelled even if it is singular.

### 3.5 The gradient of $J$ and minimising the cost function

Equation Eq. (7) is minimised by iteratively adjusting  $\delta\chi$  until a convergence criterion is met, indicating that a point close to the minimum of  $J[\delta\chi]$  has been found. The gradient vector,  $\nabla_{\delta\chi} J$ , is used with a conjugate gradient algorithm to perform this  
225 task.  $\nabla_{\delta\chi} J$  is found by differentiating  $J[\delta\chi]$ :

$$\nabla_{\delta\chi} J = \delta\chi - \delta\chi^b + \mathbf{U}^T \sum_{t=0}^T \mathbf{M}_{0 \rightarrow t}^T \mathbf{H}_t^T \mathbf{R}_t^{-1} [\mathbf{H}_t \mathbf{M}_{0 \rightarrow t} \mathbf{U} \delta\chi - \mathbf{d}(t)], \quad (11)$$

where  $\mathbf{d}(t)$  is the difference between the observations at time  $t$  and the model's version of them based on the reference state Eq. (6b). Equation Eq. (11) requires the Jacobians  $\mathbf{H}_t$  and  $\mathbf{M}_{0 \rightarrow t}$ , the CVT  $\mathbf{U}$ , and their adjoint counterparts. The evaluation of Eq. (11) can be made more efficient by the following standard algorithm.

- 230 1. Set the reference state at  $t = 0$  to the background state,  $\mathbf{x}^r = \mathbf{x}^b$ .
2. Do the outer loop.
  - (a) For the first outer loop,  $\delta\chi^b = 0$ , otherwise compute  $\delta\chi^b = \mathbf{U}^{-1} (\mathbf{x}^b - \mathbf{x}^r)$ .
  - (b) Compute  $\mathbf{x}^r(t)$  over the time window,  $1 \leq t \leq T$  with the non-linear model,  $\mathbf{x}^r(t) = \mathcal{M}_{t-1 \rightarrow t}(\mathbf{x}^r(t-1))$ .
  - (c) Compute the reference state's observations,  $\mathbf{y}^{\text{mr}}(t) = \mathcal{H}_t(\mathbf{x}^r(t))$ .
  - 235 (d) Compute the differences,  $\mathbf{d}(t) = \mathbf{y}(t) - \mathbf{y}^{\text{mr}}(t)$ .
  - (e) Set  $\delta\chi = 0$  and  $\delta\mathbf{x} = 0$ .
  - (f) Do the inner loop.

- i. Integrate the perturbation trajectory over the time window,  $1 \leq t \leq T$ , with the linear forecast model,  $\delta \mathbf{x}(t) = \mathbf{M}_{t-1 \rightarrow t} \delta \mathbf{x}(t-1)$ .
- 240 ii. Compute the perturbations to the model observations,  $\delta \mathbf{y}^m(t) = \mathbf{H}_t \delta \mathbf{x}(t)$ .
- iii. Compute  $\Delta(t)$  vectors defined as  $\Delta(t) = \mathbf{H}_t^T \mathbf{R}_t^{-1} [\delta \mathbf{y}^m(t) - \mathbf{d}(t)]$ .
- iv. Set the adjoint state  $\lambda(T+1) = 0$ .
- v. Integrate the following adjoint equation backwards in time,  $T \geq t \geq 0$ ,  $\lambda(t) = \Delta(t) + \mathbf{M}_{t \rightarrow t+1}^T \lambda(t+1)$ .
- vi. Compute the gradient as follows,  $\nabla_{\delta \chi} J = \delta \chi - \delta \chi^b + \mathbf{U}^T \lambda(0)$ .
- 245 vii. Use the conjugate gradient algorithm to adjust  $\delta \chi$  to reduce the value of  $J$ .
- viii. Compute the new increment in model space using the CVT,  $\delta \mathbf{x} = \mathbf{U} \delta \chi$ .
- ix. Go to step 2(f)i until inner loop convergence criterion is satisfied.
- (g) Update the reference state,  $\mathbf{x}^r \rightarrow \mathbf{x}^r + \delta \mathbf{x}$ .
- (h) Go to step 2a until outer loop convergence criterion is satisfied. At convergence set  $\mathbf{x}^a = \mathbf{x}^r$ .

250 3. Run a non-linear forecast from  $\mathbf{x}^a$  for the background of the next cycle, and longer forecasts if required.

The full procedure (adapted for 3DFGAT, where the linear model is omitted) is shown graphically in Sect. 4.7.

### 3.6 System tests

The system has a special suite to check aspects of operators that are coded. Operators that have an adjoint counterpart are subject to an adjoint test to demonstrate that the adjoint has been coded correctly. This includes the linearised observation  
 255 operators, and components of  $\mathbf{U}$ . Many of these operators are sub-divided into constituents that are tested separately (e.g. interpolation, halo swapping, and Fourier transforms). For a coded operator,  $\mathbf{A}$ , with input  $\mathbf{v}_{\text{in}}$ , and its coded adjoint  $\mathbf{A}^T$ , the adjoint test computes the left- and right-hand sides of the following formula, which must agree to machine precision to gain confidence that the coded adjoint is correct:

$$(\mathbf{A} \mathbf{v}_{\text{in}})^T \mathbf{A} \mathbf{v}_{\text{in}} \stackrel{?}{=} \mathbf{v}_{\text{in}}^T \mathbf{A}^T \mathbf{A} \mathbf{v}_{\text{in}}, \quad (12)$$

260 where a random vector  $\mathbf{v}_{\text{in}}$  will normally suffice. The CVT needs to be inverted in the gradient algorithm when using more than one outer loop (step 2a in Sect. 3.5), and in calibrating the  $\mathbf{B}$ -matrix (Sect. 4.3). These operators are subject to an *inverse test* to demonstrate that the inverse has been coded correctly. This is done by reading in a perturbation state, and then passing it through  $\mathbf{A} \mathbf{A}^{-1}$ . The result is output, which can be compared to the original field read-in. A test that the gradient of the cost function (as computed for the minimisation) is valid can be confirmed in a gradient test, which is also provided as part of the  
 265 test suite. The gradient test estimates progressively more accurate finite-difference approximations to the gradient and checks that they converge to the analytically computed gradient Eq. (11). Other tests are possible that have not been included in this version of ABC-DA, e.g. checks that the innovation statistics, namely  $\left\langle (\mathbf{y} - \mathbf{y}^m)(\mathbf{y} - \mathbf{y}^m)^T \right\rangle$  equals to  $\mathbf{R} + \mathbf{H} \mathbf{B}^{\text{ic}} \mathbf{H}^T$  (where  $\mathbf{y}^m(t)$  is the background's version of the observations and the angled brackets indicate average over a large number of DA cycles with the same observation network).

This section is a description of the current scientific configuration of the ABC-DA system. This section also contains some technical information and can be read in conjunction with the user documentation available on GitHub at (*ABC-DA\_1.4da/docs/Documentation.*), where more information is available, including names of the executables to be run, the namelist variables that have to be set, and the input and output file names. References are made to this document in the sections below in the form of *GitHubDoc*§*x*.

275 The code is divided into master programs that perform specific tasks. The relevant variables are set in a namelist file (filenames, options, switches, and parameters), and then the relevant executable is run. A list of the available master routines is listed in *GitHubDoc*§2, and instructions on how to download and build the code are found in *GitHubDoc*§3.

#### 4.1 Construction of a model state and making a forecast

The initial conditions for a model run may be generated using the program *Master\_PrepABC\_InitState* (*GitHubDoc*§4.1).

280 The code can take a slice from a specific Met Office Unified Model (UM) file, or can generate a simple idealised pressure ‘blob’ of specified position and size (or a combination of these). When initial fields are taken from the UM, they need to be adjusted to make them compatible with the ABC model. This involves a number of steps: (i) adjusting the fields towards the E and W edges of the domain to be consistent with the periodic boundary conditions; (ii) adding a constant to the  $v$  field to force its integral over each level to zero to allow GB Eq. (2a) (balance condition Eq. (2b) though is not enforced to allow some imbalance); (iii) computing  $\tilde{\rho}'$  from  $v$  with Eq. (2a), and then adding a constant to force its integral over each level to zero; (iv) 285 computing  $b'$  to satisfy the HB condition Eq. (3); and (v) setting  $w'$  so that the 3D winds have zero divergence. A forecast can be made from these initial conditions using the program *Master\_RunNLModel* (*GitHubDoc*§4.2) by numerically integrating equations Eq. (1).

#### 4.2 The CVTs (B-matrix) implemented

290 ABC-DA has a variety of options implemented to model the **B**-matrix using control variable transforms (CVTs, Sect. 3.4) and this section describes the current implementation. The transforms are most easily understood by describing first the inverse CVTs (since they allow the difference ‘spaces’ to be defined starting in model space and working towards the control space). The CVT operators defined are used in many of the programs mentioned in later sections.

##### 4.2.1 The inverse parameter transform, $\mathbf{U}_p^{-1}$

295 Recall that  $\mathbf{U}_p^{-1}$  transforms a perturbation in model variables Eq. (1) to alternative parameters that are assumed to be uncorrelated. It is needed primarily to calibrate the CVT (Sect. 4.3). The input fields in this procedure are the perturbations:  $\delta\mathbf{u}$ ,  $\delta\mathbf{v}$ ,  $\delta\mathbf{w}$ ,  $\delta\tilde{\rho}'$ ; and  $\delta\mathbf{b}'$ , and the output fields are (in the version of the code documented):  $\delta\psi$  (stream-function),  $\delta\chi_{vp}$  (velocity potential<sup>1</sup>),  $\delta\tilde{\rho}'^u$  (unbalanced scaled density),  $\delta\mathbf{b}'^u$  (unbalanced buoyancy), and  $\delta\mathbf{w}^u$  (unbalanced vertical wind). All input and output fields are a function of longitude and height. This is the algorithm for  $\mathbf{U}_p^{-1}$ .

---

<sup>1</sup>Do not confuse the velocity potential perturbation,  $\delta\chi_{vp}$ , with the control vector,  $\delta\chi$ .

300 1. Compute the stream-function:

$$\delta\psi = \nabla_x^{-1} \delta\mathbf{v}. \quad (13)$$

The operator  $\nabla_x^{-1}$  is defined as  $\nabla_x^{-1} \delta\mathbf{v} = (\partial/\partial x)^{-2} \partial(\delta v)/\partial x$ , which is based on application of the Helmholtz theorem (see e.g. Petrie et al. (2017), Sect. 4.1).

2. Compute the velocity potential (again based on the Helmholtz theorem):

$$305 \quad \delta\chi_{vp} = \nabla_x^{-1} \delta\mathbf{u}. \quad (14)$$

Note that in Eq. (13)  $\delta\psi$  depends only on the meridional wind and in Eq. (14)  $\delta\chi_{vp}$  depends only on the zonal wind. This is unlike a system that has latitude dependence where  $\delta\psi$  and  $\delta\chi_{vp}$  would each depend on both  $\delta\mathbf{u}$  and  $\delta\mathbf{v}$  as per the Helmholtz theorem.

3. Compute the GB scaled density:

$$310 \quad \delta\tilde{\rho}^{lb} = \alpha f \delta\psi / C, \quad (15)$$

which follows from application of the Helmholtz theorem for this system,  $(\delta u, \delta v) = (\partial\delta\chi_{vp}/\partial x, \partial\delta\psi/\partial x)$ , applied to the GB equation Eq. (2a). The value  $\alpha = 1$ , unless the system is configured to turn off GB in this transform, in which case  $\alpha = 0$ .

4. Compute the balanced scaled density after it has been vertically regressed:

$$315 \quad \delta\tilde{\rho}^{lbr} = \mathbf{R}_\rho \delta\tilde{\rho}^{lb}. \quad (16)$$

The vertical regression (VR) operator  $\mathbf{R}_\rho$  has the form  $\mathbf{R}_\rho = \mathbf{C}^{\delta\tilde{\rho}' \delta\tilde{\rho}^{lb}} \left( \mathbf{C}^{\delta\tilde{\rho}^{lb} \delta\tilde{\rho}^{lb}} \right)^{-1}$ , where  $\mathbf{C}^{\delta\tilde{\rho}^{lb} \delta\tilde{\rho}^{lb}}$  is the correlation matrix between a previously computed population of  $\delta\tilde{\rho}^{lb}$  perturbations with itself, and  $\mathbf{C}^{\delta\tilde{\rho}' \delta\tilde{\rho}^{lb}}$  is the correlation matrix between  $\delta\tilde{\rho}^{lb}$  and  $\delta\tilde{\rho}'$ . The justification for the use of  $\mathbf{R}_\rho$  is given in Appendix B. The system can be configured to turn off this step (and is not used anyway if  $\alpha = 0$  in in step 3).

320 5. Compute the unbalanced scaled density:

$$\delta\tilde{\rho}'^u = \delta\tilde{\rho}' - \delta\tilde{\rho}^{lbr} \quad (17)$$

$$(\delta\tilde{\rho}'^u = \delta\tilde{\rho}' \text{ if } \alpha = 0).$$

6. Compute the HB buoyancy:

$$\delta\mathbf{b}'^b = \beta \mathbf{L}^{hb} \delta\tilde{\rho}'. \quad (18)$$

325 The operator  $\mathbf{L}^{hb}$  is defined as  $\mathbf{L}^{hb} \delta\tilde{\rho}' = C \partial\tilde{\rho}' / \partial z$ , as in Eq. (3). The value  $\beta = 1$ , unless the system is configured to turn off HB, in which case  $\beta = 0$ .

7. Compute the unbalanced buoyancy:

$$\delta \mathbf{b}'^u = \delta \mathbf{b}' - \delta \mathbf{b}'^b \quad (19)$$

$$(\delta \mathbf{b}'^u = \delta \mathbf{b}' \text{ if } \beta = 0).$$

330 8. Compute the anelastically balanced vertical wind:

$$\delta \mathbf{w}^b = \gamma \mathbf{L}^{ab} \delta \mathbf{u}. \quad (20)$$

Using Eq. (1d), the operator  $\mathbf{L}^{ab}$  is defined as  $\mathbf{L}^{ab} \delta \mathbf{u} = -(1/\tilde{\rho}_0) \int dz \partial(\tilde{\rho}_0 \delta u)/\partial x$  (integrating from the ground to height  $z$ ), and  $\delta \mathbf{w}^b$  is the component of the vertical wind that, with  $\delta \mathbf{u}$ , has zero 3D divergence (sometimes called *anelastic balance* (AB), see Sect. 3.1.1 of Pielke (2002)). The value  $\gamma = 1$ , unless the system is configured to turn off AB, in which case  $\gamma = 0$ .

335

9. Compute the unbalanced vertical wind:

$$\delta \mathbf{w}^u = \delta \mathbf{w} - \delta \mathbf{w}^b \quad (21)$$

$$(\delta \mathbf{w}^u = \delta \mathbf{w} \text{ if } \gamma = 0).$$

Some of these steps may be omitted according to user options, as specified above. The above steps may be written more

340 compactly as the following ‘super matrix’:

$$\delta \chi = \mathbf{U}_p^{-1} \delta \mathbf{x},$$

$$\begin{pmatrix} \delta \psi \\ \delta \chi_{vp} \\ \delta \tilde{\rho}'^u \\ \delta \mathbf{b}'^u \\ \delta \mathbf{w}^u \end{pmatrix} = \begin{pmatrix} \mathbf{0} & \nabla_x^{-1} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \nabla_x^{-1} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & -\alpha \mathbf{R}_\rho \frac{f}{C} \nabla_x^{-1} & \mathbf{0} & \mathbf{1} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & -\beta \mathbf{L}^{hb} & \mathbf{1} \\ -\gamma \mathbf{L}^{ab} & \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \delta \mathbf{u} \\ \delta \mathbf{v} \\ \delta \mathbf{w} \\ \delta \tilde{\rho}' \\ \delta \mathbf{b}' \end{pmatrix}. \quad (22)$$

It is noted here that this particular form of transform is not *necessarily* the most appropriate form for convective-scale systems, e.g. GB in step 3 and HB in step 6 *may* not be relevant. There is, however, expected to be some GB at the larger scales represented, and HB at even shorter scales. Furthermore these relationships are still used in some operational systems, so their inclusion in this study is justified. The use of other balance relationships is possible, including statistical balance relationships (e.g. Derber and Bouttier (1999); Chen et al. (2013); Bannister et al. (2020)). An alternative balance relationship that may be applicable at convective-scale is mentioned in the summary.

