Impacts of a spatially varying random parameter scheme on cloud cover in MOGREPS

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Introduction

Numerical Weather Prediction (NWP) forecast error arises from uncertainty in various components of the modelling system. A key component of this is model error which can be attributed to **sub-grid scale uncertainty** and **knowledge uncertainty**. The finite resolution of numerical models means that the effect of processes at scales too small to be resolved by the model need to be estimated (or parameterized). Ensemble Prediction Systems (EPS) are used to build statistics of likely forecast states from running multiple realisations of the same forecast, by perturbing the initial conditions of each ensemble member. However, it has not been practically possible to generate initial condition perturbations that result in sufficient dispersion of the ensemble members so that ensemble spread matches the forecast error at all lead-times and for all forecast fields. This problem is addressed by adding a model-error component to the ensemble system, such as perturbing the tendencies calculated by the physics parameterization schemes differently in each member. The common approach to do this is the Stochastically Perturbed Physics Tendency (SPPT) method (Buizza *et al*, 1999).

Arguably, **knowledge uncertainty** affects model uncertainty in an orthogonal sense. Here, there is uncertainty in the values of the parameters used in the parameterization schemes. These parameters are carefully tuned to minimise forecast error in a spatio-temporal average sense. However, in specific areas at specific times, these parameters may well not be set optimally. The perturbed parameter scheme, **Random Parameters**, seeks to address this uncertainty of the value of the parameters, by varying them during the model forecast (RP2) or by choosing different values for different ensemble members.

A recent development in this method is to use a spatially-varying perturbation pattern to modulate the parameters in space (RP3). A simple way to do this is to use the same random pattern designed for the SPPT scheme, which has a prescribed spatial length-scale of 500km and evolves smoothly over time using an AR1 process and a decorrelation time-scale of 6 hours (Fig. 1).

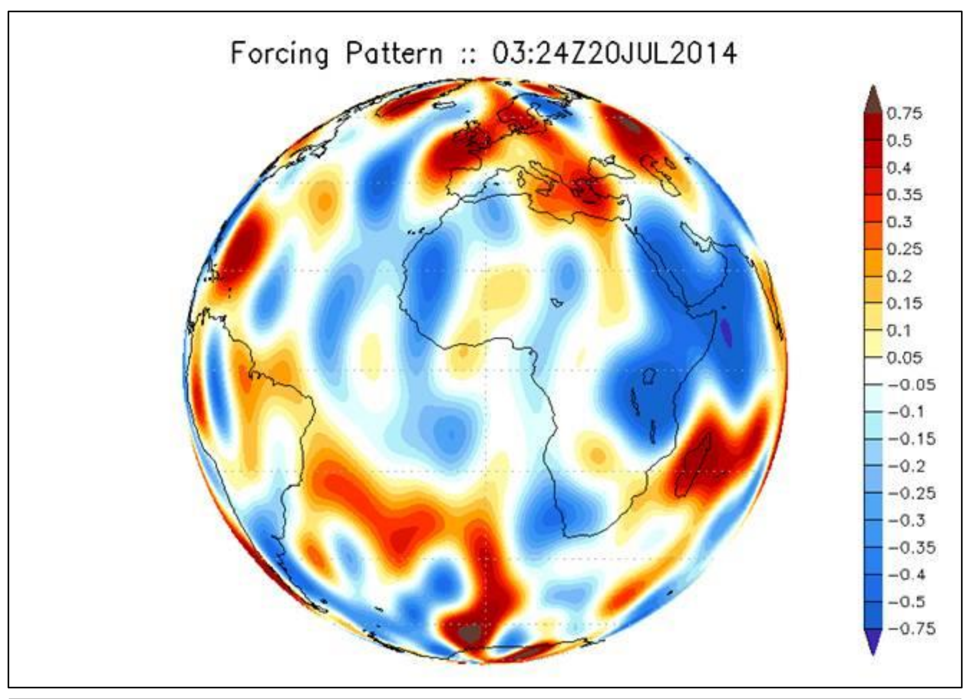


Figure1: Sample 2D perturbation pattern used in RP3 with horizontal scale of 500km and σ = 1/√12

Previous work

Typically, **Random Parameters** have only a modest impact on increasing dispersion in medium-range forecast ensembles. However, specifically targeted aspects of the model forecast can be improved. Figure 2 shows the relative impact of RP2 on spread against SKEB (Tennant *et al*, 2010) and ETKF initial condition perturbations (Bowler *et al*, 2008) for 250hPa temperatures in the tropics during a two-month trial. RP2 is comparable to SKEB in the tropics.

