Representing model uncertainty using the multiparametrization method

L.Descamps, C. Labadie and E. Bazile

Centre National de Recherches Météorologiques
Toulouse, France
laurent.descamps@meteo.fr

ABSTRACT

Model error is now recognize as an important source of uncertainty in Numerical Weather Prediction. Several approaches have been proposed to represent model uncertainty in Ensemble Prediction Systems. The multi-parametrization technique is based on the use of several physical parametrization schemes in the same forecast model to account for model errors. After a short description of the multiparametrization approach basis, its implementation and effects on the Météo-France Ensemble Prediction System are addressed.

1 Introduction

Probabilistic prediction, in the form of ensemble prediction, has now become an important component of Numerical Weather Prediction. Ensemble prediction consists of performing in parallel a number of numerical forecasts, the dispersion of the forecasts being taken as an estimate of the uncertainty on the future state of the atmosphere. The two main sources of forecast uncertainty are initial condition error and model error. Model error can arise from parameter and parametrization deficiencies or misrepresentation of subgrid scale processes. Since a few years several attempts have been made to represent model uncertainty in ensemble forecasting systems (EFS). Up to now there is no unique approach the scientific community has agreed upon. Some have promoted stochastic dynamical approaches to represent model uncertainty due to unrepresented sub-grid processes (Palmer 2001). Others have suggested to stochastically perturb the physics tendencies (Buizza et al. 1999), the use of parameter variations in the physical packages (Stainforth and coauthors 2005) or multiple physics schemes (thereafter multiparametrization approach, (Murphy et al. 2004, Houtekamer et al. 1996)) to account for parametrization uncertainty. It has also been shown that the multimodel approach could be an efficient alternative to account for model uncertainty (Hagededorn et al. 2005).
The present paper presents a short overview of the multiparametrization method and its impact on an operationnal global Ensemble Prediction system (EPS) . The basics of the approach are remind in section 2. Section 3 briefly presents the EPS of Météo-France and the implementation of the multiparametrization technique in this operational system. Using classical probabilistic scores, section 4 shows the impact of the approach on EPS skill. A summary and a brief discussion are given in section 5.

2 The multiparametrization approach

The multiphysics approach assumes that the major part of forecast error is linked with the underlying assumptions required to parametrize the subgrid scale processes. Therefore, it promotes the use of a variety of physical parametrization schemes in the same forecast model to account for model uncertainties. For a particular physical phenomenon, for example shallow convection, a wide variety of parametriza-

tion schemes have been developped and proposed in the past decades by the scientific community to properly represent it in a numerical model. The schemes differ on how convection and its effect on the flow are represented. None of them is perfect but the variety of the schemes could be view as a sample of the uncertainty in the representation of the physical phenomenon.
An important underlying assumption of the multiparametrization approach is that the different schemes should produce different evolutions of the atmosphere but with comparable global skill. On a day to day basis the differences between forecasts based on different parametrization schemes should reflect the uncertainty of the flow evolution while over a long period of time the different forecasts should have the same statistical skill.
This point has been for example verified in a 1997 paper of Wang and Seaman. Using the MM5 Mesoscale model (Dhudia 1993), the authors compare four cumulus parametrization schemes for six different precipitation events over the United States of America. They show that on a case to case basis the different schemes produce different evolutions of the convective activity. Concerning the general skill of the schemes they conclude that 'None of the schemes consistently out performs the others by a wide margin or in all measures of skill'.

2.1 Effectiveness of the multiparametrization approach

The effectiveness of the multiphysics approach has been confirmed in several studies. For global Ensemble Prediction System (EPS), Houtekamer et al. (1996) and Charron et al. (2010) show that it has a positive impact on the Canadian EPS skill. Houtekamer et al. show that the use of multiphysics increases by about 20% of the ensemble spread. Charron et al. (2010) note that it has a positive impact on the reliability component of the Brier Skill Score (BSS) for 24h rainfall and mid-tropospheric temperature. Focusing on strong convective events, Stensrud et al. (2000) and Jones et al. (2007) show that the use of multiple parametrization schemes in a Mesoscale Local Area Model-EPS has a positive impact on forecast skill, especially when large-scale forcing is weak.
In a recent paper, Berner et al. (2011) used two 10 members Short-Range EFS with a Mesoscale model over the United States of America. One ensemble uses multiparametrization approach, the other uses Spectral Kinetic Energy Backscatter technique (SKEB). The authors conclude that SKEB outperforms multiparametrization technique for upper air variables. For near-surface variable, multiphysics approach outperforms SKEB. The best performing ensemble system is obtained by combining the two approaches (this last point has also been pointed out by Charron et al. (2010) and Hacker et al. (2011)).