345

#### 4.2.2 The forward parameter transform, $\mathbf{U}_p$

350  $\mathbf{U}_p$  transforms perturbations of parameters to model space. This transform (and its adjoint) is used at each iteration of the Var algorithm. The input fields in this procedure are the parameter field perturbations:  $\delta \psi$ ,  $\delta \chi_{vp}$ ,  $\delta \tilde{\rho}'^u$ ,  $\delta \mathbf{b}'^u$ , and  $\delta \mathbf{w}^u$ ; and the output fields are  $\delta \mathbf{u}$ ,  $\delta \mathbf{v}$ ,  $\delta \mathbf{w}$ ,  $\delta \tilde{\rho}'$ , and  $\delta \mathbf{b}'$ . This is the algorithm for  $\mathbf{U}_p$ .

1. Compute the zonal wind based on the Helmholtz theorem:

$$\delta \mathbf{u} = \nabla_x \delta \chi_{vp}. \quad (23)$$

355 2. Compute the meridional wind (also based on the Helmholtz theorem):

$$\delta \mathbf{v} = \nabla_x \delta \psi. \quad (24)$$

3. Compute the anelastically balanced vertical wind,  $\delta \mathbf{w}^b$  Eq. (20).

4. Compute the total vertical wind:

$$\delta \mathbf{w} = \delta \mathbf{w}^b + \delta \mathbf{w}^u. \quad (25)$$

360 5. Compute the balanced scaled density,  $\tilde{\rho}^b$  Eq. (15).

6. Compute the vertically regressed balanced scaled density,  $\delta \tilde{\rho}'^{br}$  Eq. (16).

7. Compute the total scaled density:

$$\delta \tilde{\rho}' = \delta \tilde{\rho}'^{br} + \delta \tilde{\rho}'^u. \quad (26)$$

8. Compute the hydrostatically balanced buoyancy,  $\delta \mathbf{b}^b$  Eq. (18).

365 9. Compute the total buoyancy:

$$\delta \mathbf{b}' = \delta \mathbf{b}^b + \delta \mathbf{b}^u.$$

Again, some of these steps may be omitted according to user options, as set out in Sect. (4.2.1). The above steps may be written more compactly as the super matrix:

$$\begin{aligned} \delta \mathbf{x} &= \mathbf{U}_p \delta \chi, \\ \begin{pmatrix} \delta \mathbf{u} \\ \delta \mathbf{v} \\ \delta \mathbf{w} \\ \delta \tilde{\rho}' \\ \delta \mathbf{b}' \end{pmatrix} &= \begin{pmatrix} \mathbf{0} & \nabla_x & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \nabla_x & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \gamma \mathbf{L}^{ab} \nabla_x & \mathbf{0} & \mathbf{0} & \mathbf{1} \\ \alpha \mathbf{R}_\rho \frac{f}{C} & \mathbf{0} & \mathbf{1} & \mathbf{0} & \mathbf{0} \\ \alpha \beta \mathbf{L}^{hb} \mathbf{R}_\rho \frac{f}{C} & \mathbf{0} & \beta \mathbf{L}^{hb} & \mathbf{1} & \mathbf{0} \end{pmatrix} \begin{pmatrix} \delta \psi \\ \delta \chi_{vp} \\ \delta \tilde{\rho}'^u \\ \delta \mathbf{b}^u \\ \delta \mathbf{w}^u \end{pmatrix}. \end{aligned} \quad (27)$$

Using Eq. (22) and Eq. (27) it may be confirmed that  $\mathbf{U}_p \mathbf{U}_p^{-1} = \mathbf{I}$ . The adjoint of Eq. (27) is constructed directly from the code.

### 4.2.3 The inverse spatial transform, $\mathbf{U}_s^{-1}$

In the current configuration, the spatial transform comprises separate horizontal ( $\mathbf{U}_h$ ), vertical ( $\mathbf{U}_v$ ), and scaling ( $\mathbf{\Sigma}$ ) trans-  
 375 forms. The order of these transforms may vary. The first ordering is called the ‘classic transform order’ (CTO, since this was the transform order in the first Met Office Var system, Wlasak and Cullen (2014)):

$$\mathbf{U}_s^{-1} = \mathbf{U}_h^{-1} \mathbf{U}_v^{-1} \mathbf{\Sigma}^{-1}, \quad (28)$$

and the second is called the ‘reversed transform order’ (RTO):

$$\mathbf{U}_s^{-1} = \mathbf{U}_v^{-1} \mathbf{U}_h^{-1} \mathbf{\Sigma}^{-1}. \quad (29)$$

380  $\mathbf{\Sigma}$  is a diagonal matrix of background error standard deviations of the parameters, as a function of longitude and height (although options are implemented to allow the standard deviation to be a function of height only, or a constant for each parameter). After the parameters have been divided by  $\mathbf{\Sigma}$ , the problem remains one of modelling the covariances between spatial points in space.

There are separate spatial operators for each parameter defined in Sect. 4.2.1, and so strictly we should define the overall  
 385 spatial transforms as block-diagonal forms, but we instead adopt a casual way of describing the transforms to avoid getting bogged down in notation. Depending on the context, these transforms may represent all parameters at once (as done in Sect. 3.4), single parameters, or to individual horizontal levels or vertical columns (as is done below).

$\mathbf{U}_h$  and  $\mathbf{U}_v$  have the same generic form, as follows:

$$\mathbf{U}_{h/v}^{-1} = \mathbf{G} \mathbf{\Lambda}^{-1/2} \mathbf{F}^T, \quad (30a)$$

$$390 \text{ so } \mathbf{U}_{h/v} = \mathbf{F} \mathbf{\Lambda}^{1/2} \mathbf{G}^T, \quad (30b)$$

where  $\mathbf{F}$  is the (exact or assumed) matrix of eigenvectors (columns of  $\mathbf{F}$ ) of the covariance matrix that is being modelled,  $\mathbf{\Lambda}^{1/2}$  is the diagonal matrix of eigenvalues, and  $\mathbf{G}$  is any orthonormal square matrix ( $\mathbf{G}^T \mathbf{G} = \mathbf{I}$ ) of the same dimensions as  $\mathbf{\Lambda}^{1/2}$ . In Eq. (30a),  $\mathbf{F}^T$  projects a state onto the eigenvectors (mutually uncorrelated by definition),  $\mathbf{\Lambda}^{-1/2}$  scales the projections so they have have unit variance, and  $\mathbf{G}$  is an arbitrary rotation. If the complete CVT had this form (but also incorporating  $\mathbf{\Sigma}$ ),  
 395 then the implied covariance would, by Eq. (10), be  $\mathbf{\Sigma} \mathbf{F} \mathbf{\Lambda}^{1/2} \mathbf{G}^T \left( \mathbf{\Sigma} \mathbf{F} \mathbf{\Lambda}^{1/2} \mathbf{G}^T \right)^T = \mathbf{\Sigma} \mathbf{F} \mathbf{\Lambda}^{1/2} \mathbf{G}^T \mathbf{G} \mathbf{\Lambda}^{1/2} \mathbf{F}^T \mathbf{\Sigma} = \mathbf{\Sigma} \mathbf{F} \mathbf{\Lambda} \mathbf{F}^T \mathbf{\Sigma}$ , where  $\mathbf{F} \mathbf{\Lambda} \mathbf{F}^T$  is the eigenvalue decomposition of the covariance matrix in question. In this illustration, the CVT is an exact representation of the covariances, but when this procedure is applied in practice it is only an approximate covariance model, e.g. due to the separation of the horizontal and vertical transforms [or to the application of approximate eigenvectors](#). The structure of the actual implied covariances can be investigated with the software suite (Sect. 4.4).

400 In the ABC-DA system, we use the following for  $\mathbf{F}$  and  $\mathbf{G}$  in Eq. (30).

- For the horizontal transform,  $\mathbf{U}_h^{-1}$ ,  $\mathbf{F}$  is called  $\mathbf{F}_h$  whose columns comprise horizontal plane waves of the form  $\sim \exp i k x$ , where  $i = \sqrt{-1}$  and  $k$  is the wavenumber (each column of  $\mathbf{F}_h$  is a different  $k$ ). In this context,  $\mathbf{F}_h^T$  represents a horizontal Fourier transform. This makes the assumption that the eigenvectors of the horizontal covariance matrix are

plane waves, and the eigenvalues in  $\mathbf{\Lambda}_h$  are their variances. This is equivalent to assuming horizontal error covariances that are homogeneous (see e.g. Bartello and Mitchell (1992); Berre (2000); Bannister (2008b)).  $\mathbf{G}$  is set to  $\mathbf{I}$  in the horizontal transform.

- For the vertical transform,  $\mathbf{U}_v^{-1}$ ,  $\mathbf{F}$  is called  $\mathbf{F}_v$  whose columns are the eigenmodes of a vertical covariance matrix (labelled with  $\nu$ , see below), and  $\mathbf{\Lambda}_v$  are their variances.  $\mathbf{G}$  is set either to  $\mathbf{F}_v$  to give a symmetric vertical transform, or to  $\mathbf{I}$ , depending on user choice.

The spaces that these operators work in depends on the chosen order of the transforms and on whether the vertical transform is symmetric or not. The following summarises these options and is repeated for each parameter, and can be read with Fig. 1 which shows how the transforms change the horizontal and vertical co-ordinates.

- For the CTO,  $\mathbf{U}_v^{-1}$  operates vertically on a field that is a function of  $x$  and  $z$ . The vertical eigenvectors/values are those of a pre-computed horizontally averaged vertical covariance matrix, and so these matrices themselves are not dependent on horizontal position in ABC-DA.

- For the symmetric vertical transform option,  $\mathbf{U}_v^{-1} = \mathbf{F}_v \mathbf{\Lambda}_v^{-1/2} \mathbf{F}_v^T$ , the output of  $\mathbf{U}_v^{-1}$  is also a field that is a function of  $x$  and  $z$ . The horizontal transform,  $\mathbf{U}_h^{-1}$ , then operates horizontally on such a field. The horizontal eigenvalues are those of pre-computed horizontal covariance matrices (one for each  $z$  in ABC-DA). The output of  $\mathbf{U}_h^{-1}$  is a field that is a function of  $k$  and  $z$  (see Fig. 1a). This combination of options allows a different horizontal covariance to be specified for each vertical level.

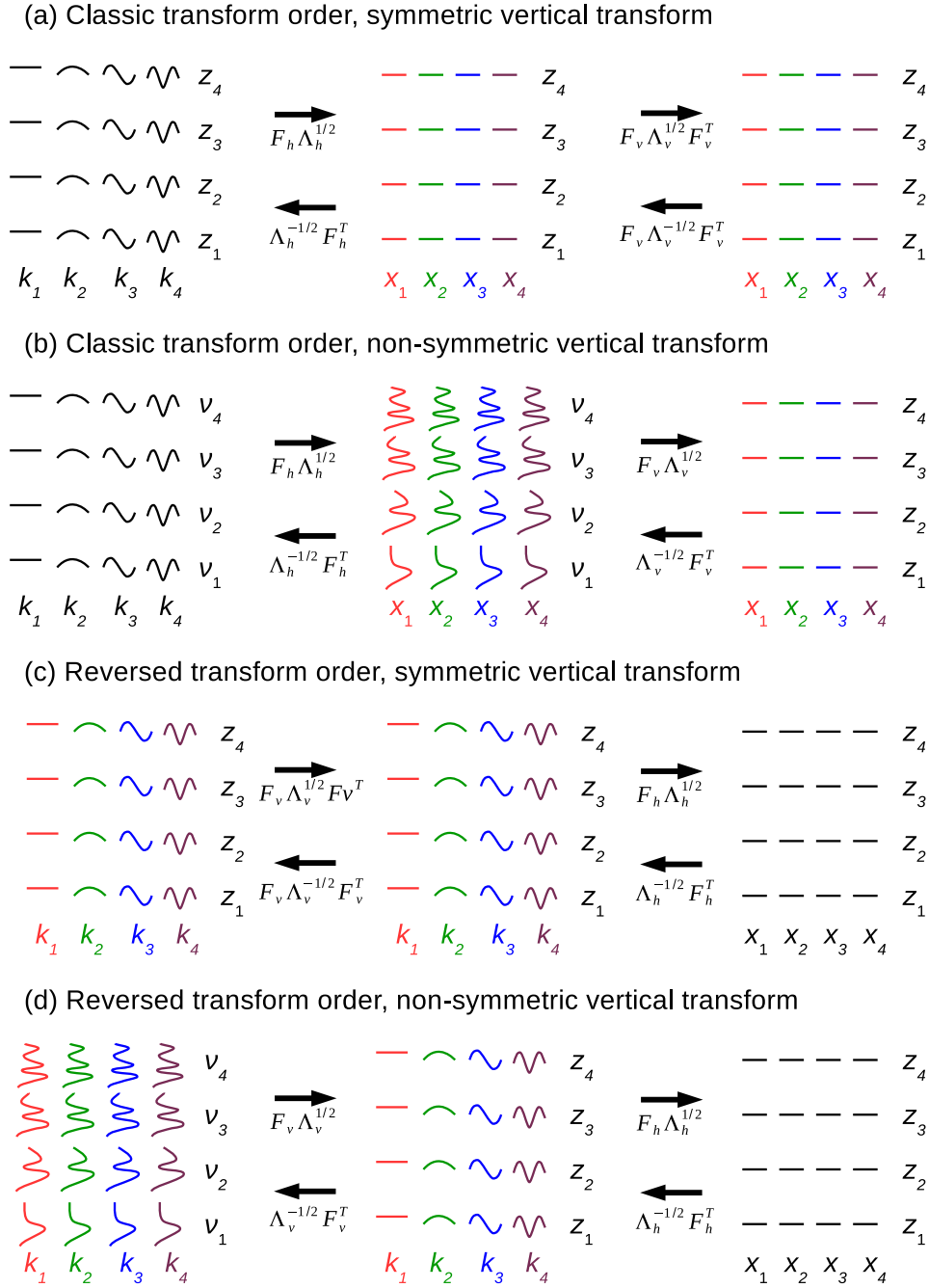
- For the non-symmetric vertical transform option,  $\mathbf{U}_v^{-1} = \mathbf{\Lambda}_v^{-1/2} \mathbf{F}_v^T$ , the output of  $\mathbf{U}_v^{-1}$  is a field that is a function of  $x$  and vertical eigenmode index,  $\nu$ . The horizontal transform,  $\mathbf{U}_h^{-1}$ , then operates horizontally on such a field. The horizontal eigenvalues are those of pre-computed horizontal covariance matrices (one for each  $\nu$  in ABC-DA). The output of  $\mathbf{U}_h^{-1}$  is a field that is a function of  $k$  and  $\nu$  (see Fig. 1b). This combination of options allows a different horizontal covariance to be specified for each vertical mode, effectively allowing horizontal and vertical length-scales to be associated.

- For the RTO,  $\mathbf{U}_h^{-1}$ , operates horizontally on a field that is a function of  $x$  and  $z$ . The horizontal eigenvalues are those of pre-computed horizontal covariance matrices (one for each  $z$  in ABC-DA). The output of  $\mathbf{U}_h^{-1}$  is a field that is a function of  $k$  and  $z$ . The vertical transform,  $\mathbf{U}_v^{-1}$ , uses a separate set of vertical eigenvectors/values for each  $k$ .

- For the symmetric vertical transform option, the output of  $\mathbf{U}_v^{-1}$  is also a field that is a function of  $k$  and  $z$  (see Fig. 1c).
- For the non-symmetric vertical transform option, the output of  $\mathbf{U}_v^{-1}$  is a field that is a function of  $k$  and  $\nu$  (see Fig. 1d).

We would expect no difference between the implied covariances of the symmetric and non-symmetric vertical transform options in the reversed case, although both options exist in the code.





**Figure 1.** Schema to illustrate the different options for the spatial transforms as indicated by the panel titles (these are combinations of classic and reversed transform orders, and symmetric and non-symmetric vertical transforms). Representations of the vertical direction include model levels (labeled with  $z_1, z_2$ , etc.) and vertical modes ( $\nu_1, \nu_2$ , etc.). Representations of the horizontal direction include model grid-points ( $x_1, x_2$ , etc.) and Fourier modes ( $k_1, k_2$ , etc.). Moving from left-to-right indicates the forward transform, and from right-to-left indicates the inverse transform. The horizontal transform is always done independently for each vertical co-ordinate ( $z_i$ -to- $z_i$  or  $\nu_i$ -to- $\nu_i$ ), and the vertical transform is always done independently for each horizontal co-ordinate ( $x_i$ -to- $x_i$  or  $k_i$ -to- $k_i$ , as guided by the colours). The co-ordinates used in the control space in each option are indicated on the left-most panels.

