We appreciate the reviewer's detailed comments on the manuscript. Those comments has helped improve and clarify the submitted manuscript. Especially, we have added more detailed information on how BUMP NICAS and HDIAG works. Please find our response to each of your comments below.

1. *Line 56: "heigh" -> "height"*

Done.

2. *Line 67: "United" -> "Unified"*

Done.

3. *Line 132-133: Can you clarify the purpose of using the same level only for calculating regression coefficients for $\delta\psi$ and $\delta\chi$? Do you think their vertical cross-correlations are weak/negligible?*

It could be possible to have vertical cross-correlations between $\delta\psi$ *and* $\delta\chi$*.* This could be tested and evaluated if that explains bigger amount of total sample variance (shown in Figure 2b). In this manuscript, however, we have considered the level-by-level correlation between $\delta\psi$ *and* $\delta\chi$, following Wu et al. (2002).

We have added a text "**..., following Wu et al. (2002).**"

4. *Line 138: I think this manuscript can contribute much to the research community. If the authors can include how BUMP implements these operators from the algorithm perspective in detail, this manuscript can be at a higher level.*

Thank you for the suggestion. We have improved the description on how BUMP VBAL, VAR, and especially NICAS works in the last paragraph of section 3.1 as follows: "**The BUMP Vertical BALance (VBAL) driver is used for K_2 and K_2^T . It is based on the explicit vertical covariance matrices defined for a set of latitudes, and interpolated at the model grid points latitude. The BUMP VARiance (VAR) driver is used for Σ and Σ^T . It simply applies the pre-computed error standard deviations. The spatial correlation matrix is pre-computed from the given correlation lengths with BUMP-NICAS. Similar to the GSI recursive filters, NICAS works in the grid-point space. However, it applies the convolution function explicitly, instead of recursively for GSI. Thus, the choice of the convolution function in NICAS is free, as long as it is positive-definite. We choose**

a widely-used fifth-order piecewise function of Gaspari and Cohn (1999), which resembles the Gaussian function but is compactly supported. To make the explicit convolution affordable for high-dimensional systems, it is actually performed on a low-resolution unstructured mesh. A linear interpolation is required from the unstructured mesh to the full model grid. Finally, an exact normalization factor is pre-computed and applied to ensure that the whole NICAS correlation operator is normalized (i.e. diagonal elements of the equivalent correlation matrix are "1"). Thus, the NICAS correlation matrix can be written as: $C=NS\widetilde{C}S^TN^T$, where $\widetilde{C}$ is the convolution operator on the low-resolution mesh, S is the interpolation from the mesh to the full model grid, and N is the diagonal normalization operator. The low-resolution mesh density can be locally adjusted depending on the diagnosed correlation lengths (or provided by the user)."

Also, we have added more description on BUMP VAR and especially HDIAG in the last two paragraph of section 3.2 as follows: "**For Σ, the BUMP VAR driver calculates variances for $\delta\psi$, $\delta\chi_u$, δT_u, δq, and $\delta p_{s,u}$ from the samples and filters them horizontally to damp the sampling noise. The horizontal smoother is also based on NICAS, with an appropriate mean-preserving normalization factor.**

The correlation matrix, C, consists of blocks that specify the univariate spatial correlation for $\delta\psi$, $\delta\chi_u$, δT_u, δq, and $\delta p_{s,u}$. The BUMP Hybrid DIAGnostic (HDIAG) driver diagnoses the horizontal and vertical correlation lengths used in modeling C parameters. HDIAG can diagnose the horizontal and vertical spatial correlations from the samples. First, it defines a low- resolution unstructured mesh. Around each mesh node, diagnostic points are randomly and isotropically drawn for different horizontal separation classes. Second, HDIAG calculates the horizontal correlation between each mesh node and its own diagnostic points from the samples, at all levels. The vertical correlation is also calculated at each mesh node, between each level and the neighboring levels. The third step is a horizontal averaging of these raw correlations over all the mesh nodes. The average is binned depending on the level and the horizontal separation for the horizontal correlation, and depending on the concerned levels for the vertical correlation. As a final step, HDIAG fits a Gaspari and Cohn (1999) function for each averaged correlation curve. Thus, we obtain horizontal and vertical correlation length values for each level. These profiles can be stored and provided to NICAS in order to model the spatial correlation operator."

5. *Line 147: You directly used GFS forecasts to calculate the static error statistics. Are GFS forecasts appropriate to be used to represent MPAS model errors? I doubt it.*

Thank you for your comment. As you mentioned, it is natural to use MPAS Model's own forecast samples to diagnose the B parameters to consider the MPAS Model's own characteristics. In this initial development and validation work, however, we have wanted to use the pre-existing forecast samples from external model. After submission of this manuscript, we did use the MPAS Model's own forecast samples (still with NMC-type perturbations) to diagnose the B parameters, but with a recent version of JEDI-MPAS source code (early June 2023). To summarize, the overall structures of B parameters (such as regression coefficients, vertical profiles of horizontal- and vertical correlation lengths) diagnosed from MPAS-based samples was similar to that from GFS-based samples. The largest difference was in the error standard deviation parameters, which were in larger values for MPAS-based samples, especially in the upper levels. In one-month cycling experiment, this lead to a reduction in temperature and wind RMSEs in 6 hour forecasts fields in the upper levels. In future efforts of further refinement on the JEDI-MPAS static B, we will definitely use the MPAS Model's own forecast samples (either NMC or ensemble types of samples).

6. *Line 152: Using NCL first seems to make the procedure complicated. Is it an essential step, or the alternative strategies exist?*

Unfortunately, it is essential step for current strategy and yes, this makes the B training procedure a bit complicated. As described in the manuscript, it is not trivial to solving a Poisson equation efficiently on the unstructured grid. However, this step is only required once when we generate the perturbation samples for stream function and velocity potential from zonal and meridional wind.

7. *Line 166-171: This is one novelty part relative to the other utilities (e.g., gen_be_v2 in GSI), right? I suggest the authors give more details about HDIAG.*

We have added more description on BUMP HDIAG in the last paragraph of section 3.2 . Please see the response on the reviewer's 4th comment above.

8. *Figure 8: Is it the same observation location used as Fig.7, but for the zonal wind? Can you clearly state the location of the single zonal wind observation and mark it in Fig. 8?*

Yes, the location is the same for zonal wind observation and temperature observation. It is marked as "x" in the left-mid panel. We also added the "x" mark in the other panels and revised the Figure 8 caption as follows: "**Same as Fig. 7, except from a single zonal wind observation with 1 ms^{-1} innovation and 1 ms^{-1} observation-error standard deviation, located at (38.68° W, 40.41° N) on model level 15 with a marker ×.**"

9. *Figure 9: Same as the comment for Fig. 8. Please mark the location of the assimilated observations.*

The observation location is marked with “x” in the revised figure.

Reference

Gaspari, G. and Cohn, S. E.: Construction of correlation functions in two and three dimensions, Quarterly Journal of the Royal Meteorological Society, 125, 723–757, https://doi.org/https://doi.org/10.1002/qj.49712555417, 1999.

Wu, W.-S., Purser, R. J., and Parrish, D. F.: Three-dimensional variational analysis with spatially inhomogeneous covariances, Monthly Weather Review, 130, 2905–2916, https://doi.org/10.1175/1520-0493(2002)130<2905:TDVAWS>2.0.CO;2, 2002.