Table 1: List of experiments and perturbed values [min; default; max]

Name	Perturbation Scheme	RHCrit	FSD	EntCoef
Ctl	RP2	[0.875; 0.92; 0.946]	*Not perturbed*	*Not perturbed*
Exp1	RP3	[0.84; 0.92; 0.95]	[1.25; 1.41; 1.6]	*Not perturbed*
Exp2	RP3	[0.84; 0.92; 0.95]	[1.25; 1.41; 1.6]	[2.75; 3.0; 4.0]

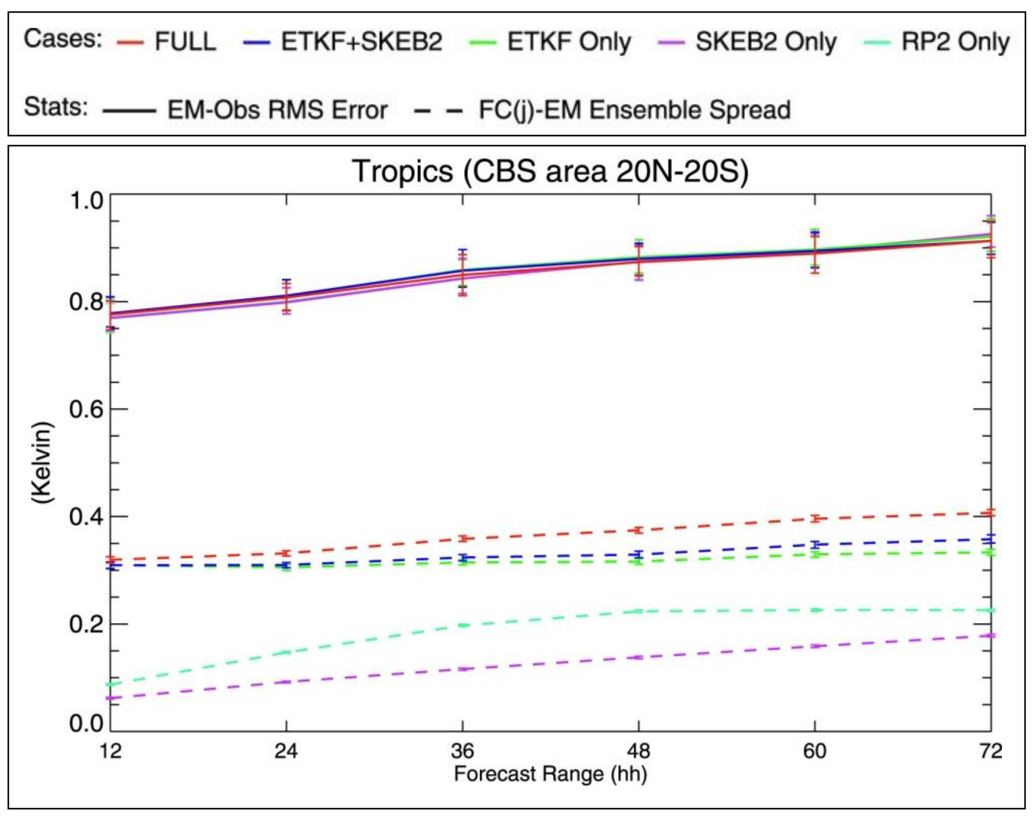


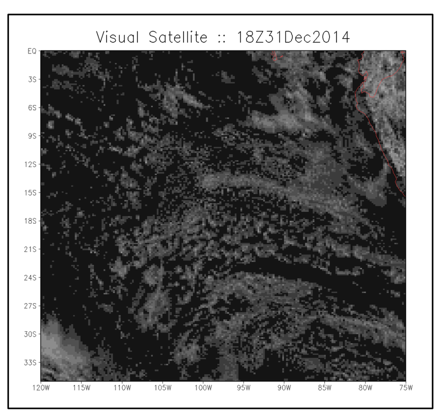
Figure 2: RMSE of ensemble mean (solid) and spread (dashed) of 250hPa temp vs obs with forecast lead-time Jul-Aug 2014