#### 4.2.4 The forward spatial transform, $\mathbf{U}_s$

The forward spatial transforms follow in a straightforward way from the inverses defined in Sect. 4.2.3, namely for the CTO:

$$\mathbf{U}_s = \Sigma \mathbf{U}_v \mathbf{U}_h, \quad (31)$$

and for the RTO:

$$440 \quad \mathbf{U}_s = \Sigma \mathbf{U}_h \mathbf{U}_v. \quad (32)$$

The adjoint operators follow in a straightforward manner.

### 4.3 Calibrating the CVTs (B-matrix)

The CVTs comprise many sub-matrices that need to be determined in a calibration procedure. The operators to be determined are the regression operator  $\mathbf{R}_\rho$  (part of the parameter transform mentioned in Sects. 4.2.1 and 4.2.2), and  $\Sigma$ ,  $\Lambda_h$ ,  $\mathbf{F}_v$ , and  $\Lambda_v$  (parts of the spatial transforms mentioned in Sects. 4.2.3 and 4.2.4). [The number of pieces of information to be determined in this procedure is explored in Appendix A.](#) These matrices are determined from model training data in five stages, all using the program *Master\_Calibration* (*GitHubDoc*§4.4) and they are stored in a covariance file, which is produced by this routine. It is impossible to use a genuine sample of forecast errors to calibrate the B-matrix, so instead we use ensembles of forecast perturbations, which are considered proxies of forecast error (Buehner, 2005; Pereira and Berre, 2006). The five calibration stages are described here, and example outputs are shown for a standard set-up (experiment GB+VR+ to be described in Sect. 5.1).

#### 4.3.1 Generate a population of training data from UM fields

This is calibration run stage 1 (*Master\_Calibration* is run with the namelist variable *CalibRunStage* set to 1). This takes data from one or more UM files (one or more ensembles of forecasts) and extracts multiple longitude/height slices from these files to construct an effective ‘super ensemble’. These are each adjusted to make them compatible with the ABC model (as in Sect. 4.1) followed by a short forecast of specified length (in our examples one hour). [These procedures are intended to give the ensemble members properties of the ABC model rather than the Unified Model from which they came, although the degree to which this has been achieved is not demonstrated.](#) The super ensemble is output from this stage. Also specified at this stage are the model parameters (in the example to be described,  $A = 0.02 \text{ s}^{-1}$ ,  $B = 0.01$ , and  $C = 10000 \text{ m}^2 \text{ s}^{-2}$ ), and user settings for the transform options mentioned in Sect. 4.2 (here, unless stated otherwise, the control options use GB ( $\alpha = 1$ ), Sect. 4.2.1 step 3; VR, step 4; HB ( $\beta = 1$ ), step 6; no anelastic balance ( $\gamma = 0$ ), step 8; the CTO, Sect. 4.2.3; non-symmetric vertical transform, Sect. 4.2.3; and parameter standard deviations that are a function of vertical level only). These are all output in a provisional covariance file (netCDF format). At this stage this file is blank apart from containing information on these options for future reference. These user options are read from this file in later stages of the calibration where the above mentioned matrices are computed and output to this covariance file. Technical information is given in *GitHubDoc*§4.4.1 and the ensemble members can be plotted using the Python program specified there.

In this paper, a super ensemble of 260 members is used. Appendix A shows that this is more than adequate to determine the spatial transforms matrices and the vertical regression matrix.

### 4.3.2 Generate a population of forecast perturbations

470 This is calibration run stage 2 (*Master\_Calibration* is run with the namelist variable *CalibRunStage* set to 2). The forecasts output from stage 1 are converted to means and perturbations from the means. See *GitHubDoc*§4.4.2, which includes plotting information.

### 4.3.3 Compute the vertical regression matrix $\mathbf{R}_\rho$

This is calibration run stage 3 (*Master\_Calibration* is run with the namelist variable *CalibRunStage* set to 3). The perturbations  
475 from stage 2 are used to calculate populations of  $\delta\tilde{\rho}'^b$  Eq. (15). The vertical correlations between  $\delta\tilde{\rho}'^b$  with itself, and  $\delta\tilde{\rho}'$  with  $\delta\tilde{\rho}'^b$  are then used to compute  $\mathbf{R}_\rho$  in the way specified in point 4 of 4.2.1 (see also Appendix B).  $\mathbf{R}_\rho$  is then output to the covariance file created in stage 1. See *GitHubDoc*§4.4.3, which includes plotting information.

Panels (a) and (b) of Fig. 2 compare example  $\delta\tilde{\rho}'$  and  $\delta\tilde{\rho}'^b$  fields. The large-scale pattern of these fields is similar, with  $\delta\tilde{\rho}'^b$  being smoother and lower magnitude than  $\delta\tilde{\rho}'$ , indicating that the unbalanced contributions to  $\delta\tilde{\rho}'$  are at smaller scales (as  
480 expected). Panel (c) shows an example  $\mathbf{R}_\rho$  matrix and panel (d) shows its effect on  $\delta\tilde{\rho}'^b$ , showing its ability to modify values and vertical scales.

### 4.3.4 Perform the inverse parameter transform on the forecast perturbations

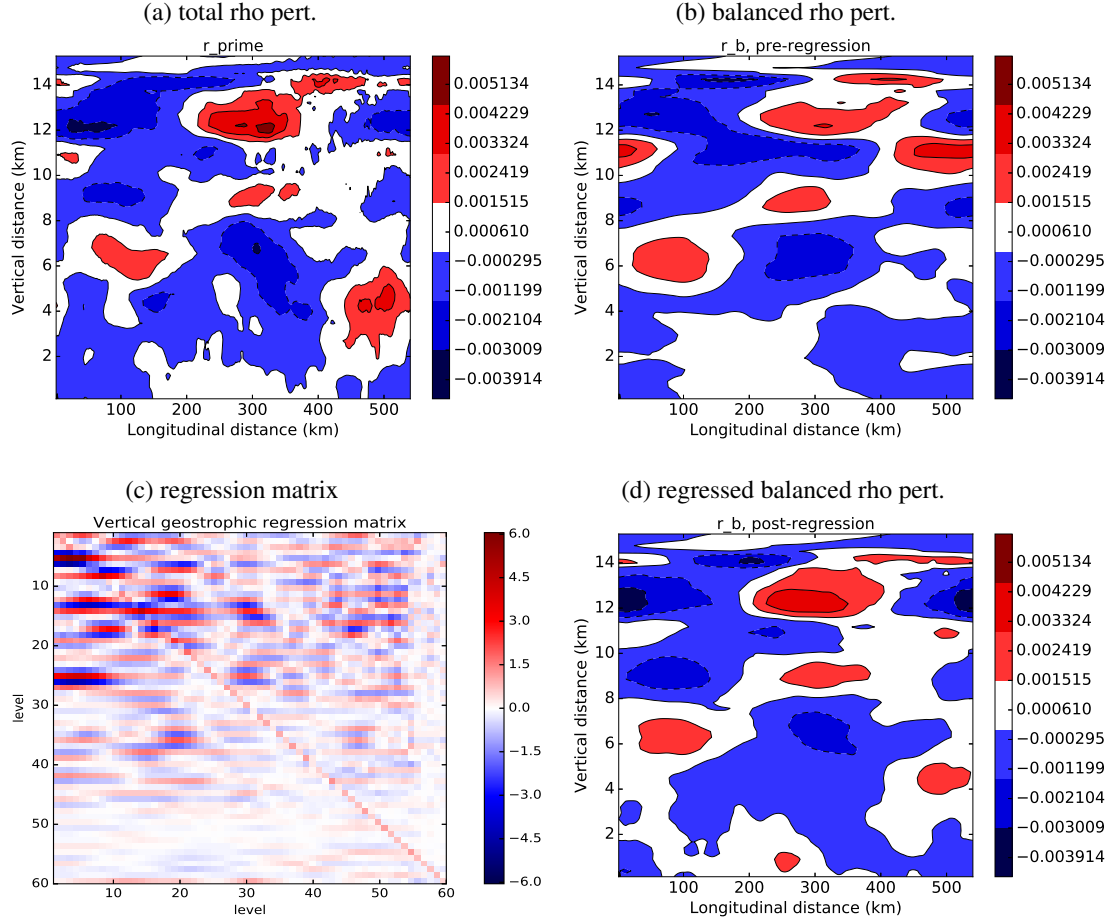
This is calibration run stage 4 (*Master\_Calibration* is run with the namelist variable *CalibRunStage* set to 4). The perturbations from stage 2 are transformed to parameters using the procedure represented by  $\mathbf{U}_p^{-1}$  (Sect. 4.2.1), and then output. The  
485 mean states found from stage 2 are also used in some of the calculations, e.g.  $\tilde{\rho}_0$  is used in step 8 of that procedure. See *GitHubDoc*§4.4.4, which includes plotting information.

### 4.3.5 Calibrate the spatial transforms for each parameter

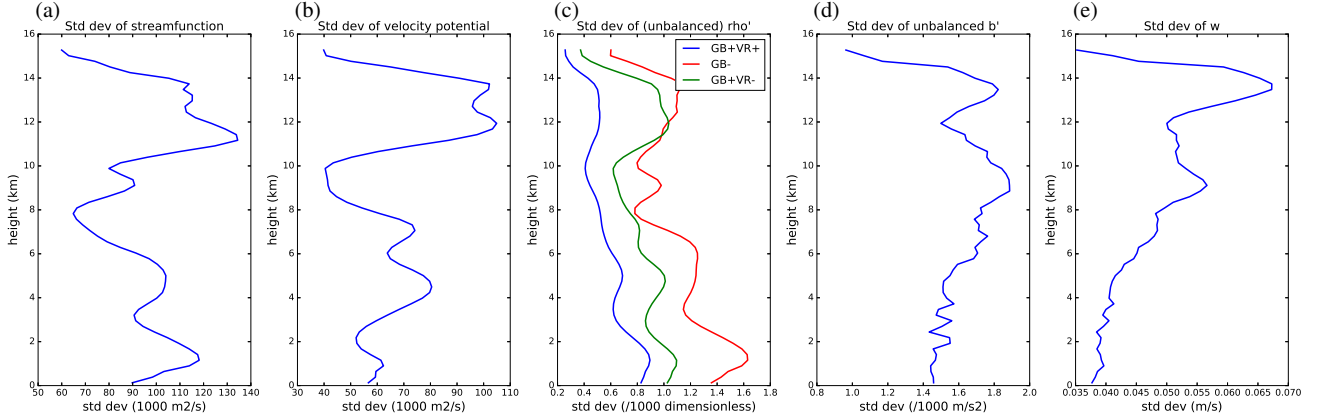
This is calibration run stage 5 (*Master\_Calibration* is run with the namelist variable *CalibRunStage* set to 5). The perturbations from stage 4 are used to diagnose the matrices  $\Sigma$ ,  $\mathbf{F}_v$ ,  $\mathbf{A}_v$ , and  $\mathbf{A}_h$  for each of the five control parameters.

490 The blue lines of Fig. 3 show the background error standard deviations (diagonal elements of  $\Sigma$ ) for the control experiment described above (see the Fig. caption for a succinct summary). The parameters show some variability with height, although none of the parameters shows variations of  $\Sigma$  of orders of magnitude. Note that the heights in the ABC model do not correspond with those in the real atmosphere<sup>2</sup>. The large variability of  $w$  (panel e) at model heights around 13/14 km for instance does not

<sup>2</sup>This is the case because, for simplicity, the irregularly-spaced UM model levels are assigned new regularly-spaced heights in the ABC model when generating training data in Sect. 4.3.1.



**Figure 2.** Plots comparing an example total scaled density perturbation,  $\delta\tilde{\rho}'$ , with the diagnosed balanced part,  $\delta\tilde{\rho}^b$ ; and showing the effect of the regression matrix. Panel (a):  $\delta\tilde{\rho}'$  (output from stage 2 of the calibration procedure), panel (b):  $\delta\tilde{\rho}^b$  (diagnosed from the stream-function as in Eq. (15)), panel (c): the regression matrix  $\mathbf{R}_\rho$  (found from stage 3), and panel (d): its effect on  $\delta\tilde{\rho}^b$ , i.e.  $\delta\tilde{\rho}^{b/r} = \mathbf{R}_\rho\delta\tilde{\rho}^b$ . Note that in (c) the lowermost level corresponds to the top of the matrix.



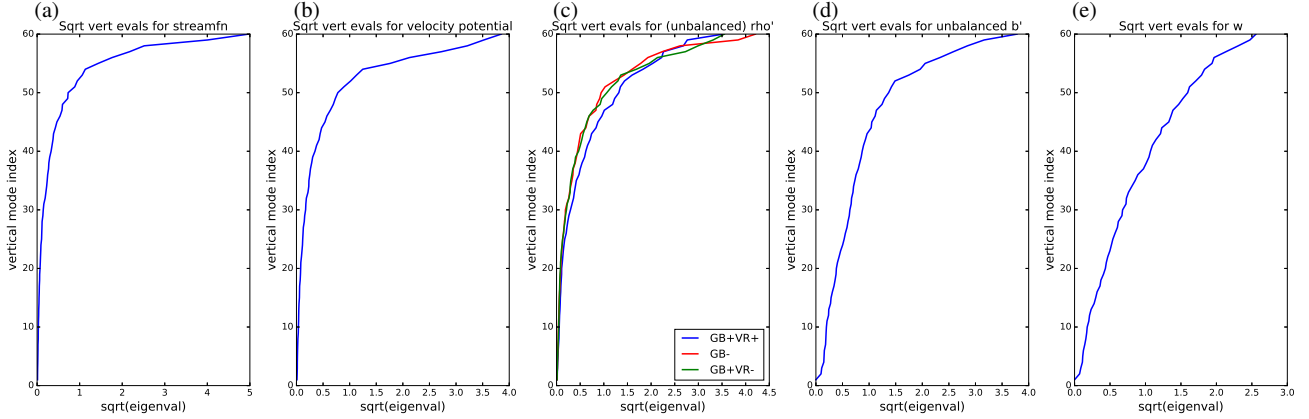
**Figure 3.** Profiles of background error standard deviations for the five control parameters with height: (a) stream-function  $\delta\psi$ , (b) velocity potential  $\delta\chi_{vp}$ , (c) unbalanced scaled density  $\delta\tilde{\rho}^u$ , (d) unbalanced buoyancy  $\delta b^u$ , and (e) vertical wind  $\delta w$ . The blue lines are for the experiment described in the text – namely GB and VR are switched on in the parameter transform. In panel (c) the red line is for the experiment with GB (and hence VR) switched off, and the green line is for the experiment with GB switched on and VR switched off. In the other panels all experiments yield the same profiles. The values have been smoothed using a running average over the nearest five levels.

lie in the ABC model’s stratosphere, and in any case without radiative forcing in the ABC model and an ozone layer, we would not expect signatures of the stratosphere to be present.

The blue lines of Fig. 4 show the square-root of the eigenvalues of the vertical covariance matrix (diagonal elements of  $\Lambda_v^{1/2}$ )<sup>3</sup>. We find the vertical covariance matrices of each parameter over each super ensemble member, and over each longitude. Each  $y$ -axis in Fig. 4 is the (integer) vertical model index. The eigensolver sorts these into ascending value of eigenvalue and so the physical meaning of the modes can be unclear. For instance examining the eigenvectors by eye (not shown), for parameters  $\delta\psi$  (a),  $\delta\chi_{vp}$  (b), and  $\delta\tilde{\rho}^u$  (c), the vertical modes of low index have vertical profiles that are generally rapidly oscillating, and have more weight in the lower model levels than in the upper ones. As the vertical mode index increases, the oscillations become less rapid and tend to have weight over the entire depth of the model atmosphere. There is no obvious trend concerning the vertical modes of  $\delta b^u$  (d) and  $\delta w$  (e). The values in Fig. 4 are of comparable magnitude between parameters because the vertical error covariance matrices are formed from the populations after they have been normalized with  $\Sigma^{-1}$  – see Eq. (31) and Eq. (32).

