A stochastic dynamics method for ensemble seasonal forecasts with the CNRM-CM5.1 GCM

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Outline

Adding stochastic perturbations to a coupled GCM can improve the ensemble spread and skill scores at a seasonal time scale (*Weisheimer et al., 2011*). Stochastic perturbations of the prognostic variables of the atmospheric component of CNRM-CM5.1 are implemented to increase spread and correct initial tendency errors estimated as in *Guldberg et al., 2005*. Optimal perturbations (drawn within the current month of the hindcast period) show a potential for substantial improvements. Flow-dependent perturbations were also implemented and tested.

Stochastic dynamics method

The stochastic dynamics method (*Batté and Déqué, 2012*) is an additive stochastic perturbation technique. Prognostic variables T, q, and Ψ are perturbed by adding random draws of initial tendency error corrections of the ARPEGE-Climat v5.2 atmospheric component.

$$\mathbf{X}(t+\Delta t) = \mathbf{X}(t) + \mathbf{M}(\mathbf{X}(t), t) + \delta\mathbf{X}_t$$

The implementation follows three steps :

1. Nudged 32-year run : CNRM-CM5.1 model is nudged (τ = 1 day) towards ERA-Interim reanalysis data (1979-2010).

2. NDJF season nudged hindcast : a four-member ensemble is run, starting from initial conditions of step 1 for Nov. 1979-2010, and nudged more weakly (τ = 1 month) towards ERA-Interim. Corrections toward ERA-Interim make up the perturbation population $\{\delta\mathbf{X}\}$.

3. Retrospective forecast : starting from initial conditions of step 1, a seasonal re-forecast for each NDJF season is run, perturbing each ensemble every 6 hours with random draws of a $\delta\mathbf{X}$ within the calendar month (in cross-validation mode).

Flow-dependent perturbations

Flow-dependent initial tendency error corrections have been shown to improve GCM climate simulations at a seasonal time scale (*D'Andrea and Vautard, 2000*).

Two flow-dependent stochastic dynamics methods were implemented, by sorting the $\{\delta\mathbf{X}\}$ population according to the tercile of Niño 3.4 surface temperature in the hindcast, or using statistical classification of the global streamfunction in the hindcast for each month, at different vertical levels (k-means type algorithm for the first EOFs of the streamfunction field).

Re-forecasts and evaluation

INI : reference CNRM-CM5.1 ensemble with perturbations drawn only at the initial time step for each member.

SD RAND : a random $\delta\mathbf{X}$ is drawn every 6 hours during the run according to the calendar month.

SD SEQ5 : a random sequence of $\delta\mathbf{X}$ corresponding to 5 consecutive days of the hindcast period is drawn every 5 days.

SD N34 : a random $\delta\mathbf{X}$ is drawn from a $\{\delta\mathbf{X}\}_{SST}$ population according to the tercile of Niño 3.4 SST of the previous month of the forecast.

SD Ψ18 / **SD Ψ10** : perturbations for the following five days are drawn in population $\{\delta\mathbf{X}\}_k$ according to the class *k* the average streamfunction of the last pentad at model level 18 / 10 (≈ 500 hPa / 200 hPa respectively) belongs to.

MONM : the time average of $\delta\mathbf{X}$ for all other years of the re-forecast period and the current month is added at each time step.

SD OPT (« optimal perturbations ») : a random $\delta\mathbf{X}$ is drawn from the current month and year of the re-forecast period.

Each ensemble is run with 15 members for NDJF 1979-2010 and compared to ERA-Interim data (GPCP v2.2 data for precipitation).