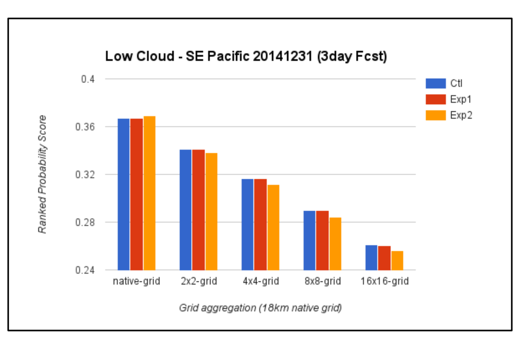
Experiments

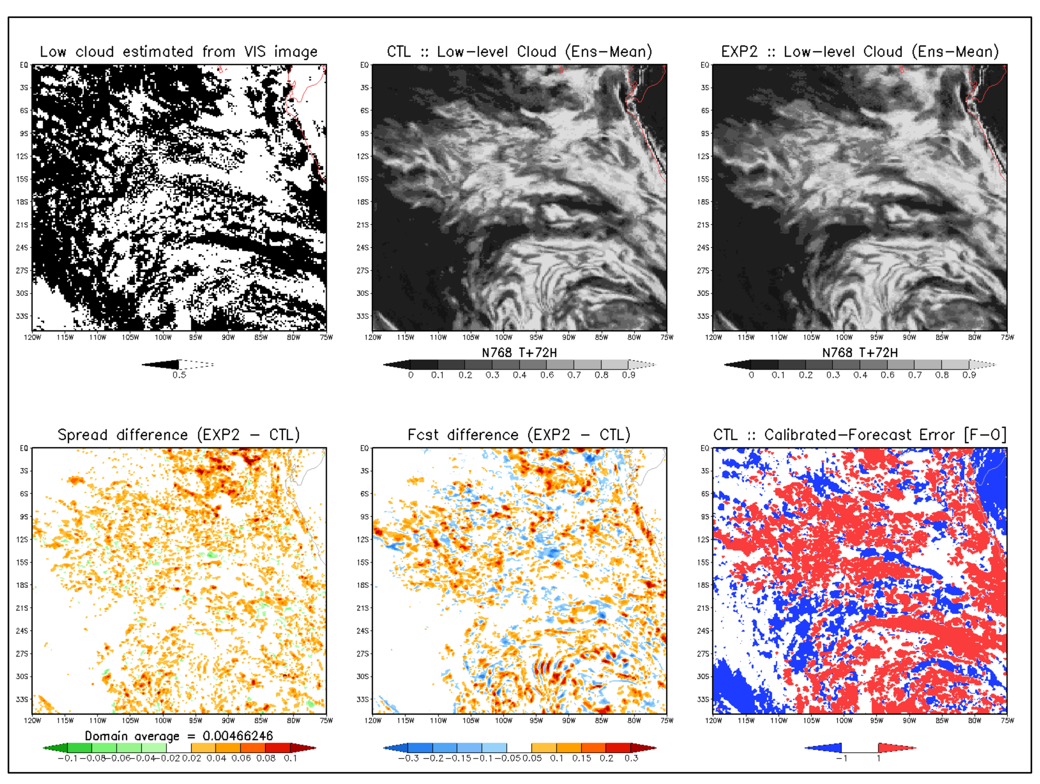
The parameters perturbed in this study (Table 1), focus on sub-grid scale and knowledge uncertainty of cloud properties. RHCrit specifies the level of saturation (critical humidity) where large-scale clouds form, a lower value increases cloud. Fractional standard deviation (FSD) controls the magnitude of subgrid cloud variability. An increased FSD makes clouds more transmissive. The convection scheme uses an entrainment coefficient to control the amount of dry air entrained into convective clouds. An increased value dilutes clouds with more dry air.

This work considers a case study where a 25-member ensemble was run at different resolutions starting 12Z 28-Dec-2014 out to five days. The only perturbations used in this experiment were generated by the RP2 (control) and RP3 schemes, i.e. without initial condition perturbations.