Calibrating the vertical transform involves (for the CTO) constructing a single global vertical covariance matrix or (for the RTO) constructing one vertical covariance matrix for each wavenumber. The eigenvalues and eigenvectors follow from this procedure. The eigenvectors of the horizontal covariance matrix though are assumed to be plane waves. In the case of the CTO with a non-symmetric vertical covariance matrix for example, the horizontal variances follow from passing each ensemble

<sup>3</sup>In principle the vertical covariance matrix should actually be a correlation (rather than covariance) matrix given that the populations have been divided by  $\Sigma$ . Due to the approximations made, the diagonal elements of this matrix may not be exactly unity.

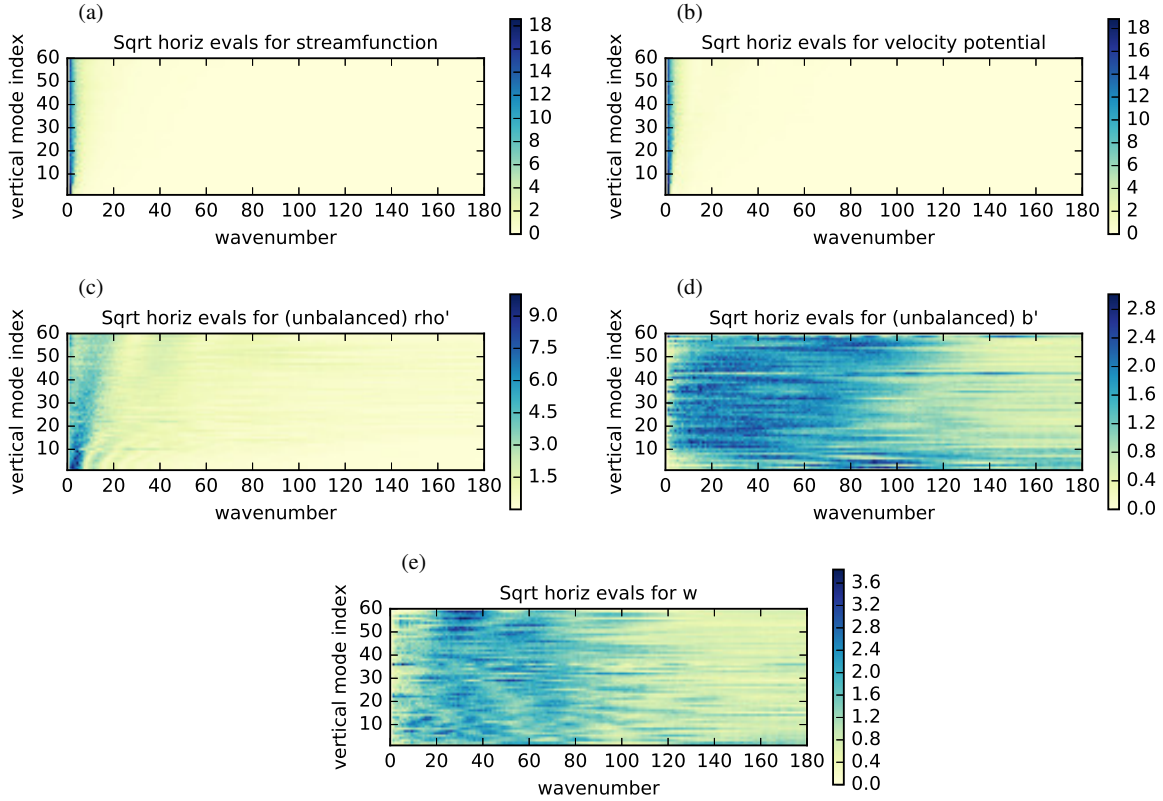


**Figure 4.** Profiles of the square-root of the vertical eigenvalues for the five control parameters as a function of vertical mode index,  $\nu$ : (a)  $\delta\psi$ , (b)  $\delta\chi_{vp}$ , (c)  $\delta\tilde{\rho}^u$ , (d)  $\delta b^u$ , and (e)  $\delta w$ . The blue lines are for the experiment described in the text – namely GB and VR switched on. In panel (c) the red line is for the experiment with GB (and hence VR) switched off, and the green line is for the experiment with GB switched on and VR switched off. In the other panels all experiments yield the same profiles.

510 perturbation ( $\delta\mathbf{x}$ ) through the partial inverse transform to give  $\delta\boldsymbol{\eta} = \mathbf{F}_h^T \mathbf{U}_v^{-1} \boldsymbol{\Sigma}^{-1} \mathbf{U}_p^{-1} \delta\mathbf{x}$ . Here each  $\delta\boldsymbol{\eta}$  is a field which is function of  $k$  and  $\nu$ . This ensemble is then used to estimate the variances of  $\delta\boldsymbol{\eta}$ ,  $\Lambda_h^0(k, \nu)$ .

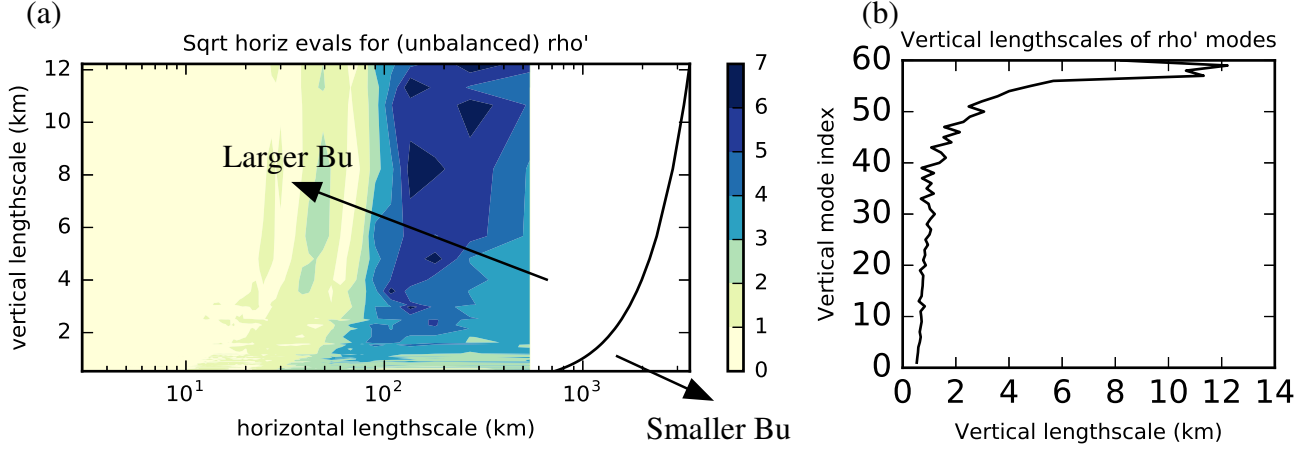
Figure 5 shows the square-root of the horizontal variances (diagonal elements of  $\Lambda_h^{1/2}$ ). In the particular configuration that has a non-symmetric vertical transform, there is a different horizontal variance spectrum for each vertical mode, so the axes in Fig. 5 are wavenumber,  $k$ , and vertical model index,  $\nu$ . The spectra for  $\delta\psi$  (a) and  $\delta\chi_{vp}$  (b) are similar and represent  
 515 perturbations with long horizontal correlation length-scales (most weight is at small wavenumbers). Their similarities are explained by the fact that the fields are related to the horizontal winds in the same way:  $v = \partial\delta\psi/\partial x$  and  $u = \partial\delta\chi_{vp}/\partial x$ . The spectra for  $\delta\tilde{\rho}^u$  (c) show that perturbations in this parameter have shorter horizontal length-scales than in (a) and (b), and the length-scale reduces with higher vertical modes. This suggests that perturbations with broader vertical scales (generally higher vertical mode index) tend to have shorter horizontal scales. The spectra for the remaining parameters,  $\delta b^u$  (d) and  $\delta w$  (e) show  
 520 that perturbations of these parameters are courser still and there is no obvious pattern with vertical mode index.

The same data plotted in Fig. 5c (for  $\delta\tilde{\rho}^u$ ) are also plotted in Fig. 6a, but with transformed co-ordinates to facilitate further interpretation. In Fig. 6a the variance square-roots are shown as a function of horizontal length-scale,  $l_h$ , and vertical length-scale,  $l_v$ .  $l_h$  is related to horizontal wavenumber index,  $k$  (an integer), as  $l_h = L_h/k$  (where  $L_h = 540$  km is the horizontal domain length, and excluding  $k = 0$  since it gives an infinite  $l_h$ ), and  $l_v$  is related to the vertical eigenmode index for  $\delta\tilde{\rho}^u$  in  
 525 the way outlined in Appendix C. For reference, panel b shows  $l_v$  for each vertical mode of  $\delta\tilde{\rho}^u$ , which confirms that higher  $\nu$  is broadly associated with deeper structures. Furthermore, modes with deeper structures have fewer nodes (not shown). Incidentally this correspondence between  $\nu$  and  $l_v$  is also found for the vertical modes of  $\delta\psi$ , which represent the balanced scaled density increments.



**Figure 5.** The square-root of the horizontal variances (colours) as a function of horizontal wavenumber and vertical mode index for the five control parameters: (a)  $\delta\psi$ , (b)  $\delta\chi_{vp}$ , (c)  $\delta\tilde{\rho}^u$ , (d)  $\delta\mathbf{b}^u$ , and (e)  $\delta\mathbf{w}$ .

Returning to panel a, the Rossby radius of deformation,  $L_R$ , has also been plotted (the black curve). This has been estimated using a shallow water interpretation, i.e.  $L_R = \sqrt{g l_v}/f$  (e.g. Cullen (2006)). The Burger number,  $Bu$ , is defined as  $Bu = L_R/l_h$ , and it follows that all of the represented variability in these unbalanced modes has large  $Bu$ . Dynamical theory says that for  $l_h \ll L_R$  (i.e.  $Bu \gg 1$ ) the rotational wind is a potential vorticity (PV)-like variable and for  $l_h \gg L_R$  ( $Bu \ll 1$ ) the mass variable becomes a PV-like variable (e.g. Cullen (2003); Katz et al. (2011)). PV is often associated with balanced flow, and so the above theory suggests that the unbalanced mass variable ( $\delta\tilde{\rho}^u$ ) should vanish – and hence have vanishing variance – for  $Bu \ll 1$ . Figure 6a shows that for  $10^1 \text{ km} \lesssim l_h \lesssim 10^3 \text{ km}$ , the variance of  $\delta\tilde{\rho}^u$  does increase as  $Bu$  increases, showing some consistency with the dynamical theory at synoptic scales. It further suggests that a rotational wind variable, like  $\delta\psi$  is a reasonable variable to capture the balanced part of the flow at synoptic scales.



**Figure 6.** (a) The same horizontal spectra of Fig. 5c but shown as a function of horizontal ( $l_h$ ) and vertical ( $l_v$ ) length-scales. Also shown in (a) is the Rossby radius of deformation,  $L_R$ , plotted as a function of  $l_v$  (black line). The Burger number is defined as  $Bu = L_R/l_h$ . (b) Vertical length-scales ( $x$ -axis) of the vertical modes ( $y$ -axis) for the unbalanced scaled density control parameter, calculated according to Appendix C.

#### 4.4 The implied B-matrix

The covariance model is completely described by (i) the parameter transform presented in Sect. 4.2.2, (ii) the results presented  
540 in Sect. 4.3.5, and (iii) other statistics like the vertical eigenvectors themselves (not shown). The software suite has a program  
to compute the implied covariances (*Master\_ImpliedCov*, see *GitHubDoc*§4.6) which uses information in the CVT file output  
by the calibration procedures. The program acts with the combination of matrices  $\mathbf{U}\mathbf{U}^T$  on a vector which is zero apart from  
one element (which we call the source point), which is set to unity (in the example below, this element corresponds to  $\delta\tilde{\rho}'$  near  
the centre of the domain). Completing the matrix algebra, the implied super matrix (for fields  $\delta\mathbf{u}$ ,  $\delta\mathbf{v}$ ,  $\delta\mathbf{w}$ ,  $\delta\tilde{\rho}'$ ,  $\delta\mathbf{b}'$ ) is found  
545 from Eq. (10),  $\mathbf{U} = \mathbf{U}_p \mathbf{U}_s$ , and Eq. (27):

$$\begin{pmatrix} \mathbf{B}_u^{\text{ic}} & 0 & \gamma \mathbf{B}_u^{\text{ic}} \mathbf{L}^{\text{abT}} & 0 & 0 \\ 0 & \nabla_x \mathbf{B}_s^\psi \nabla_x^T & 0 & \alpha \frac{f}{C} \nabla_x \mathbf{B}_s^\psi \mathbf{R}_\rho^T & \alpha \beta \frac{f}{C} \nabla_x \mathbf{B}_s^\psi \mathbf{R}_\rho^T \mathbf{L}^{\text{hbT}} \\ \gamma \mathbf{L}^{\text{ab}} \mathbf{B}_u^{\text{ic}} & 0 & \gamma^2 \mathbf{L}^{\text{ab}} \mathbf{B}_u^{\text{ic}} \mathbf{L}^{\text{abT}} + \mathbf{B}_s^w & 0 & 0 \\ 0 & \alpha \frac{f}{C} \mathbf{R}_\rho \mathbf{B}_s^\psi \nabla_x^T & 0 & \alpha^2 \frac{f^2}{C^2} \mathbf{B}_s^{\psi_r} + \mathbf{B}_s^{\tilde{\rho}^u} & \alpha^2 \beta \frac{f^2}{C^2} \mathbf{B}_s^{\psi_r} \mathbf{L}^{\text{hbT}} + \beta \mathbf{B}_s^{\tilde{\rho}^u} \mathbf{L}^{\text{hbT}} \\ 0 & \alpha \beta \frac{f}{C} \mathbf{L}^{\text{hb}} \mathbf{R}_\rho \mathbf{B}_s^\psi \nabla_x^T & 0 & \alpha^2 \beta \frac{f^2}{C^2} \mathbf{L}^{\text{hb}} \mathbf{B}_s^{\psi_r} + \beta \mathbf{L}^{\text{hb}} \mathbf{B}_s^{\tilde{\rho}^u} & \mathbf{B}_{b'}^{\text{ic}} \end{pmatrix}, \quad (33)$$



where the following definitions have been made for convenience:

$$\mathbf{B}_s^p = \mathbf{U}_s^p \mathbf{U}_s^{pT} \quad p = \delta\psi, \delta\chi_{vp}, \delta\tilde{\rho}'^u, \delta\mathbf{b}'^u, \text{ or } \delta\mathbf{w}^u, \quad (34a)$$

$$\mathbf{B}_u^{\text{ic}} = \nabla_x \mathbf{B}_s^{\chi_{vp}} \nabla_x^T, \quad (34b)$$