Results

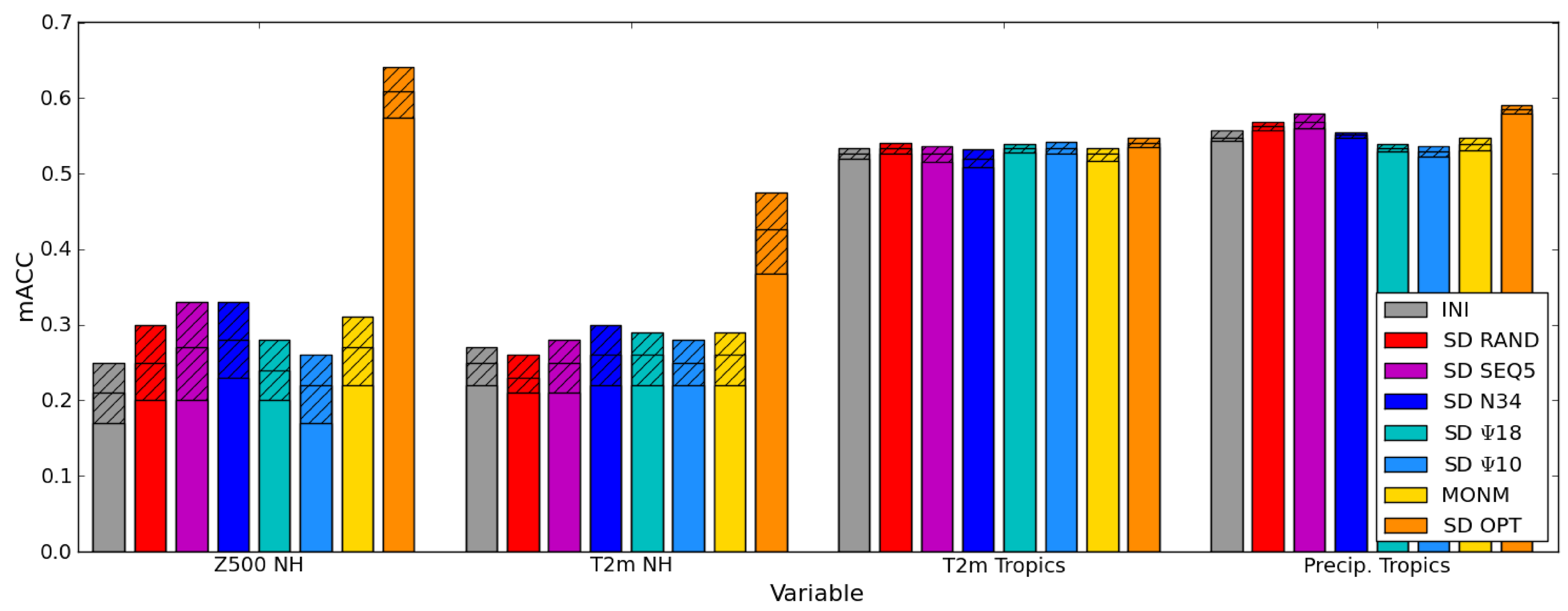

Fig 1 : mACC (*Déqué and Royer, 1992*) for DJF 1979-2010 re-forecasts with respect to ERA-Interim (for Z500 and T2m) and GPCP v2.2 (for precipitation). Dashed boxes show the 5%-95 % range and average of scores for random draws of 9 out of 15 ensemble members. NH is for mid-latitudes from 30°N to 75°N.