3 The PEARP system

PEARP (Prevision d'ensemble ARPege) is the operationnal EPS of Météo-France. PEARP uses the ARPEGE model (courtier et al. 1991) with an horizontal spectral truncation of T538 and a stretching factor of 2.4 (variable horizontal resolution with a maximum of 15km over France). There are 65 levels on the vertical with a top level at 50km. The ensemble size is 35 members including a control 'unperturbed' member, which is a 'coarser resolution' version of the deterministic operational ARPEGE forecast, and 34 perturbed members centered around the control one. PEARP is running twice a day at 06UTC (72h forecast range) and at 18UTC (108h forecast range).

3.1 Initial perturbations

The initial perturbations of PEARP are built by combining a small ensemble data assimilation system (AEARP) with Tl95 singular vectors (SVs). The SVs are computed over 7 different areas (EU-

RAT (30N/80W/65N/40E), the complement of EURAT over Northern hemisphere, Southern hemisphere (30S/90S) and four tropical areas where cyclonic activities is likely to occur), with different optimization times (18h for Europe and Tropical areas, 24h for all other) and norms (Kinetic Energy norm for Tropical SVs, dry Total Energy norm for all other).

3.2 Model error

In PEARP, the multiphysics approach is used with a set of 10 differents physical parametrizations sets, including the ARPEGE operational physical package (see table 1). We consider two different vertical diffusion schemes : the Louis scheme (Louis 1979 thereafter L79), and a prognostic Turbulent Kinetic Energy scheme (TKE, cuxart et al. 2000, Bazile et al. 2008, Bouteloup et al. 2009). For shallow convection we use the 'modified Richardson number' formulation proposed by Geleyn (1987 thereafter G87) or a mass flux scheme (thereafter KFB approach) written by Bechtold et al. (2001) based on a CAPE closure with an updraft derived from Kain and Fritsch (1993). For deep convection we use the Bougeault mass flux scheme with the orginal closure on the moisture convergence (1985, thereafter B85) or the CAPE formulation. For computing oceanic fluxes we consider the classical Charnock formulation (Charnock 1955, thereafter C55) and the ECUME (Exchange Coefficients from Multi-campaigns Estimates) scheme (Belamari 2005).
Slightly modified version of some schemes are also used. In $CAPE_{mod}$ and $B85_{mod}$ deep convection is allowed only if cloud top is above 3000m. In TKE_{mod}, the parametrization is used without horizontal advection. In $ECUME_{mod}$, ECUME is used with a modified tuning for the exchange coefficient for the humidity to reduce the evaporation over the sea.
An objective deterministic evaluation of each of the combination has been done. Over two one-month periods (March 2008 and December 2010) and for different variables (500hPa geopotential height, 850hPa temperature, 850hPa wind speed, mean sea level pressure, 24h precipitation) it has been verified that, as assumed in the multiparametrization approach, the different combinations have similar global skills.

number	diffusion scheme	shallow convection	deep convection	oceanic fluxes
ref	TKE	KFB	B85	ECUME
001	L79	G87	B85	C55
002	L79	KFB	$CAPE_{mod}$	ECUME
003	TKE	KFB	B85	$ECUME_{mod}$
004	L79	KFB	$B85_{mod}$	C55
005	L79	G87	CAPE	C55
006	L79	G87	CAPE	ECUME
007	L79	KFB	$CAPE_{mod}$	C55
008	TKE_{mod}	KFB	B85	ECUME
009	TKE	KFB_{mod}	B85	$ECUME_{mod}$

Table 1: Physical parametrizations used in PEARP, see section 2 for details.

4 Impact of the multiparametrization approach on PEARP

Using classical probabilistic scores, impact of the multiparametrization approach on PEARP skill has been evaluated. Two PEARP configurations have been running : a reference system (REF) which does not include any technique for taking into account model error and another one (MUP) which include the