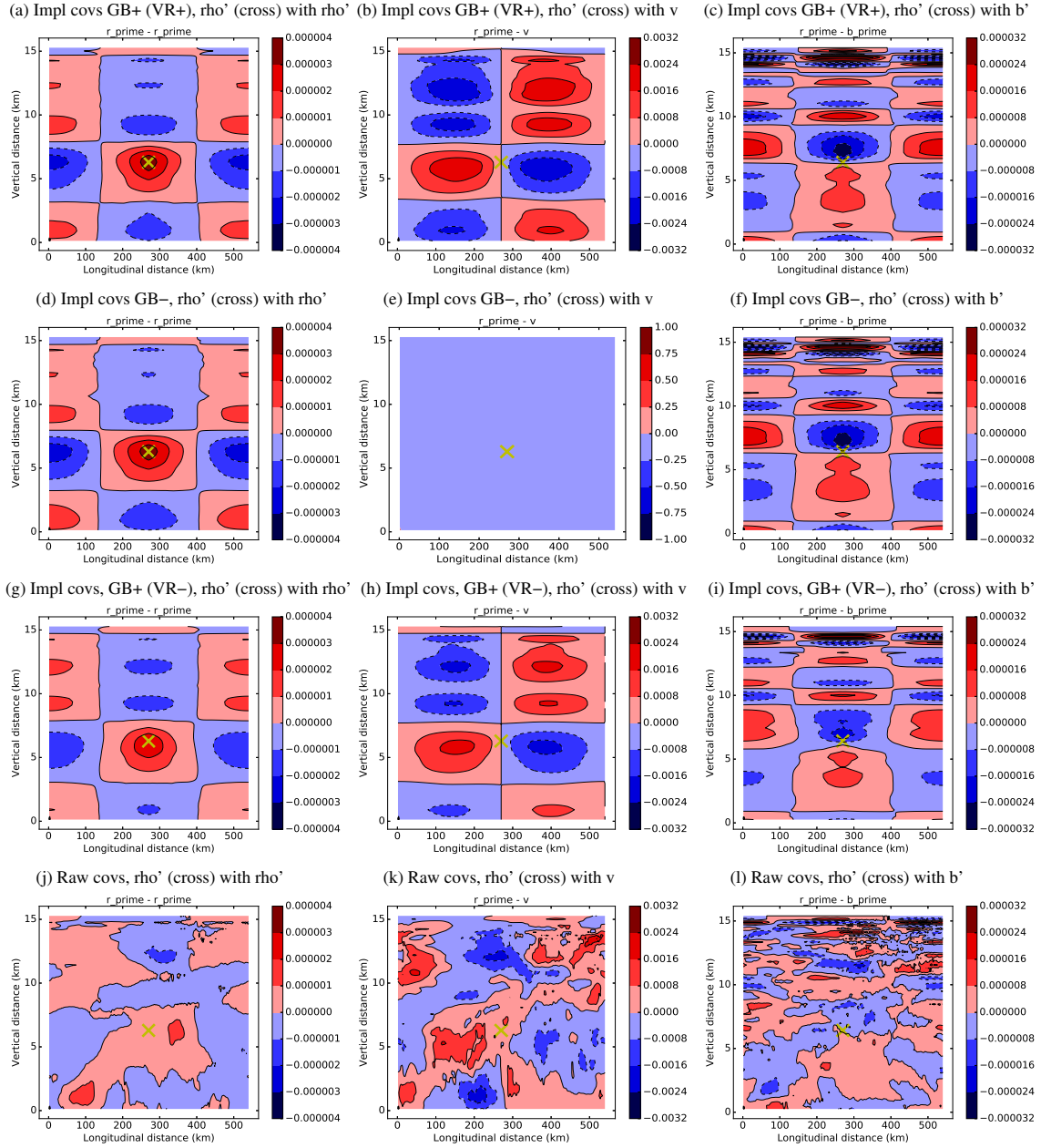
$$550 \quad \mathbf{B}_s^{\psi_r} = \mathbf{R}_\rho \mathbf{B}_s^\psi \mathbf{R}_\rho^T, \quad (34c)$$

$$\mathbf{B}_{b'}^{\text{ic}} = \alpha^2 \beta^2 \frac{f^2}{C^2} \mathbf{L}^{\text{hb}} \mathbf{B}_s^{\psi_r} \mathbf{L}^{\text{hb}T} + \beta^2 \mathbf{L}^{\text{hb}} \mathbf{B}_s^{\tilde{\rho}'^u} \mathbf{L}^{\text{hb}T} + \mathbf{B}_s^{\mathbf{b}'^u}. \quad (34d)$$

Recall that the factors  $\alpha$ ,  $\beta$ , and  $\gamma$  are set to 1 or 0 to turn on or off geostrophic, hydrostatic, or anelastic balance in the covariance model (Sect. 4.2). Equation Eq. (34a) represents the implied spatial covariances, where  $p$  (parameter) is short for each control parameter listed in Eq. (34a). Notice that Eq. (33) is a symmetric matrix (as required), where the diagonal blocks  
555 are the implied covariances of the model variables. The structure of the terms in Eq. (33) reveals the way that the covariances have been modelled. For example, the implied covariance of  $\delta\tilde{\rho}'$  is the 4,4th block,  $\alpha^2 \frac{f^2}{C^2} \mathbf{B}_s^{\psi_r} + \mathbf{B}_s^{\tilde{\rho}'^u}$ , and comprises a balanced contribution (the first term, which depends upon the covariance structure of  $\delta\psi$ ), and an unbalanced contribution (the second term, which is independent). Other variables have a similar decomposition.

This equation is too complicated to illustrate the implied geographical covariance structure, so a selection of the implied  
560 covariances Eq. (10) are computed and shown graphically in the top row of Fig. 7. All panels represent the covariances between a source point ( $\delta\tilde{\rho}'$  at the position of the cross) with (a)  $\delta\tilde{\rho}'$ , (b)  $\delta\mathbf{v}$ , and (c)  $\delta\mathbf{b}'$ . For comparison, the bottom row shows the respective raw sample covariances found from the population of 260 forecasts used to calibrate the covariance model (found using the program *Master\_RawCov*, see *GitHubDoc*§4.7). We regard the [signals contained in the raw covariances](#) as a [rough \(row-rank\)](#) guide to the covariances that should ideally be modelled by the CVT.

565 The autocovariances in (a) have a region of positive correlations about the source point, with regions of negative correlation towards the east, west, above, and below. This broad structure is apparent in the raw covariance (j) although the implied values are two to four times larger. The covariances between  $\delta\tilde{\rho}'$  and  $\delta\mathbf{v}$  in (b) show dipole patterns in the horizontal due to GB imposed according to Eq. (2a). This is done in the CVT via the 2,4th block of Eq. (33), which spreads out the source point with  $\mathbf{B}_s^\psi \mathbf{R}_\rho^T$ , evaluates the horizontal gradient, and then multiplies by  $\alpha \frac{f}{C}$ . Physically, (b) is the meridional wind response  
570 (an anti-cyclone) to a positive density perturbation at the cross, [and these covariances mean that this pattern would appear in the  \$v\$  analysis increments when assimilating a single  \$\tilde{\rho}'\$  measurement at the cross.](#) The pattern in (b) is evident in the raw covariance in (k), but the implied version is slightly too large. Finally, the covariances between  $\delta\tilde{\rho}'$  and  $\delta\mathbf{b}'$  in (c) show the hydrostatic response of the density perturbation, which is the 5,4th block of the CVT. There are two contributions to the  $\delta\tilde{\rho}'$ - $\delta\mathbf{b}'$  covariances: one involves the route  $\delta\tilde{\rho} \rightarrow \delta\psi \rightarrow \delta\mathbf{b}'$  (exploiting GB and HB), and the other involves the route  $\delta\tilde{\rho} \rightarrow \delta\tilde{\rho}'^u \rightarrow$   
575  $\delta\mathbf{b}'$  (exploiting only HB). A closer inspection of Eq. (33) reveals that the 5,4th block is equal to  $\beta \mathbf{L}^{\text{hb}}$  (proportional to the vertical derivative operator – see line after Eq. (18)) acting on the 4,4th block, which is the  $\delta\tilde{\rho}'$  response. Figure 7 shows that (c) is indeed related to the vertical derivative of (a). The structure of (c) comprises complicated bands of positive and negative covariances, and [again this pattern would appear in the  \$b'\$  analysis increments when assimilating a single  \$\tilde{\rho}'\$  measurement at the cross.](#) The structure in (c) is evident in the raw covariances (l) suggesting that HB is followed by the forecasts to some extent  
580 although the implied covariances are up to about three times larger.



**Figure 7.** A selection of covariances (panel columns) found in different ways (rows). All covariances are between the source point ( $\delta\tilde{\rho}'$  at the cross) and  $\delta\tilde{\rho}'$  (left column),  $\delta\tilde{v}$  (middle column), and  $\delta\tilde{b}'$  (right column) at the field locations. The rows correspond to: implied covariances when GB and VR are used in the CVT (GB+VR+, top row), implied covariances when GB is not used (GB-, second row), implied covariances when GB is used and VR is not used (GB+VR-, third row), and when covariances are calculated directly from the population used to calibrate each CVT (bottom row). Red (blue) indicates positive (negative) covariances.

## 4.5 Observations and observation operators

ABC-DA currently supports observation operators for direct (point) observations of  $u, v, w, \tilde{\rho}', b'$ , a conserved tracer,  $\sqrt{u^2 + v^2}$ , and  $\sqrt{u^2 + v^2 + w^2}$ . These correspond to observation codes 1-8 respectively. Observations are read-in via a text file, which specifies the time of each observation, its longitudinal and height position, the observation code, the observation value itself, and its error standard deviation. The format of the input file is specified in *GitHubDoc*§4.8. The observation operators employ a bi-linear interpolation and observation errors are assumed to be uncorrelated.

The user may extend the range of observation operators available by assigning a new observation code, and adding a new branch in the observation operator and adjoint routines. Furthermore, observations are assigned a batch number. This is not used in the current code, but it may be used by the user to allow for correlated errors within each batch.

## 4.6 Generating data for twin experiments

The program *Master\_MakeBgObs*, see *GitHubDoc*§4.8, is available to generate an observation network, to generate synthetic random observations given an observation network (for later assimilation), and to generate a random background state that is consistent with the background errors as specified in a CVT file. Further details are as follows.

- An observation network is a specification of a grid of observation times, locations, error standard deviations, and which synthetic observations to make (but not the observation values themselves). For example, the user may wish to generate synthetic observations of  $s = \sqrt{u^2 + v^2}$  in an  $N_x^s \times N_z^s$  grid between  $x_1^s$  and  $x_2^s$  and  $z_1^s$  and  $z_2^s$  and synthetic observations of  $\tilde{\rho}'$  in an  $N_x^{\tilde{\rho}'} \times N_z^{\tilde{\rho}'}$  grid between  $x_1^{\tilde{\rho}'}$  and  $x_2^{\tilde{\rho}'}$  and  $z_1^{\tilde{\rho}'}$  and  $z_2^{\tilde{\rho}'}$ . Running *Master\_MakeBgObs* with the option to generate this observation network (specified in an input file) will produce a text file containing entries for each individual observation (where it should be made, when it should be made, which quantity should be measured, and at what precision – see *GitHubDoc*§4.8). This file could be made by hand, but this software option exists to make the task less tedious. Once produced, this file can be edited by removing, adding, or altering individual observation points.
- Pseudo observations are generated according to the output from the above procedure, and an ABC model initial condition ('truth') file. Running *Master\_MakeBgObs* in this mode will run a forecast from the initial conditions, generate 'true observations' from the forecast, and will then add observation noise to each observation. The output from this stage is a file of synthetic observations which can then be assimilated (Sect. 4.7). The true observations are also output within this data file, which can be used later for error analysis. The user may wish to generate synthetic observations for an identical twin experiment by using the same model parameters (i.e.  $A, B, C$ ) as will be used in the DA, or may wish to run a non-identical twin experiment with different parameters. As with the procedure for generating the observation network, this file can be edited, or instead made by hand from scratch. For example, the user may want to add, remove, or change individual observations in order to investigate the effect on the assimilation.

- A valid background state may be generated with the program *Master\_MakeBgObs*. The ‘truth’ state (conventionally that used to generate the synthetic observations) is perturbed with a random state  $\delta\mathbf{x} = \mathbf{U}\delta\boldsymbol{\chi}$  Eq. (8), where  $\delta\boldsymbol{\chi}$  is drawn from  $N(0, \mathbf{I})$ . The information used to describe the CVT,  $\mathbf{U}$  is found from a specified CVT file.

#### 4.7 Data assimilation

615 The program that performs a DA cycle is called *Master\_Assimilate*, see *GitHubDoc*§4.9. The inputs to this program are: (i) a background state (e.g. as generated in Sect. 4.6), (ii) a set of observations (e.g. as generated in Sect. 4.6), and (iii) a description of the  $\mathbf{B}$ -matrix (in a CVT as found using the calibration procedure in Sect. 4.3). The assimilation methods currently available are 3DVar and 3DFGAT, although the code is flexible enough to allow other methods (e.g. 4DVar, EnVar, etc., Bannister (2017)) to be developed.

620 The algorithm for 3DFGAT (the preferred option in the current version) is shown in Fig. 8. The reference state,  $\mathbf{x}^r$ , is set to the background,  $\mathbf{x}^b$ , which is then used to compute the innovations,  $\mathbf{d}(t)$ , computed at their appropriate times within the DA window. The control space perturbation,  $\delta\boldsymbol{\chi}$  is set to zero.  $\mathbf{d}(t)$  and  $\delta\boldsymbol{\chi}$  enter the inner loop minimisation (pink box), where the residuals,  $\mathbf{r}(t)$ , are computed. These are used in the calculation of  $\nabla_{\delta\boldsymbol{\chi}} J_o$ , where  $J_o$  is the observation term of the cost function. This is added with the background contribution,  $\nabla_{\delta\boldsymbol{\chi}} J_b$ , giving the total cost function gradient. This is used with a

625 descent algorithm – in our case a conjugate gradient algorithm – which provides the increment,  $\Delta\delta\boldsymbol{\chi}$ . The switch is flipped (red arrow inside the pink box) so that the inner loop procedure is repeated with the  $\delta\boldsymbol{\chi}$  that is updated with  $\Delta\delta\boldsymbol{\chi}$ . Once converged, the reference state is incremented by  $\mathbf{U}\delta\boldsymbol{\chi}$ . This ends the first outer loop iteration. If further outer loop iterations are required, the switch is flipped (red arrow outside of the pink box), so that the incremented  $\mathbf{x}^r$  is fed into the innovation calculation. The  $\mathbf{x}^r$  at the final outer loop is the analysis,  $\mathbf{x}^a$ .

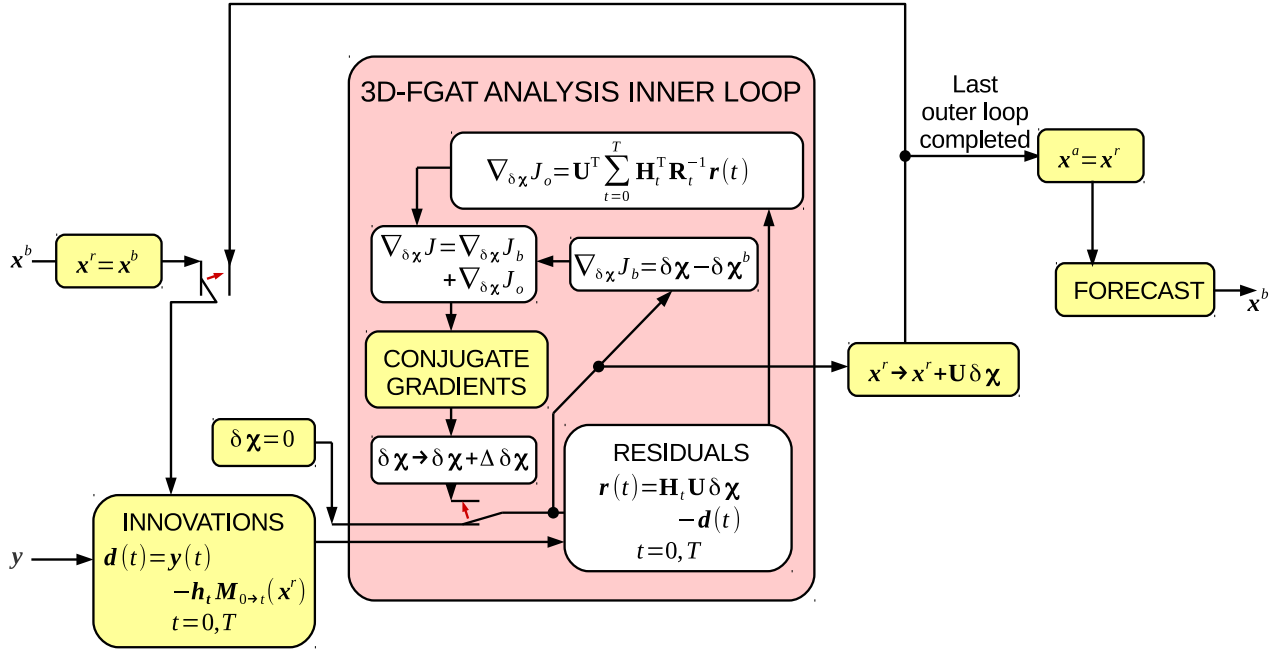
630 In addition to the analysis, and the analysis increment, there are many diagnostic outputs from the DA, as detailed in *GitHubDoc*§4.9. This includes the reference states at each outer loop, the gradient  $\nabla_{\delta\mathbf{x}} J_o$ , the values of the cost function with iteration, and versions of the observations file with extra information. The last file is output for each outer loop and includes the model observation values computed from  $\mathbf{x}^r$  (the  $\mathbf{x}^r$  corresponding to the last outer loop is  $\mathbf{x}^a$ ), the innovation,  $\mathbf{d}(t)$ , the residual,  $\mathbf{r}(t)$ , and the gradient of the observation term in the cost function with respect to the model observation,  $\mathbf{R}_t^{-1}\mathbf{r}(t)$ .