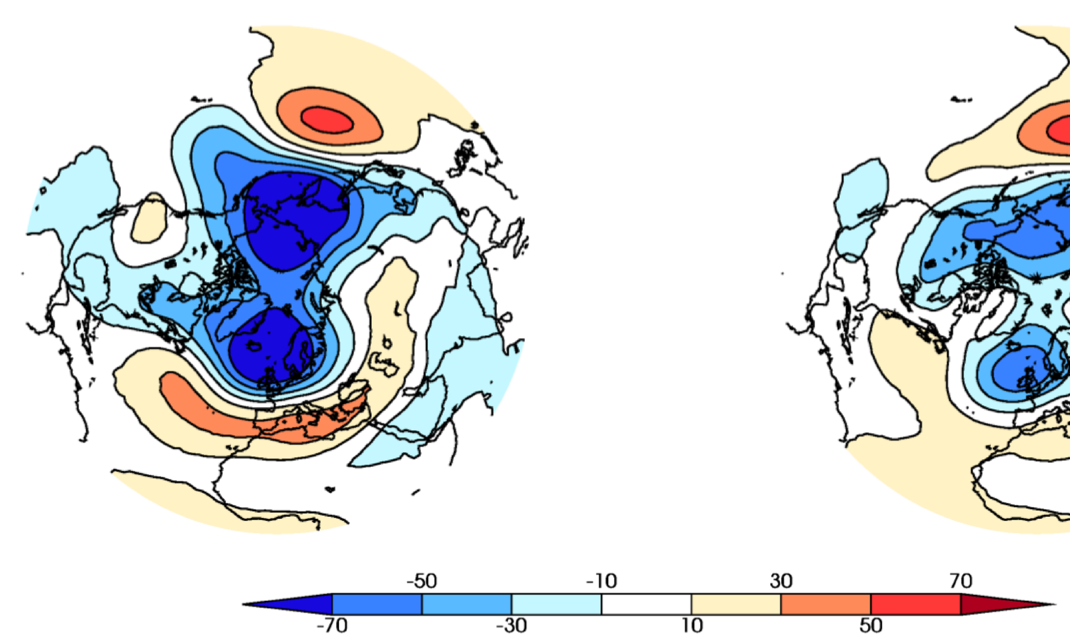

Fig 2 : Mean bias (in meters) for DJF Northern Hemisphere Z500 for runs INI (left) and SD RAND (right). All SD and MONM ensembles have similar bias for NH Z500.

Main results

· mACC scores are improved with SD RAND and SD SEQ5 for Northern Hemisphere Z500 and precipitation over the Tropics (fig. 1). Optimal perturbations show a high potential of improvement over the Northern Hemisphere mid-latitudes, and much less so over the Tropics.

· Most of the improvement over the NH mid-latitudes is due to bias reduction (fig. 2), as shown with the MONM scores.

· Monthly mACC scores for 2-meter temperature over the Niño3.4 region (fig. 3) are improved with ensembles SD Ψ18 and SD Ψ10. Scores with monthly mean perturbations and for SD N34 are poorer than other SD ensembles after 2 months lead.

· Similar conclusions can be drawn from probabilistic scores such as RPSS (fig. 4). SD SEQ5 appears to be the best stochastic dynamics method overall.

· The variability of the streamfunction during free forecasts is not well represented by the classes derived from the nudged hindcast run. Fig. 5 shows the class *k* from which the perturbations are drawn during each pentad of the run for each ensemble member, for 3 random years. Very few classes are explored by the ensemble members leading to ensemble under-dispersion.

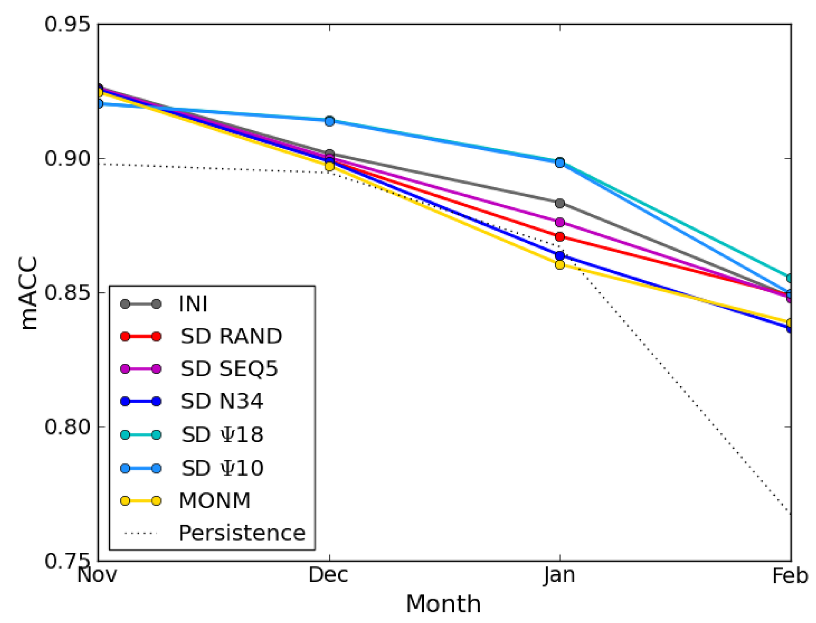

Fig 3 : Monthly mACC score for Niño3.4 T2m 1979-2010 re-forecasts with respect to ERA-Interim, and persistence.