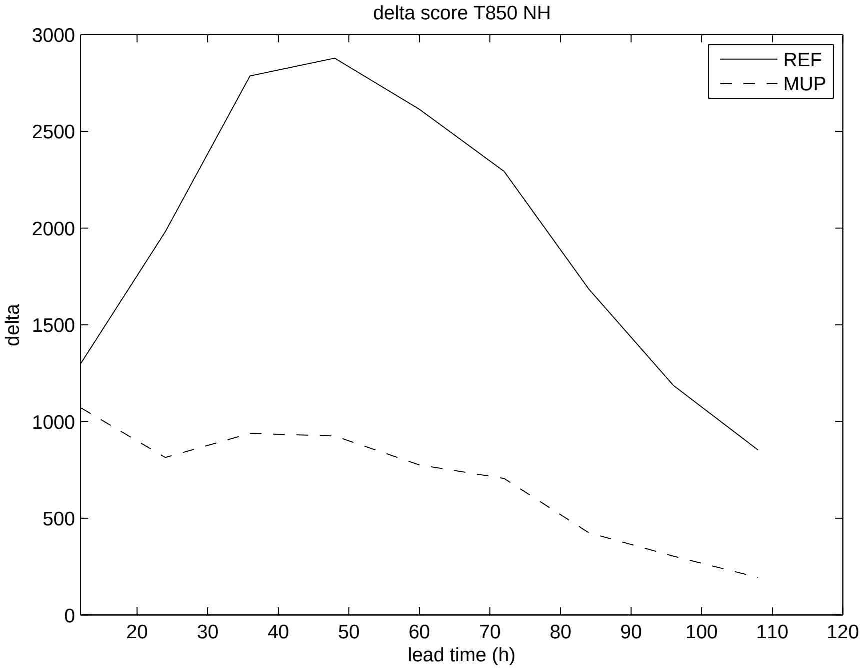

Figure 1: Evolution of the δ score, as a function of lead time, for 850hPa temperature, for two expermients: REF (solid line) and MUP (dash line).

multiparametrization approach.
Scores have been computed over two one-month periods (March 2008, December 2010) for synoptic scale variables (850hPa temperature, 500hPa geopotential height, 850hPa wind speed, mean sea level pressure) and local weather variables (24h precipitation, 10 meter wind speed). For synoptic scale variables scores have been computed against ARPEGE analysis. For local weather variables SYNOP observations have been used as the reference.

Figure 1 shows the time evolution of the δ score for 850hPa temperature over Norhtern Hemisphere (20N/90N) comPuted over March 2008. The δ score is a measure of the effective flatness of the rank histogram (Candille and Talagrand 2005). The rank histogram is a measure of the reliability of an EPS: the flatter the histogram (the lower the δ score), the better the reliability.
It can be seen that the MUP experiment has a significantly better score than the REF experiment. For the REF experiment, the increase of the δ score between 24h and 72h is caused by a systematic negatif biase of the forecasts ('J shape' rank histograms, not shown). In the MUP experiment, the use of different physical packages which have different biases (positive or negative) allows to obtain flatter histograms and a natural decrease of δ score with forecast lead time.
Using the multiparametrization approach greatly improves the reliability of PEARP for 850hPa temperature. The same results (not shown) have been found for other variables and for other measure of reliability such as the reduced centered random variable (Candille et al. 2007).

Figure 2 shows the time evolution of the Brier Skill Score (BSS) for 10-meter wind speed over an Europe-Atlantic area (20N/60W/72N/40E) computed over December 2010. The event used to compute BSS has, over the verification period, a climatological frequency of 0.5. The BSS is a positively oriented score: the higher the BSS, the better the resolution of the system. It can be observed that the MUP

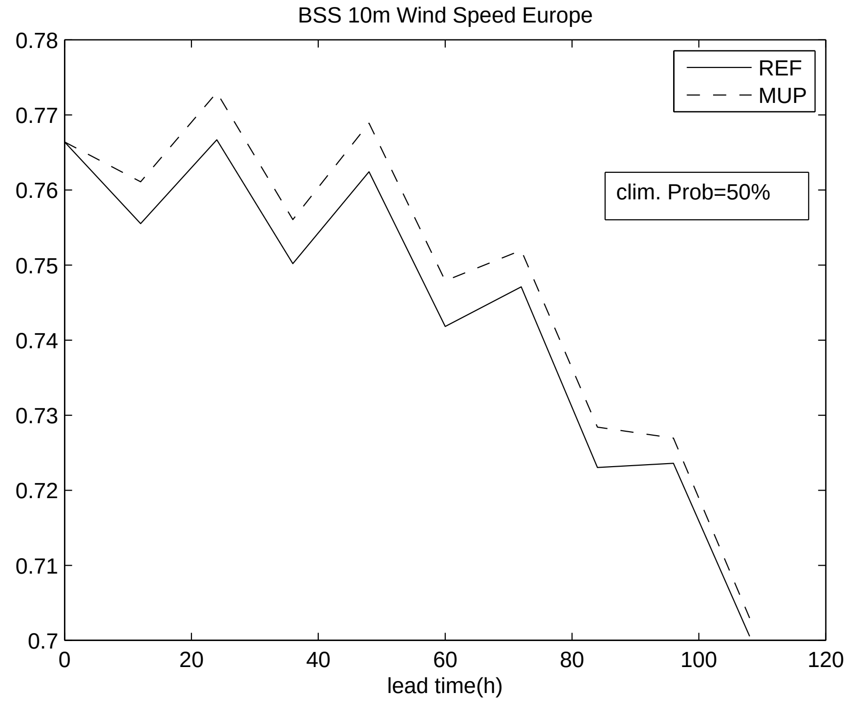

Figure 2: Evolution of the Brier Skill Score, as a function of lead time, for 10m wind speed, for two expermients: REF (solid line) and MUP (dash line).