635 These diagnostics can be plotted using the python program specified in *GitHubDoc*§4.9. A selection of example diagnostics is shown in Sect. 5 in connection with the study on the effect of the GB conditions in the CVT.

#### 4.8 Cycling

A (provided) bash script controls the schedule of tasks to perform DA cycling, see *GitHubDoc*§5. The background state for the first cycle is made using the procedure in 4.6, but subsequent backgrounds are found from forecasts originating from each

640 analysis. The script also propagates the true state from one cycle to the next, for generation of the synthetic observations and for subsequent monitoring.



**Figure 8.** The outer and inner loops of the variational 3DFGAT procedure. The main inputs into the algorithm are the background state,  $x^b$ , and the observations,  $y$ . The algorithm inside the pink box is the inner loop. The small red arrows represent switches in the data flow. The initial positions (shown) are changed after the first iteration. This algorithm incorporates cycling, where the forecast made (on the right hand side) is fed back (on the left hand side) for the next assimilation window. The full 4DVar algorithm to calculate the gradient  $\nabla_{\delta x} J$  (essentially part of the inner loop) is given in Sect. 3.5. Note that  $\delta x^b = U^{-1} (x^b - x^r)$ .

Summary statistics of cycling experiments, and comparative diagnostics between pairs of cycling experiments can be computed and plotted using python programs provided. The study in Sect. 5 shows many of these diagnostics, which may be regarded as examples.

## 645 5 An investigation of balance in modelling the B-matrix

Most Var system began their lives serving global models on relatively coarse grids. In mid- and high-latitude regions, and when only relatively large scales are represented, a significant portion of the flow fields are related via GB and HBs (GB and HB). Most Var systems use this property to imply relationships between variables, which impact the background error covariance statistics, and a similar approach is often followed in systems that use much finer grids (as is done in Sect. 4.2 for ABC-DA). Since GB becomes a less important constraint at smaller scales (Berre, 2000; Bannister et al., 2011; Petrie et al., 2017), the research question arises concerning whether using such a constraint in the B-model is necessary, or indeed harmful in convective-scale DA.

Some regional Var systems, such as those for the ALADIN (Aire Limitée Adaption Dynamique et développement InterNational, Berre (2000)) and WRF (Weather Research and Forecasting model, Chen et al. (2013)) models couple mass and wind fields via a linear regression operator, trained from sample data. The degree of balance represented by these operators will be appropriate to the training sample. Other systems, such as the current configuration of ABC-DA (Sect. 4.2), the Met Office (Ingleby, 2001; Bannister, 2008b), and HIRLAM (HIgh Resolution Limited-Area Model, Gustafsson et al. (2001)) impose analytic GB operators. Analytic relationships are ‘cleaner’ and more physical than regressions, but their current forms are not so adaptive to the underlying conditions. Geophysical balances are not only sensitive to scale and latitude, but also to precipitation, where heavy precipitation leads to a weakening of the balance between mass and wind (e.g. Caron and Fillion (2010); Chen et al. (2016)). Few, if any, studies have examined the effect of switching off the GB constraint completely in the  $\mathbf{B}$ -matrix in convective-scale systems. This is one way to affect the implied covariances ( $\alpha = 1 \rightarrow 0$  in Eq. (33)). Other suggestions have been made to change the nature of the wind coupling in  $\mathbf{B}$  at convective-scale. Sun et al. (2016) e.g. compared using  $\psi, \chi$ -based uncorrelated control parameters with  $u, v$ -based ones (with the associated change of the CVT). Their comparison of these two alternative sets of wind control parameters was not so straightforward as their  $\psi, \chi$ -based set used a linear regression-type balance with mass variables, while their  $u, v$ -based set did not. This did not allow a clean analysis of the effect of the change of parameters verses the effect of turning off the balance constraint.

## 5.1 Description of the DA experiments

In this section we do three DA experiments each with its own configuration as described below.

- Experiment GB+VR+ This experiment mirrors the operational configuration of the Met Office DA system. In this configuration  $\delta\tilde{\rho}'$  is decomposed into a GB part,  $\delta\tilde{\rho}'^b$ , and an unbalanced part,  $\delta\tilde{\rho}'^u$  ( $\alpha = 1$  in Eq. (27) and Eq. (33)) and uses the VR operator,  $\mathbf{R}_\rho$ , to modify the calculation of the balanced scaled density perturbation increments from the streamfunction increment.  $\delta\mathbf{b}'$  is decomposed into an HB part,  $\delta\mathbf{b}'^b$ , and an unbalanced part,  $\delta\mathbf{b}'^u$  ( $\beta = 1$ ).  $\delta\mathbf{w}$  is analysed as though it were completely unbalanced ( $\gamma = 0$ ). The ordering of the vertical and horizontal transforms is the CTO, and the non-symmetric vertical transform is used. As a reminder, the implied covariances for GB+VR+ are shown in the top row of Fig. 7.
- Experiment GB- This experiment differs from GB+VR+ in that there is no balanced component of  $\delta\tilde{\rho}'$  ( $\alpha = 0$ ,  $\beta = 1$ , and  $\gamma = 0$ ). Since there is no GB operator, the VR step is irrelevant. The implied covariances for GB- are shown in the second row of Fig. 7. When calibrated with this configuration the  $\delta\tilde{\rho}'$ - $\delta\tilde{\rho}'$  covariances (d) are almost the same as for GB+VR+ (see the 4,4th block of Eq. (33) to see how  $\alpha$  affects the  $\delta\tilde{\rho}'$ - $\delta\tilde{\rho}'$  covariances). The  $\delta\tilde{\rho}'$ - $\delta\mathbf{v}$  covariances (e) are zero as expected as GB was the mechanism used to couple these two variables in the CVT (see the 2,4th block of Eq. (33)). As  $\delta\tilde{\rho}'^b = 0$  in this experiment,  $\delta\tilde{\rho}'^u = \delta\tilde{\rho}'$ , which is consistent with the variances of  $\delta\tilde{\rho}'^u$  (red line in Fig. 3(c) for GB-) being larger than those of the blue line (GB+VR+). The  $\delta\tilde{\rho}'$ - $\delta\mathbf{b}'$  covariances in Fig. 7(f) are similar to those for GB+VR+ (c), showing that the effect of GB on these statistics is small.

685 – Experiment GB+VR- This experiment differs from GB+VR+ in that no VR is performed ( $\alpha = 1, \beta = 1, \gamma = 0$ , and  $\mathbf{R}_\rho = \mathbf{I}$ ). The implied covariances for GB+VR- are shown in the third row of Fig. 7. When calibrated with this configuration the  $\delta\tilde{\rho}'$ - $\delta\tilde{\rho}'$  covariances (g) are slightly smaller than for GB+VR+. The effect on  $\delta\mathbf{v}$  (h) is noticeably smaller than in GB+VR+. In GB+VR+,  $\mathbf{R}_\rho$  has the effect of increasing the magnitude of the balanced increment ( $\delta\tilde{\rho}'^b$  is greater than  $\delta\tilde{\rho}'^b$  on average), and thus decreasing the variance of  $\delta\tilde{\rho}'^u$ . This is seen in the blue line of Fig. 3(c) (the variance of  $\delta\mathbf{b}'^u$  in GB+VR-) being smaller than the green line (GB+VR-), and explains why the geostrophic response in Fig. 7(b) is larger than in 7(h). The patterns in the  $\delta\tilde{\rho}'$ - $\delta\mathbf{b}'$  covariances, Figs. 7(c) and (i), have similar patterns but are larger in (c) for similar reasons.

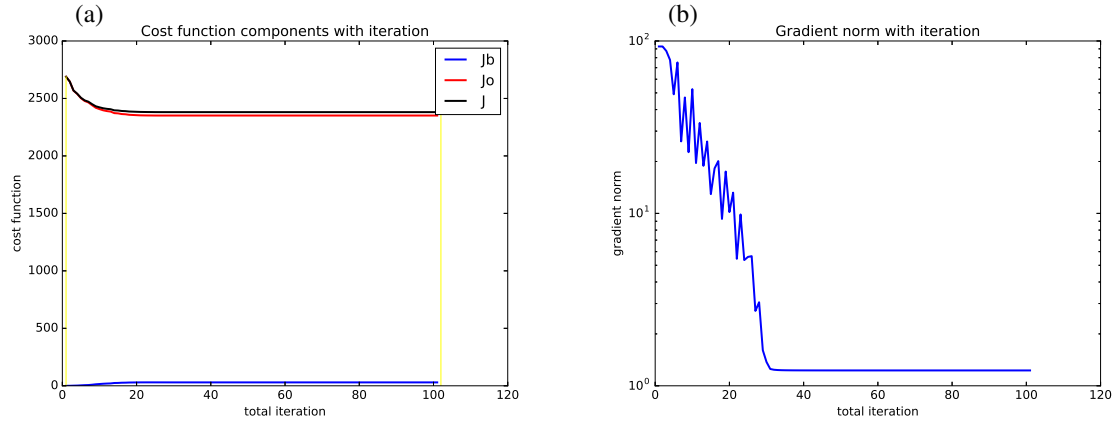
For each experiment, the initial background is found by perturbing the initial truth in a way consistent with the  $\mathbf{B}$ -matrix of each experiment (see last bullet point in Sect. 4.6). All other aspects of the assimilation are identical in all three experiments:

695 3DFGAT with a one-hour window is used for 30 DA cycles. The observations are identical in all cases, which are generated from the truth run with an error standard deviation of 0.0015. There are 2520 observations of  $\tilde{\rho}'$  in each cycle, which are spread over a  $20 \times 18$  grid of points broadly covering the domain, and over seven times ( $t = 0, 600, 1200, 1800, 2400, 3000, 3600$  s). Only one outer loop of 3DFGAT is executed per cycle with 100 inner loop iterations. This comparison is intended to be only a brief demonstration of the ABC-DA system, and we leave a more in-depth study to later papers.

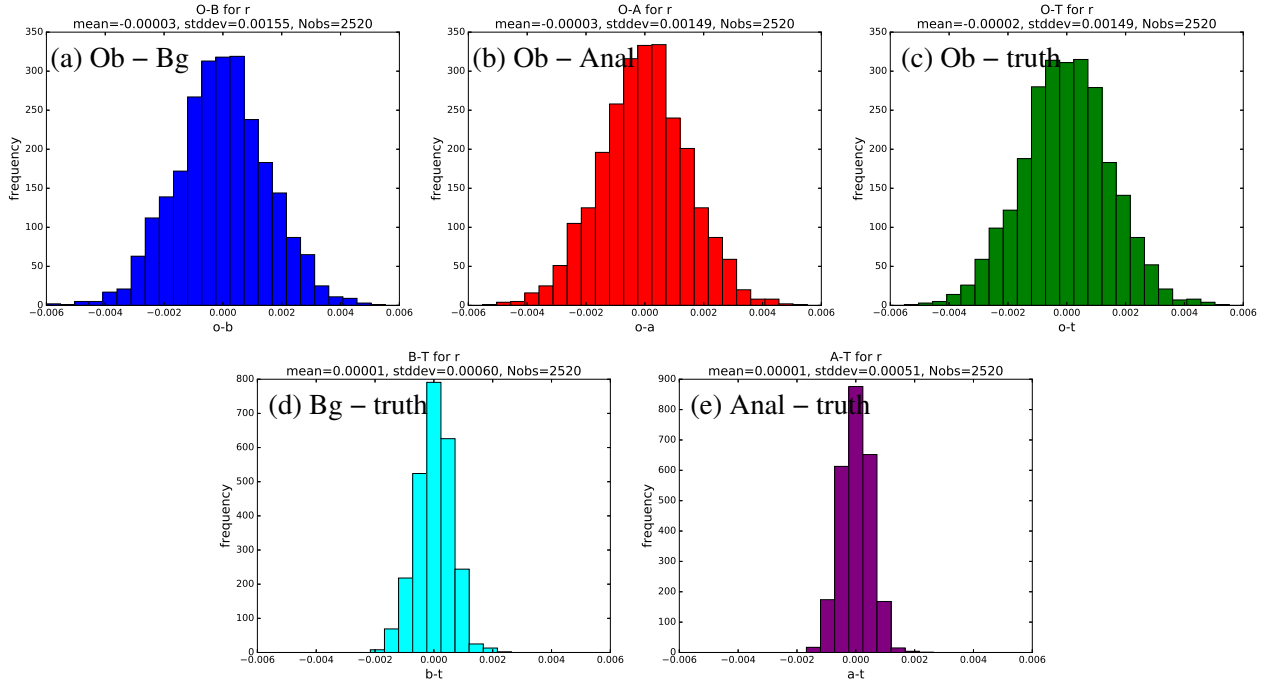
## 700 5.2 Results for experiment GB+VR+ (control experiment)

Figure 9 shows how the cost function (panel a) and the size of its gradient (b) reduce with inner loop iteration of the conjugate gradient procedure for one cycle of the GB+VR+ experiment. The total cost function,  $J$  (black in a) decreases along with the observation part,  $J^o$  (red in a) and the gradient (b), at the expense of the background part of the cost function  $J^b$  (blue in a), as expected. These results appear to show that the cost function has minimized. Figure 10 shows histograms of a selection of differences in the  $\tilde{\rho}'$  observation space (for the same cycle as Fig. 9). The top row concerns differences between the observations and  $\mathcal{H}(\mathbf{x}^b)$  (a, where  $\mathcal{H}(\bullet)$  is the combined ABC model and observation operator for the observation network described at the end of Sect. 5.1),  $\mathcal{H}(\mathbf{x}^a)$  (b), and  $\mathcal{H}(\mathbf{x}^t)$  (c). The width (standard deviation) of each is shown in the heading of each panel, showing a slight reduction from (a) to (b) as expected for the DA to have worked. The analysis is closer to the truth than is the background as expected as revealed with the histograms on the bottom row, which are  $\mathcal{H}(\mathbf{x}^b) - \mathcal{H}(\mathbf{x}^t)$  (d) and  $\mathcal{H}(\mathbf{x}^a) - \mathcal{H}(\mathbf{x}^t)$  (e).