Stratocumulus Cloud – SE Pacific Ocean

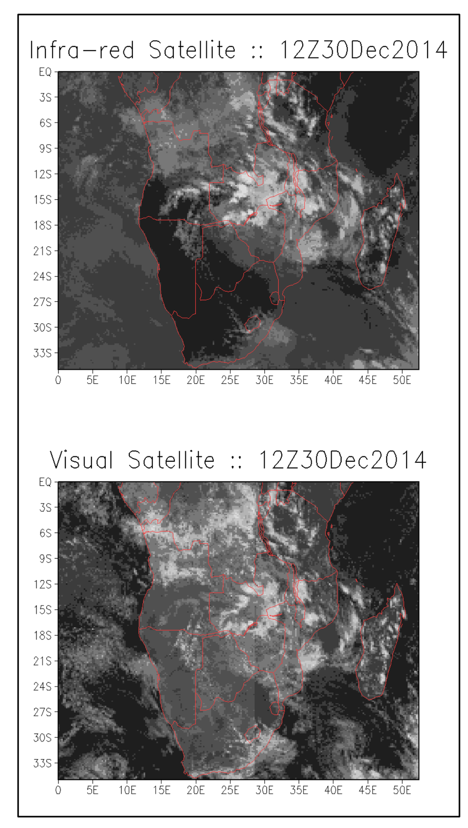


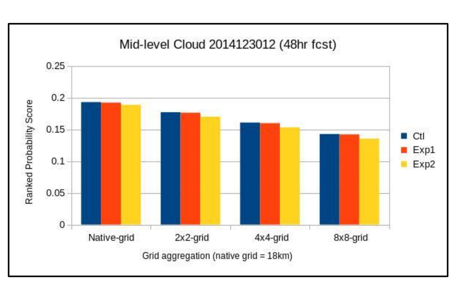


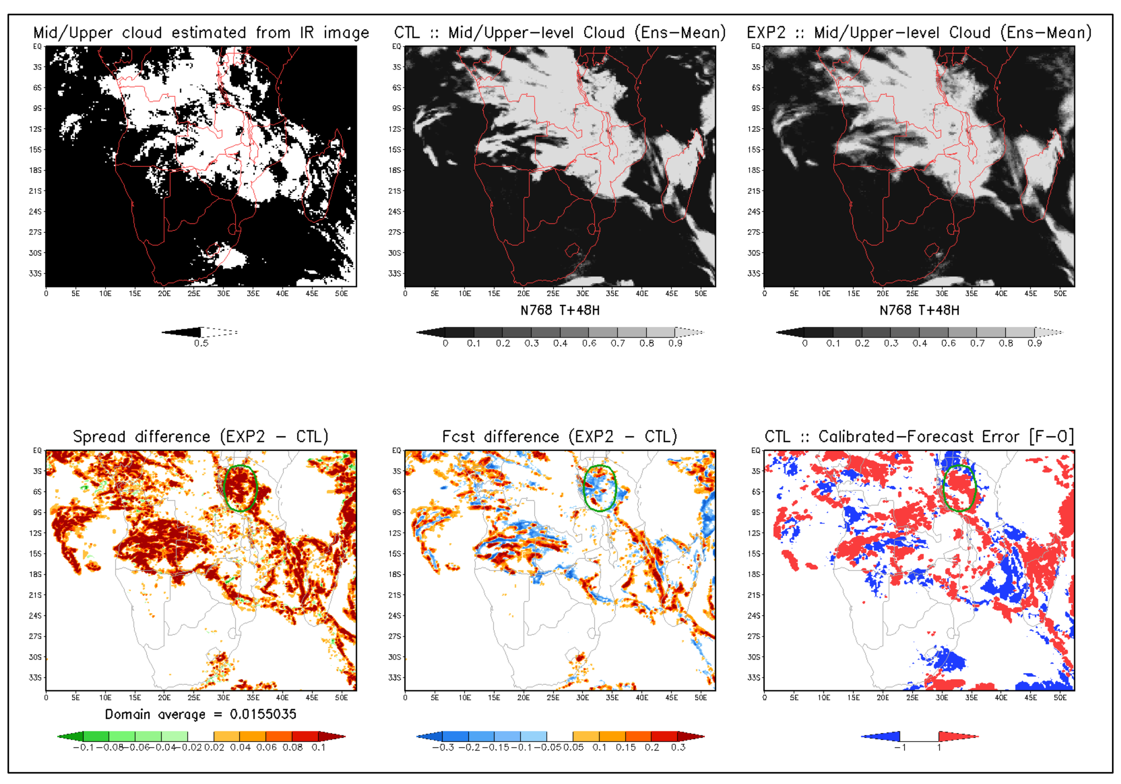


The southeast Pacific is often characterised by stratocumulus cloud that forms near the top of the marine boundary layer (top left). This type of cloud is typically poorly represented by forecast models. In this study the 3-day forecast cloud appears too diffuse (top right). The RP3 scheme does indeed increase forecast spread of the low-level cloud in the ensemble relative to the RP2 scheme (bottom right). Since the observed cloud field is speckled, it is important that verification considers aggregating the grid-points of both the forecast and the observations, because a single misplaced cloudy pixel will be double counted as incorrect, despite the overall pattern looking reasonable. When the neighbourhood method is used, the RP3 scheme does out-perform the original RP2 scheme (bottom left).

Deep Convective Cloud – Africa







Deep convection occurs daily in southern Africa during the Austral summer. In this study the 18km model has simulated the mid- and upper-level cloud well at 48-hours lead-time. However, there are still errors and it is encouraging to see the RP3 scheme showing increased spread over most areas, but most importantly often co-located with larger forecast errors. There is also some evidence of reduced forecast error, e.g. as shown by the green circle (bottom right). Increased neighbourhood verification improves the RPS, with the spatially-varying entrainment rate showing the best results.

Conclusions

A spatially varying random-parameters scheme does show potential to improve the spread of short- and medium-range forecast ensemble systems. In the case study shown, this increase in spread is often in the area of largest forecast error. The scheme also helps reduce some of the forecast error of the ensemble mean. These early positive results suggest that it is worthwhile to pursue research into spatially-varying perturbed parameter schemes.

References

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