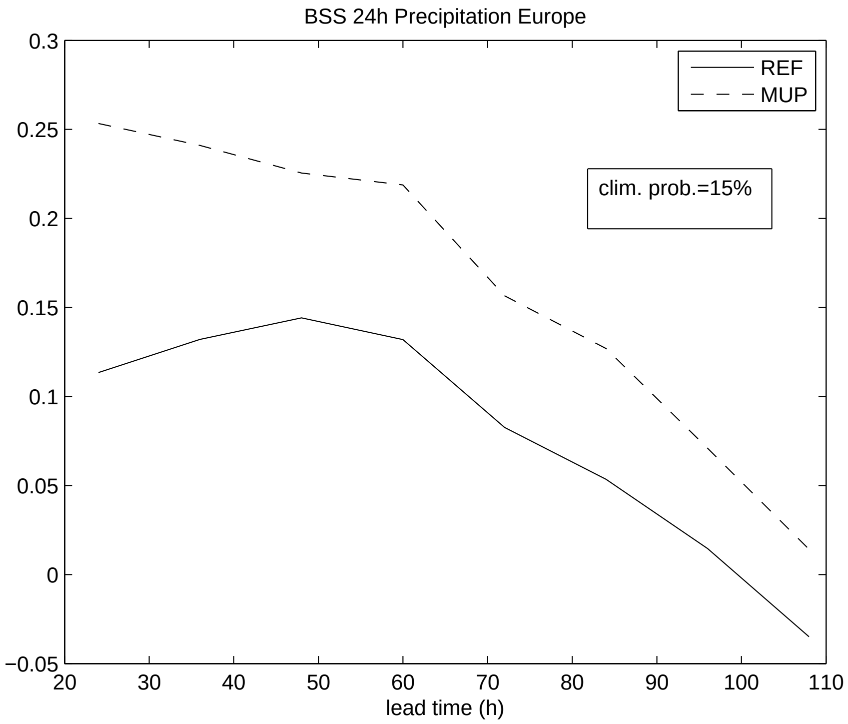

Figure 3: Same as Fig2 but for 24h precipitation.

experiment obtains better score than the REF one.
Computed over the same verification period and the same Europe-Atlantic area, figure 3 shows the time evolution of the Brier Skill Score (BSS) for 24h precipitation. The event used to compute BSS has, over the verification period, a climatological frequency of 0.15. As for figure 2 it can be seen that the use of multiparametrization significantly improve the resolution of PEARP.

For a wide range of variables and the two periods of verification used in this study, the MUP system shows better scores than the REF system (not shown). The general conclusion is that the use of the multiparametrization approach has a positive impact on the skill of the PEARP system. The positive impact is more pronounced on the reliability of Mid-Tropospheric temperature and precipitation.

5 Summary and discussion

Since a few years model error has been recognized as an important source of forecast uncertainty. Differing on the views of the nature of model error, several techniques have been proposed to represent it in EPS. The multiparametrization approach is based on the idea that most of forecast error is due to the assumptions used to develop the parametrization schemes in the Numerical Weather Prediction models. Therefore, it suggests the use of a wide range of physical parametrization schemes in the same Numerical Weather prediction System to sample model uncertainties. It implicitly assumes that the different schemes could produce different evolutions of the atmosphere while having the same global skill. The effectiveness of the multiparametrization approach has been demonstrated in a wide range of studies.

Most of papers show that using multiparametrization technique for LAM as for global EPS improves the skill of the systems. This has been confirmed in this paper for the global EPS of Météo-France. Implementing multiparametrization has greatly improved PEARP reliability and resolution.

As stressed in Charron et al. (2010) a pratical drawback of multiparametrization approach is that the maintenance of several state-of-the-art subgrid parametrizations packages within the same NWP model is very challenging. The recent development of calibration techniques and its need for reforecast data sets (Hagedorn et al. 2008, Hamill et al. 2008) potentially raises another practical problem. Using a single reforecast data set may not be sufficient to properly calibrate an EPS that uses multiple sets of parametrization schemes. One may need a reforecast data set for each of the physical package to properly represent the global behavior of the system. This could greatly increase the numerical cost of the calibration procedure.

The use of stochastic techniques could be a costless alternative to multiparametrization approach. Recent studies (Hacker at al. 2011, Palmer et al. 2009, Berner et al. 2011) have proven their ability to produce, for synoptic-scale variables, similar or better probabilistic skill than multiparametrization approach. An interesting outcome of these works is that combining stochastic-dynamic techniques with multiparametrization approach yield to the most skillfull EPS. The authors (Berner et al. 2011) argue that different model-error approaches could represent fundamentally different forms of model error.

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