715 Diagnostics collected over all 30 cycles for each variable in this experiment are shown in Fig. 11. The left panels show how the root-mean-squared (RMS) values of the fields vary in time for three versions of the fields: the truth (solid lines), the analysed fields (dotted), and a free forecast starting from the original background (dashed). For all fields except  $w$ , the assimilation overestimates the RMS field values, although the assimilation does often follow the oscillations in the true trajectory. The overestimation in the assimilation is actually nearly always worse than for the free background for  $v$ , is sometimes worse, sometimes better for  $u$  and  $b'$ , but nearly always better for  $\tilde{\rho}'$  (recall that only observations of  $\tilde{\rho}'$  are assimilated). The right panels show the RMS errors (RMSE) of the analysed (dotted) and free (dashed) fields, which we do know in such twin

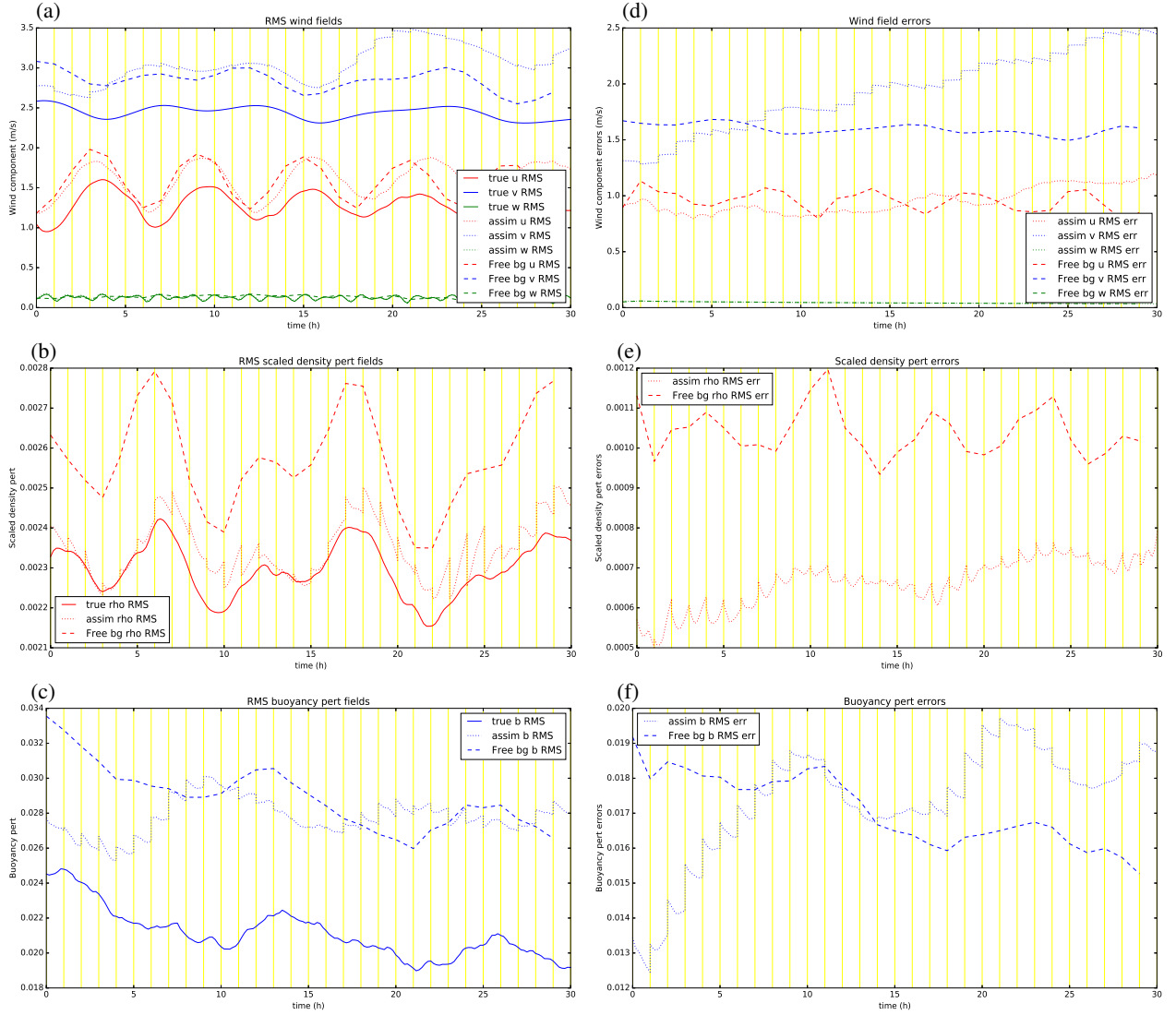


**Figure 9.** Cost function statistics as a function of inner loop iteration from the seventh cycle of the GB+VR+ experiment. Panel (a) shows the cost function contributions:  $J^b$  (blue),  $J^o$  (red), and  $J = J^b + J^o$  (black). The yellow lines mark the zeroth and hundredth (the maximum iteration) iterations. Panel (b) shows the norm of the cost function gradient.



**Figure 10.** Panels (a), (b), and (c): frequency histograms of  $y - \mathcal{H}(x)$  for the seventh cycle of the GB+VR+ experiment, where  $x$  is (a)  $x^b$  and (b)  $x^a$ , and (c)  $x^t$ . Panels (d) and (e): histograms of  $\mathcal{H}(x) - \mathcal{H}(x^t)$  where  $x$  is (d)  $x^b$  and (e)  $x^a$ . Observations are those assimilated of  $\tilde{\rho}'$ .





**Figure 11.** Left panels: RMS fields of (a)  $u$ ,  $v$ ,  $w$ , (b)  $\tilde{\rho}'$  and (c)  $b'$  for the control experiment, GB+VR+. The solid lines are for the truth trajectory, the dotted lines are for the assimilation trajectory, and the dashed lines are for the free trajectories starting from the initial background. The vertical yellow lines mark the times of the cycle boundaries where the assimilation trajectory is the analysis at the start of each cycle and the background (for the next cycle) at the end. Right panels: RMS values of the errors (trajectory minus truth) for the corresponding quantities in the left panels.

experiments. In the first few cycles the analyses are improved compared to the free run in all variables, but there comes a time where the assimilation becomes worse than the free run for most fields (especially  $v$  and  $b'$ ). The assimilation stays better than the free run for  $\tilde{\rho}'$  over all 30 cycles, and the background error covariances imposed between  $\tilde{\rho}'$ - $v$  and  $\tilde{\rho}'$ - $b'$  (panels b and c of Fig. 7) do not appear to be of benefit to  $v$  and  $b'$ , which is surprising. Note that there are no assimilation jumps in the  $u$  field because it is neither an observed variable nor correlated to  $\tilde{\rho}'$  in the **B**-matrix.

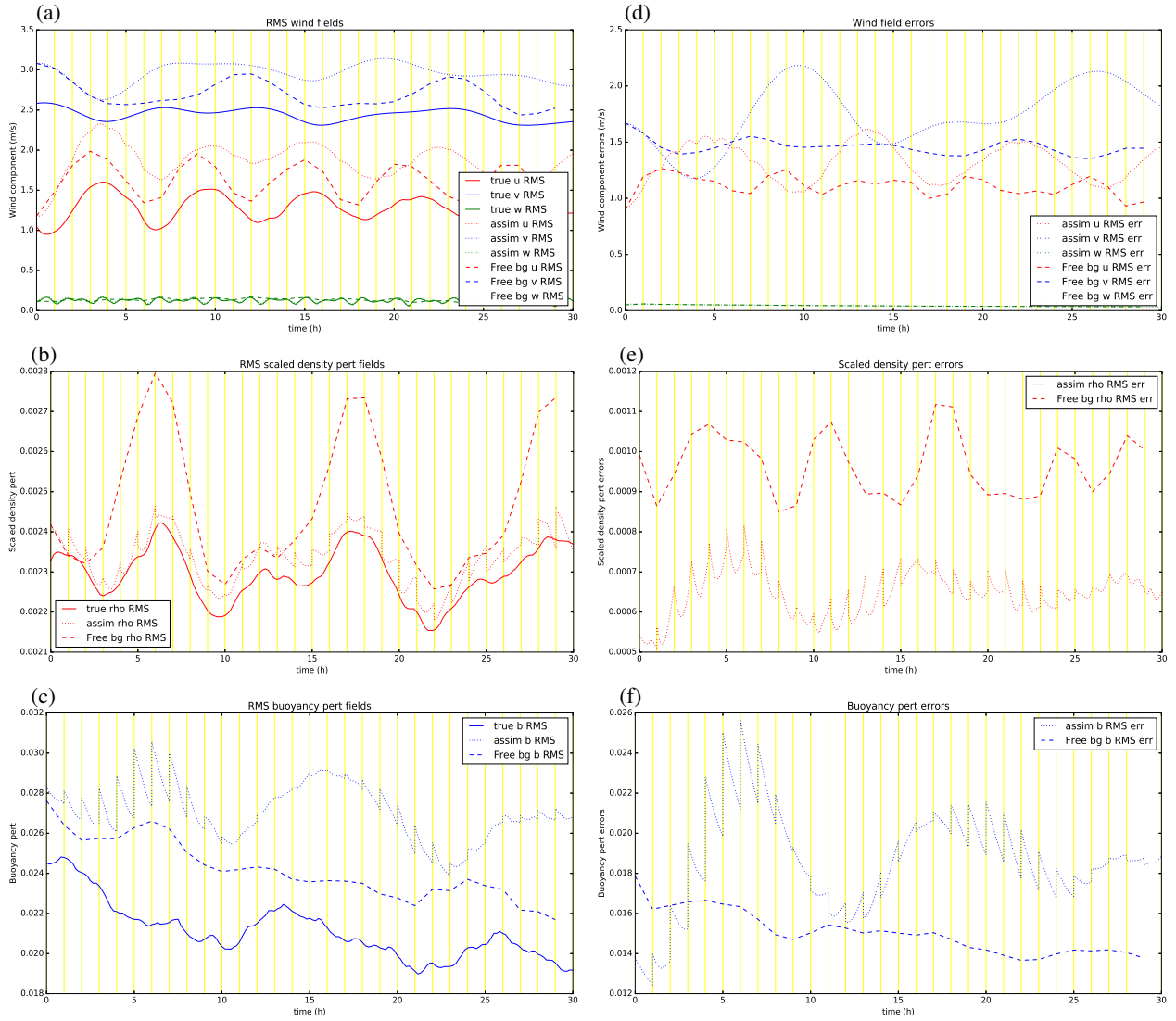
At  $t = 0$  each two trajectories of the same colour in each right panel represent background (dashed) and analysis (dotted) errors and so can be compared. For all variables (except  $u$  and  $w$ ), these two points are different at  $t = 0$ , with smaller analysis errors than background errors. This indicates that the DA does add improvement early in the cycling. Even though the analyses are closer to the observations than the backgrounds, the errors in the assimilated variables do grow with time and most of the analysis increments (the jumps at the yellow cycle boundaries) do act to increase the RMS error throughout the experiment. There are a number of possible reasons for this degradation, e.g. a poor **B**-matrix formulation for this model (including the use of balance constraints in the CVT), an inappropriate population of forecasts used to calibrate the **B**-matrix, the use of 3DFGAT rather than 4DVar, or the particular choice of observation network for this convective-scale system. Given that the assimilation performs well at  $t = 0$  (where the error in the initial background is consistent with the **B**-matrix formulation by design), it could be that, as the cycling progresses, the nature of actual background errors become very different to those assumed by the **B**-matrix. Confirming this hypothesis would require recalibrating the **B**-matrix, which is outside the scope of the present paper. We focus now on the remaining two experiments described in Sect. 5.1 to see if any changes can be made by adjusting parts of **B**.

### 5.3 Results for experiment GB-

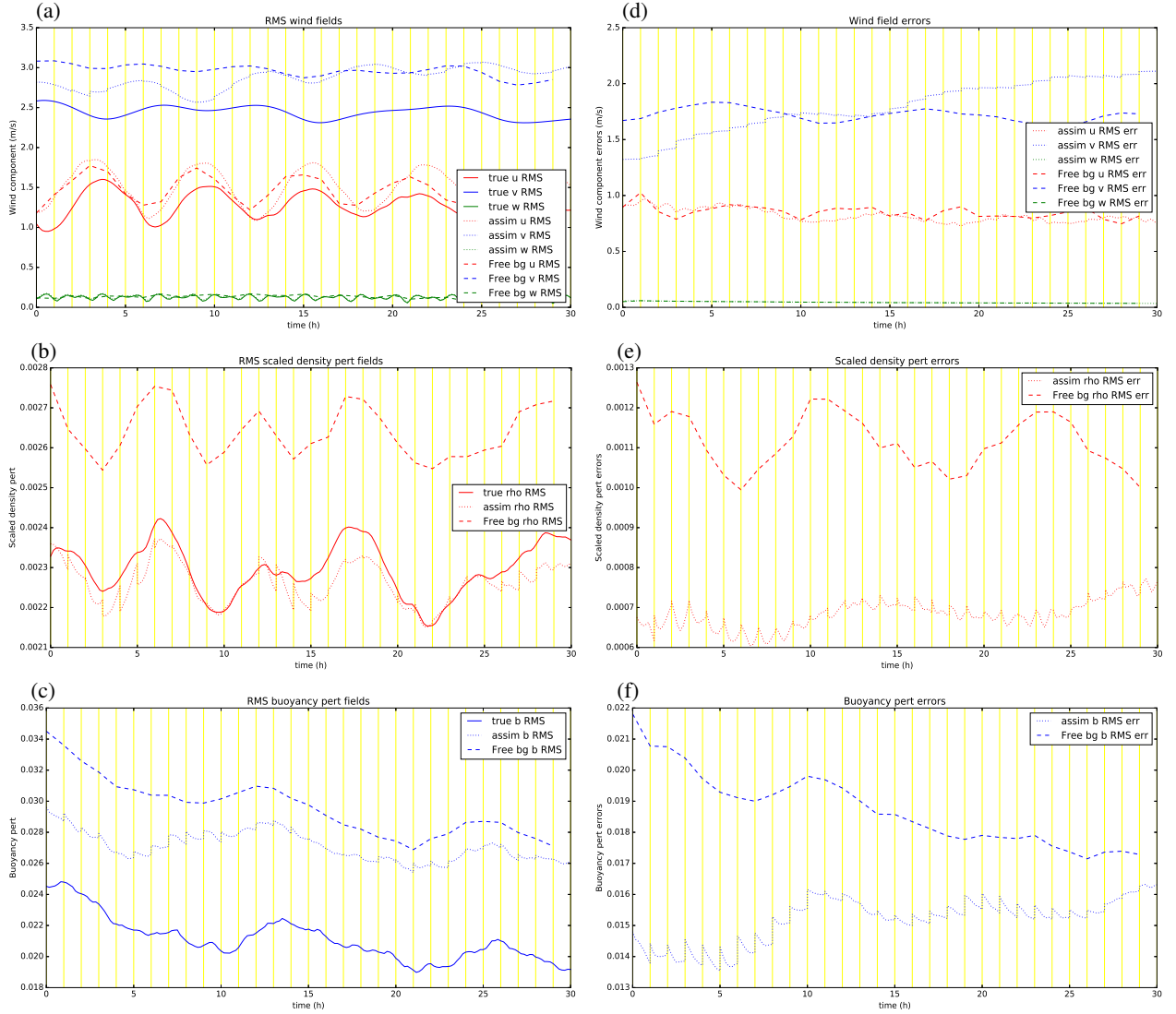
Diagnostics for the GB- experiment are shown in Fig. 12. Comparing the RMS values (left) with the GB+VR+ experiment, the analysis RMS values become further from the truth for  $u$ ,  $v$ , and  $b'$ . Note that, although the true trajectories are exactly the same as those of GB+VR+, the free trajectories are different as the initial background is consistent with a different **B**-matrix. Again comparing to GB+VR+ the RMSE analysis errors (right panels) are generally worse for GB-, but the assimilation is still able to control the  $\tilde{\rho}'$  field. This suggests that the **B**-matrix for GB- is still not consistent with errors in the one-hour background forecasts over the cycles. Note that there are no assimilation jumps in the  $u$  nor  $v$  fields because they are not correlated to  $\tilde{\rho}'$  in the **B**-matrix.

### 5.4 Results for experiment GB+VR-

VR is designed to accompany the GB operator and the configuration that included these two together in the CVT may have contributed to the relatively poor performance in Sect. 5.2. Here we run the experiment that includes the GB step in the CVT, but not the VR. Diagnostics for the GB+VR- experiment are shown in Fig. 13. Again, the true state is the same as in the previous two experiments, but the free background forecast is different due to the different **B**-matrix from which the initial background state is sampled from. The RMS values (left panels) of the assimilation are generally closer to the truth than in GB+VR+ (apart from  $u$  where they are about the same). The RMSE values (right panels) are also smaller as a fraction of the



**Figure 12.** As Fig. 11, but for experiment GB-.



**Figure 13.** As Fig. 11, but for experiment GB+VR-.

error in the free run (or at least are smaller for a longer time), although the errors in  $v$  do still eventually fail to be controlled by the DA.

The absence of VR does have the effect of weakening the effective strength of the GB between  $\delta\tilde{\rho}'$  and  $\delta v$  – compare panels b and h of Fig. 7. This is because, overall,  $\mathbf{R}_\rho$  enhances the balanced scaled density (and so the balanced scaled density is diminished when removing it). It is possible then that it is not the adoption of GB that results in the relatively poor performance of the GB+VR+ assimilation in this system, but the use of the VR.

## 6 Summary

This article is a documentation of ABC-DA, a Var system for use with the convective-scale ABC model (Petrie et al., 2017) to efficiently test new ideas for convective-scale DA. The DA currently has incremental 3DVar and 3DFGAT implemented although expansion to 4DVar, ensemble-variational, and hybrid methods is possible. The DA system has an expandable observation operator, which is currently configured to assimilate observations of all model variables, and 2D (horizontal) and 3D wind speeds. The choice of observation network is not fixed, and it is possible to specify arbitrary observation networks in space and time. The **B**-matrix is modelled in a very compact form by a control variable transform (CVT), which is implemented with a range of options. The current multivariate options include the option to use geostrophic balance (GB) to couple  $\delta\tilde{\rho}'$  and  $\delta v$ , hydrostatic balance (HB) to couple  $\delta\tilde{\rho}'$  and  $\delta b'$ , and anelastic balance to couple  $\delta u$  and  $\delta w$ . All of these balances use diagnostic relationships using analytical (rather than statistical) operators. A vertical regression (VR) step is also included (which works with the geostrophic step), to mirror the operational set-up of the Met Office's DA system. While the model increments are  $\delta u$ ,  $\delta v$ ,  $\delta w$ ,  $\delta\tilde{\rho}'$ , and  $\delta b'$ , the control parameters are  $\delta\psi$ ,  $\delta\chi$ ,  $\delta\tilde{\rho}'^u$ ,  $\delta b^u$ , and  $\delta w^u$ , which are assumed to be mutually uncorrelated. The transforms that model the spatial covariances for each control parameter are formed of vertical and horizontal parts, which model covariances in these respective directions. There are further options that control how each of these spatial transforms work, including the order in which they are used.

