

## ***Interactive comment on “Correcting for Model Changes in Statistical Post-Processing – An approach based on Response Theory” by Jonathan Demaeyer and Stéphane Vannitsem***

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[10pt,twoside]report fancyhdr,color,amsmath,amssymb [LO,RE]Review of a Manuscript for Nonlinear

Processes in Geophysics (NPG)

[Correcting for Model Changes in Statistical Post-Processing - An approach based on Response Theory](#)

### **General comments**

The authors present a new approach to tackle an important problem in the field of statistical post-processing of numerical weather prediction (NWP) model: how to post-process a NWP model when it changed and an old post-processing method has been gitted but may be no more efficient on the new version of the NWP model? Indeed

C1

post-processing usually requires a long archive of past forecasts and associated observations to efficiently learn the error structures of the NWP model with statistical methods.

Several approaches already exist to handle this problem:

- producing hindcasts with the new version of the NWP model. This is the ideal approach but is very resource intensive.
- using transfer learning approach. To the best of my knowledge, this approach has not been deeply studied for meteorology.
- using online post-processing techniques with short training windows. This allows to quickly update the post-processing, but can only correct according to the near past (which may be useless for rare events)
- using filtering techniques to correct in real-time the residual biases in the post-processed forecasts. This has the same limitations as online post-processing.
- aggregating several NWP models and post-processed version thereof. This may improve performance and allow to discard useless models, but requires to have available several (post-processed or raw) forecasts with different error structures.

The new proposed approach is based on response theory. It consists in correcting the regression coefficients of the (linear) post-processing model, based on information learned on a period where the old and new NWP models are available. This approach supposes that the changes in the NWP model are small.

The presentation is clear and the general idea well exposed. The presentation of the technical requirements is not very detailed for someone not working in modelisation, but is sufficient to understand the proposed process. The illustration with two toy models helps to clarify the approach and is a good proof-of-concept. However, it would be interesting to have a more realistic application of the approach on real data.

C2

The problem this approach tries to solve is an important one for operational purposes. Another tool to solve it is therefore welcome and its efficiency and usefulness should be further assessed by the community of meteorologists. This article is thus a precious contribution to the post-processing literature.

Naturally, since it is a brand new approach to an old problem, several questions arise that should, at the very least, be raised with, ideally, some proposals:

- since this approach supposes the changes in the model are small, we can wonder if it will really be useful for operations, where small changes in the model may not really impair post-processing. Furthermore, it should be interesting to see whether this approach improves over the use of dynamic filtering of residual biases (via Kalman filtering, classically). Do you have any hint about this alternative?
- the stated conditions for using this correcting seem very strong: a tangent model must be available, the model change has to be provided as an analytic function. These two conditions may not be observed or the models themselves may not be available. Would it be possible to follow the same procedure in a data-based approach? In other words, could it be possible to deduce the necessary correction if one has only the two sets of forecasts on a common period without access to the models themselves?
- the extend of post-processing methods that may be corrected in this way is not very clear. You state that *The only requirement is that the outcome of the minimisation of the cost functions uses averages of the systems being considered*. Does this mean that post-processing methods that do not use cost functions (such as random forest) are not eligible to this approach?

### Specific comments

C3

1. [page 3, line 5](#): The response theory approach provides an efficient correction of the post-processing scheme up to a lead time of 3 days, which matches the lead-time window where the scheme's correction is efficient.  
Do you have a reference to support this claim that post-processing is useful only up to a lead time of 3 days?
2. [page 4, line 21](#): More sophisticated approaches can be evaluated in the future.  
Could you develop about what kind of sophistication you are thinking about?
3. [page 8, line 2](#): A 2-layer quasi-geostrophic atmospheric system on a  $\beta$ -plane with an orography is considered  
For the article to be self-contained, may you add a more comprehensive definition (with equations) for this system, maybe in the appendix?
4. [page 9, line 14](#): This is different from the case considered in Reinhold and Pierrehumbert (1982), where two blocking regimes coexist with the zonal regime.  
Is there a simple explanation why your system has only one blocking regime instead of two?
5. [page 10, line](#) : Fig2 (a) and (b)  
These pictures are not very clear. In panel (b) only model 0 seems to have two attractors but from the text (page9, line 12 and elsewhere) I understand that reality also should have two attractors. Please can you clarify either the text or the pictures?
6. [page 14, line 18](#): After this critical lead time, obtaining a good accuracy requires a huge increase in the number of forecasts and tangent model integrations to perform the averaging. This problem is well-known (Nicolis, 2003; Eyink et al., 2004) and is due to the appearance of fat-tails in the distribution of the perturbations  $\delta y$  in the integrand of Eq. (39).  
Later on, you say that the distribution of perturbation has been approximated with

C4

a gaussian distribution. In the conclusion, you propose to use the CLV method to get better corrections at farther lead times. I was wondering if we could improve the correction at long lead times by using a different distribution (with fatter tails) to approximate the perturbation distribution?

7. Based on the results, it seems this approach may require a very short period where both models are available. The length of the common period (a few months?) seems to correspond to what may be available operationally in national weather services. This is a very good point, to check on real data, maybe in a future study.

### Technical corrections

1. [page 1, line 2: reforecasting](#)  
Please change into *reforecasting*
2. [page 4, line 7: given K past forecasts  \$y\_k\$](#)   
Since  $K$  is used for constants in the Ornstein-Uhlenbeck process, I would suggest using a different notation, such as  $N$  for the number of past forecasts and  $n$  for the forecast index.
3. [page 4, line 10:  \$x\_C\(\tau\)\$](#)   
I would suggest using  $y_C(\tau)$  for the corrected forecast.
4. [page 9, line 13: one characterised by a zonal circulation \(see Fig. 1\(c\)\), and another characterised by a blocking situation \(see Fig. 1\(d\)\)](#).  
I guess the references are wrong and should read Fig. 2(c) and Fig. 2(d).
5. [page 19, line 4: the minimisation of the cost functions uses averages](#)  
Please change into *the minimisation of the cost function uses averages*

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