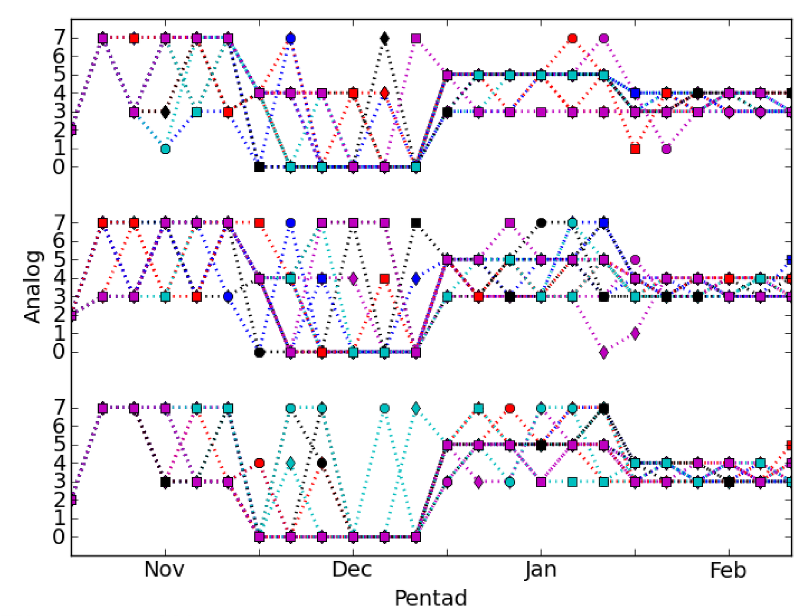

Fig 5 : Ψ_{200hPa} classes explored by the 15 ensemble members of SD Ψ10 during 3 random years of the 1979-2010 period.

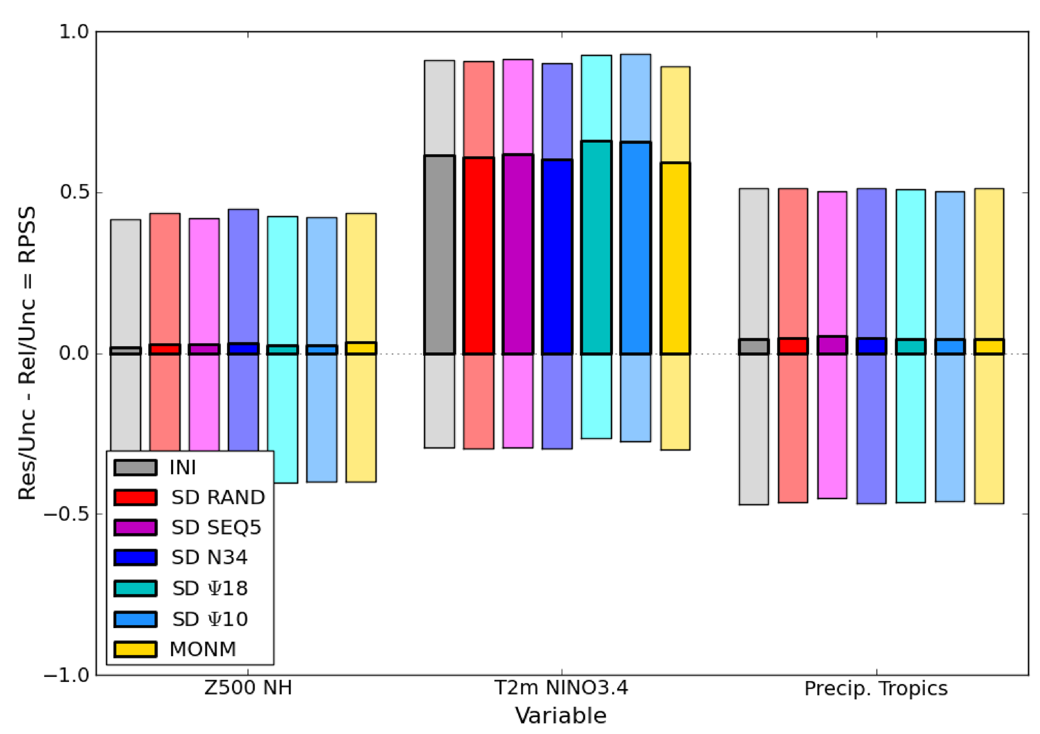

Fig 4 : RPSS (*Epstein, 1969*) and reliability – resolution decomposition for 1979-2010 DJF re-forecasts of NH Z500, Niño3.4 T2m and precipitation over the Tropics.

Perspectives

- Classification using criteria on the *perturbations* instead of the streamfunction field in the nudged run.
- Sensitivity to frequency and length of sequences of perturbations.
- Sensitivity to the variables and time scales used for nudging during steps 1 and 2.

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