ABC-DA comprises component suites to perform the following tasks.

- Run a pure model forecast of any length starting from specified initial conditions.
- Investigate linear properties of the equations of motion.
- Generate an initial ensemble of states (e.g. for calibration of the **B**-matrix).
- Calibrate the parameters that describe components of the CVT to produce a CVT file. This specifies the **B**-matrix for use in the DA program.
- Test the components of the system (e.g. adjoint tests of CVT operators).
- Generate ‘raw’ covariance maps using a specified population of states.
- Generate implied covariance maps from a specified CVT file.
- Generate sample observations (consistent with a specified **R**-matrix and truth) and a background state (consistent with a specified **B**-matrix and truth).
- Perform a cycle of Var with a specified background state, observations, and CVT file.
- Perform a run of cycled DA/forecast steps where the analysis of one cycle is used to make a background forecast for the next.

The number-crunching code is written in Fortran 90/95, the scripts are written in Bash, and the example plotting routines are written in Python 2.

A selection of diagnostics of the CVT is provided in this paper and a brief study is made to illustrate the system's performance when GB (and VR) is switched on and off in the CVT. GB is used to model the background error coupling between  $\delta\tilde{\rho}'$  and  $\delta v$ , which is zero when GB is not used, and has a classical dipole pattern ( $\delta v$  response to a point perturbation in  $\delta\tilde{\rho}'$ ) when it is used. Exploiting this balance constraint (or not) is investigated as it is a question whether it has validity in the description of convective-scale background error covariances. VR has the effect of strengthening this geostrophic relationship because it increases (decreases) the variance of the balanced (unbalanced) contributions to  $\delta\tilde{\rho}'$ .

Experiments are performed using a set of three 3DFGAT twin experiments by assimilating observations over a 30 hour forecast taken as the common truth. The three experiments are (i) using GB and VR (GB+VR+), (ii) not using GB (GB-), and (iii) using GB but not VR (GB+VR-). Each experiment has a different CVT (i.e. a different  $\mathbf{U}$ ) and hence a different implied background error covariance matrix,  $\mathbf{B}^{\text{ic}} = \mathbf{U}\mathbf{U}^T$ . An initial background state is constructed for each experiment by perturbing the truth at  $t = 0$  with  $\mathbf{U}\delta\chi$  where  $\delta\chi$  is a sample from  $N(0, \mathbf{I})$  (equivalent in model space as choosing a sample from  $N(0, \mathbf{B}^{\text{ic}})$ ). The DA/forecast is cycled hourly over 30 cycles with 2520 observations of  $\tilde{\rho}'$  per cycle. The results are summarised as follows.

- The GB+VR+ experiment does not result in a systematic reduction of errors in the model variables. In fact, for some variables (namely  $v$  and  $b'$ ), it leads to an increase in error of the analysis above the error level of the free background.
- The GB- experiment represents a degradation in performance of the unobserved variables in that the errors are above the error level of the free background for more time than in GB+VR+.
- The GB+VR- experiment represents the configuration that is the best of those tested. The errors in all variables except  $v$  are kept below the error level of the free background.

It is surprising that errors in one of the variables in particular ( $v$ ) cannot be properly corrected in these experiments. It is postulated that this outcome is not due to an inappropriate  $\mathbf{B}$ -matrix (for instance in Figs. 11 and 13), but due to the use of 3DFGAT. Separate tests with 3DVar and with all observations made at the analysis times, rather than spread throughout the analysis window (not shown), suggest that observations of  $\tilde{\rho}'$  can reduce the error in  $v$ . We have learned from these experiments that nature of the  $\mathbf{B}$ -matrix can have a significant impact on the performance of the DA. Application of GB in such a convective-scale system has a complicated effect: while experiment GB+VR- is better than experiment GB- overall, the application of GB does systematically increase errors in the  $v$  field over the 30 cycles, and ‘too much’ GB (as in experiment GB+VR+) enhances this effect. Similar studies may be done by turning on and off hydrostatic and anelastic balances.

These results highlight a difficulty of the convective-scale DA problem and they raise more questions about how this system could be improved and how it could contribute to advances in DA. A possible way forward might be to keep the current formulation of the CVT but to calibrate it with data from a different source, either as an ensemble, as differences between pairs of forecasts valid at the same time (the popular National Meteorological Center method (Parrish and Derber, 1992; Berre

820 et al., 2006)), or from a single long forecast (the so-called ‘Canadian quick’ method, Polavarapu et al., 2005). Other ways  
forward might be to replace the traditional geophysical balances with a new balance relationship that may be more suitable  
at convective-scales, such as the diagnostic equation for non-hydrostatic pressure outlined in Sect. 4.3 of Pielke (2002). The  
CVT may also though be adapted so that the DA system acts as an ensemble-variational (EnVar) system where the analy-  
sis increments are expressed as linear combinations of ensemble perturbations (e.g. Lorenc (2003); Buehner (2005)), or as a  
825 hybrid-EnVar system (a hybrid of the existing **B**-matrix and the EnVar, e.g. Wang et al. (2007)), or as part of a hybrid gain  
formulation (e.g. Penny (2014)). These approaches imply flow-dependent background error covariances (e.g. Bannister, 2017),  
but each would require a separate ensemble DA system parallel to the variational one, and would also require localisation tech-  
niques to mitigate for rank deficiency of the ensemble. These are entirely possible developments given appropriate resources.  
Studying the **B**-matrix is the main application that the author has in mind, although the system could equally well be used to  
830 study impacts of new high-resolution observations.

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## Appendix A: Number of pieces of information to make up a covariance model

- 940 This appendix shows the number of pieces of information that specifies the covariance model used in this paper. Since only analytic balance relationships are used (rather than statistically-derived ones, which would themselves require calibration from data), components only of the spatial transform ( $\mathbf{U}_s$ ) and the vertical regression ( $\mathbf{R}_\rho$ ) require calibration. Referring to Eq. (31) or Eq. (32), this includes determination of the standard deviation matrix ( $\Sigma$ ), and components of the vertical ( $\mathbf{U}_v = \mathbf{F}_v \mathbf{\Lambda}_v^{1/2}$ ) and horizontal ( $\mathbf{U}_h = \mathbf{F}_h \mathbf{\Lambda}_h^{1/2}$ ) transforms. The vertical regression,  $\mathbf{R}_\rho = \mathbf{C}^{\delta \bar{\rho}'} \delta \bar{\rho}'^b \left( \mathbf{C}^{\delta \bar{\rho}''^b} \delta \bar{\rho}''^b \right)^{-1}$  requires

Matrix	Description	Elements to be determined
$\Sigma$	Standard deviations (level-dependent only)	60
$\mathbf{F}_v$	Eigenvectors of vertical transforms	$60 \times 60$
$\Lambda_v^{1/2}$	Eigenvalues of vertical transforms	60
$\mathbf{F}_h$	Horizontal Fourier transform	0
$\Lambda_h^{1/2}$	Horizontal variances of each parameter vertical mode	$180 \times 60$
	Total per control parameter (sum of above)	14 520
	For all five control parameters	72 600
$\mathbf{C}^{\delta\tilde{\rho}'/\delta\tilde{\rho}'^b}$	Non-symmetric term in $\mathbf{R}_\rho$	$60 \times 60$
$\mathbf{C}^{\delta\tilde{\rho}'^b/\delta\tilde{\rho}'^b}$	Symmetric term in $\mathbf{R}_\rho$	$60 \times 61/2$
	Grand total	78 030

**Table A1.** Number of components of the spatial transforms that need to be estimated from data. The number of elements in column 3 are for the standard ABC system of 360 longitudes and 60 levels. Note that for  $\Lambda_h^{1/2}$ , 180 wavenumbers are specified rather than 360 as the negative wavenumbers are assumed to have the same variances as the positive ones.

945 determination of a non-symmetric and symmetric correlation matrix. Table A1 shows this information, concluding that 78 030 pieces of information are needed. In this paper, a super-ensemble of 260 members is used to estimate this background error covariance model. This provides  $260 \times 5 \times 360 \times 60 = 28080000$  pieces of information, vastly more than the number of elements needed for the covariance model. Compare this to  $n(1+n)/2$  elements to determine a full background error covariance matrix, where  $n = 5 \times 360 \times 60$  is the number of elements in the model state vector. This evaluates to 5 832 054 000, requiring 54 000 ensemble members to estimate these elements at the very least. While this is possible, it is not practical at present.

## Appendix B: Vertical regression of balanced scaled density

The direct calculation of the geostrophically balanced scaled density from Eq. (2a) (in practice found via the stream-function as in Eq. (15)) leads to difficulties with regard to the vertical continuity of the resulting  $\delta\tilde{\rho}'^b(x, z, t)$  (Lorenc et al., 2000). If 955 a function (arbitrarily chosen but independent of  $x$ , i.e.  $p(z, t)$ ) is added to  $\delta\tilde{\rho}'^b$ , then  $\delta\tilde{\rho}'^b + p$  is also a solution of Eq. (2a). This will potentially allow damaging jumps to appear with short vertical scale. According to geostrophic adjustment theory, stream-function (and hence the scaled density computed from it) is not balanced for short vertical scales (e.g. Cullen (2003)) and so the output from Eq. (15) is smoothed in the vertical. This is done by modifying the balanced scaled density with a regression operator  $\mathbf{R}_\rho$ .

960 From hereon in this appendix, we drop the  $\rho$  subscript on  $\mathbf{R}_\rho$  for brevity as the subscript will be used to indicate matrix element. We also for brevity drop the tilde, prime, and  $\delta$  notations on the scaled density fields, remembering that the fields are implicitly perturbations. One strategy for  $\mathbf{R}$  is to introduce similar vertical length-scales as those in the forecasts of total scaled

density,  $\delta\rho$ . We therefore design  $\mathbf{R}$  to minimise the following penalty:

$$\mathbf{R} = \arg \min_{\mathbf{R}} \mathcal{J}[\mathbf{R}] = \frac{1}{2} \frac{1}{N} \sum_{i=1}^N (\mathbf{R}\boldsymbol{\rho}^b(i) - \boldsymbol{\rho}(i))^T (\mathbf{R}\boldsymbol{\rho}^b(i) - \boldsymbol{\rho}(i)), \quad (\text{B1})$$

965 where  $\boldsymbol{\rho}^b(i)$  and  $\boldsymbol{\rho}(i)$  are the  $i$ th member of an  $N$ -member population of balanced and total scaled density perturbations respectively. To find the  $\mathbf{R}$  that minimises  $\mathcal{J}$ , we solve the equation  $\partial\mathcal{J}/\partial\mathbf{R} = 0$ , which is a matrix equation, with element  $a, b$  being  $\partial\mathcal{J}/\partial\mathbf{R}_{ab} = 0$ . It is convenient to expand the elements of Eq. (B1):

$$\mathcal{J}[\mathbf{R}] = \frac{1}{2} \frac{1}{N} \sum_{i=1}^N \sum_{\alpha} \left( \sum_{\beta} \mathbf{R}_{\alpha\beta} \boldsymbol{\rho}_{\beta}^b(i) - \rho_{\alpha}(i) \right)^2, \quad (\text{B2})$$

where all subscripts indicate matrix or vector element. Differentiating with respect to  $\mathbf{R}_{ab}$  gives:

$$\begin{aligned} 970 \quad \frac{\partial\mathcal{J}}{\mathbf{R}_{ab}} &= \frac{1}{N} \sum_{i=1}^N \sum_{\alpha} \left( \sum_{\beta} \mathbf{R}_{\alpha\beta} \boldsymbol{\rho}_{\beta}^b(i) - \rho_{\alpha}(i) \right) \frac{\partial}{\mathbf{R}_{ab}} \left( \sum_{\beta'} \mathbf{R}_{\alpha\beta'} \boldsymbol{\rho}_{\beta'}^b(i) \right), \\ &= \frac{1}{N} \sum_{i=1}^N \sum_{\alpha} \left( \sum_{\beta} \mathbf{R}_{\alpha\beta} \boldsymbol{\rho}_{\beta}^b(i) - \rho_{\alpha}(i) \right) \sum_{\beta'} \delta_{a\alpha} \delta_{b\beta'} \boldsymbol{\rho}_{\beta'}^b(i), \\ &= \frac{1}{N} \sum_{i=1}^N \left( \sum_{\beta} \mathbf{R}_{a\beta} \boldsymbol{\rho}_{\beta}^b(i) - \rho_a(i) \right) \boldsymbol{\rho}_b^b(i), \end{aligned} \quad (\text{B3})$$

where  $\delta_{\alpha\beta}$  in the second line is the Kronecker delta-function. Now this result is put back into matrix notation. Note that  $\left( \sum_{\beta} \mathbf{R}_{a\beta} \boldsymbol{\rho}_{\beta}^b(i) - \rho_a(i) \right) \boldsymbol{\rho}_b^b(i)$  is the  $a, b$ th element of the outer product matrix  $(\mathbf{R}\boldsymbol{\rho}^b(i) - \boldsymbol{\rho}(i)) (\boldsymbol{\rho}^b(i))^T$ , so Eq. (B3) is:

$$975 \quad \frac{\partial\mathcal{J}}{\mathbf{R}} = \frac{1}{N} \sum_{i=1}^N (\mathbf{R}\boldsymbol{\rho}^b(i) - \boldsymbol{\rho}(i)) (\boldsymbol{\rho}^b(i))^T.$$

Setting this to zero to solve for the optimal regression matrix gives:

$$\mathbf{R} \frac{1}{N} \sum_{i=1}^N (\boldsymbol{\rho}^b(i)) (\boldsymbol{\rho}^b(i))^T = \frac{1}{N} \sum_{i=1}^N (\boldsymbol{\rho}(i)) (\boldsymbol{\rho}^b(i))^T.$$

The outer product matrix – summed and divided by  $N$  – on the left-hand-side is identified as the covariance matrix of the balanced scaled density perturbations with themselves ( $\mathbf{C}^{\rho^b\rho^b}$ ), and the corresponding terms on the right-hand-side is the covariance matrix between the total scaled density perturbations and the balanced scaled density perturbations ( $\mathbf{C}^{\rho\rho^b}$ ). The optimal regression matrix is then

$$\mathbf{R} = \mathbf{C}^{\rho\rho^b} (\mathbf{C}^{\rho^b\rho^b})^{-1}. \quad (\text{B4})$$

## Appendix C: Estimation of characteristic length-scales

There is a well-defined length-scale associated with a plane wave of the form  $\exp i\kappa x$  ( $\kappa$  is wavenumber,  $x$  is position), this being the wavelength,  $l = 2\pi/\kappa$ . For a periodic domain of length  $L$ , the allowed wavenumbers are  $\kappa = 2k\pi/L$  ( $k$  wavenumber

index, integer), and so the wavelength is  $L/k$ . There is no similar analytical relationship between the vertical mode index,  $\nu$ , and the vertical length-scale,  $l_v$ , but it is possible to estimate the characteristic length-scale as follows. Suppose that  $f(z)$  is an oscillatory function (e.g. a particular vertical eigenvector (column of  $\mathbf{F}_v$ ) of one of the vertical covariance matrices introduced in Sect. 4.2.3). Let its Fourier transform be  $\bar{f}(m)$ , where  $m$  is the spectral co-ordinate (i.e.  $f(z) \propto \sum_m \bar{f}(m) \exp i2m\pi z/L_v$ , where  $L_v$  is the vertical extent of the model). Treating  $|\bar{f}(m)|^2$  as the weight of the contribution from wavenumber index  $m$ , the characteristic value of  $m$  is:

$$\langle m \rangle = \sum_m |\bar{f}(m)|^2 m / \sum_m |\bar{f}(m)|^2. \quad (\text{C1})$$

This translates to a vertical length-scale of  $l_v = L_v / \langle m \rangle$ . This is the procedure used to make Fig. 6b. We note that the Fourier transform assumes periodicity, which is not a property of the fields in the vertical direction, but since we are after only a rough estimate of  $l_v$ , we assume that this inconsistency does not have a major impact.