IDŐJÁRÁS

Quarterly Journal of the Hungarian Meteorological Service
Vol. 119, No. 2, April – June, 2015, pp. 241–265

Application of the AROME non-hydrostatic model at the Hungarian Meteorological Service: physical parameterizations and ensemble forecasting

Balázs Szintai[1]*, **Mihály Szűcs**[1], **Roger Randriamampianina**[2], and **László Kullmann**[1]

[1] *Hungarian Meteorological Service,*
Kitaibel Pál u. 1., H-1024 Budapest, Hungary

[2] *Norwegian Meteorological Institute*
P.O. Box 43, Blindern, N-0313 Oslo, Norway

**Corresponding author E-mail:szintai.b@met.hu*

(Manuscript received in final form November26, 2014)

Abstract—At the Hungarian Meteorological Service (HMS), the AROME non-hydrostatic numerical weather prediction model has been running operationally since the end of 2010. The horizontal resolution is 2.5 km, thus it is assumed that deep convection is explicitly resolved. To achieve this, apart from increasing the horizontal and vertical resolution of the model, advanced physical parameterizations have to be applied. In this paper, some recent developments in connection with dynamics and physical parameterizations performed at the HMS are described. Model sensitivities related to horizontal diffusion, microphysics, turbulence, and shallow convection are discussed. Main features of the applied surface scheme "SURFEX" are highlighted as well as developments in connection with the prognostic treatment of vegetation. Recent work focusing on high resolution probabilistic forecasting with the AROME model is also summarized. It is shown that the AROME model is able to adequately predict severe weather events, however, as resolution increases, the importance of a probabilistic forecasting approach increases. An initial condition perturbation method and a model error representation scheme are described and their impact in an AROME-EPS test configuration is also presented.

Key-words: numerical weather prediction, physical parameterization, semi-Lagrangian horizontal diffusion, convection permitting ensemble system

1. Introduction

Thanks to the fast evolution in computing technology, more national numerical weather prediction centers can run models with increased resolutions. Using high-resolution models is very important in predicting fast-developing and intense atmospheric events. Good prediction of such hazardous events can protect lives and properties. Hence, investing in development of such models is very important for environmental and societal protection.

Hungary, together with several other European countries, has been participating in the ALADIN (Aire Limitée Adaptation Dynamique Développement International) consortium since 1991. The ALADIN consortium was initiated by France. The aim of this consortium is to develop a short-range limited-area numerical weather prediction (NWP) model. As a result of this collaboration, the ALADIN/AROME model family has emerged and is constantly being developed in the participating countries.

At the beginning of the ALADIN collaboration, the ALADIN model was a hydrostatic NWP model and was designed to run at relatively coarse horizontal resolutions (i.e., not higher resolution than 8 km), where the hydrostatic approximation (vertical acceleration of air is neglected) is valid. By the beginning of the new millennium, it became possible to run operational non-hydrostatic models at a horizontal resolution of 2–3 km. At Météo-France, the AROME (Application of Research to Operations at Mesoscale) project was initiated in 2002 with the aim to develop a non-hydrostatic NWP model running at 2.5 km horizontal resolution (*Seity et al*., 2011). The AROME model has three main components: the non-hydrostatic ALADIN dynamical core (*Bubnová et al*., 1995; *Benard et al*., 2010), the atmospheric physical parameterizations, which are taken from the French Meso-NH research model (*Lafore et al*., 1998), and the SURFEX surface model (*Le Moigne et al*., 2009). A mesoscale data assimilation system with a three-dimensional variational (3D-VAR; *Fischer et al*., 2005) scheme for the upper-air and an optimum interpolation (OI) technique for the surface analysis provides reliable initial condition for the AROME model.

The AROME model is now used in several countries of the ALADIN and HIRLAM (HIgh Resolution Limited Area Model) consortia. At the Hungarian Meteorological Service (HMS), work related to the AROME model started in 2006. After five years of scientific and technical development, the AROME model became operational in December 2010. In the beginning of the operational implementation, the model ran four times a day (at 00, 06, 12, and 18 UTC) at a horizontal resolution of 2.5 km, and provided forecasts up to 48 hours for a domain covering the Carpatian Basin (*Fig. 1*). The initial conditions were provided by the ALADIN/Hungary (Hereafter ALADIN/HU) limited area model (LAM) (*Horányi et al*., 1996), while lateral boundary conditions are obtained from the ECMWF/IFS (European Centre for Medium-

Range Weather Forecasts / Integrated Forecast System) model. The ALADIN/HU model has its own three-dimensional variational (3DVAR) data assimilation system (*Bölöni*, 2006, *Randriamampianina,* 2006), which is partly inherited by the AROME model. The AROME assimilation system, using only conventional observations, was operationally implemented in March 2013 (*Mile et al*., 2014). The short-range forecasts of AROME are mainly used by the forecasters of HMS to produce early warnings of severe weather events. Furthermore, products derived from AROME are utilized by wind energy farms to plan their production.

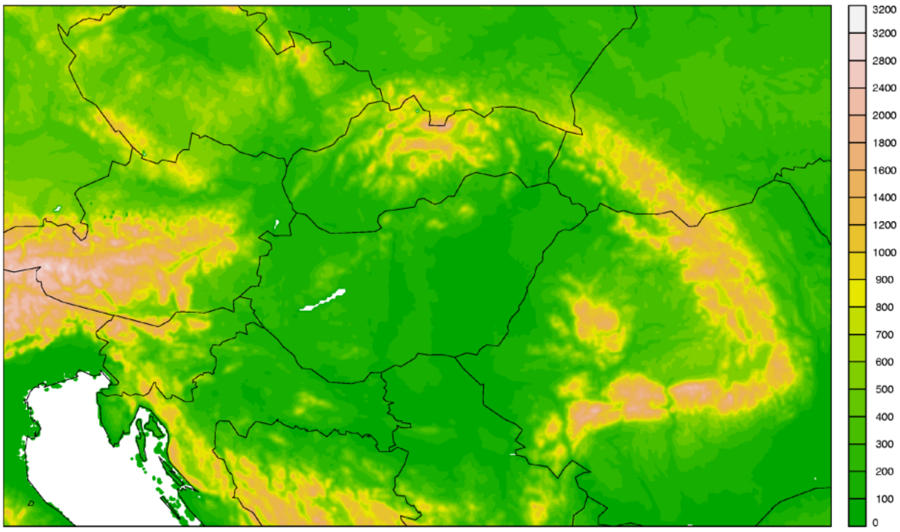

Fig. 1. Domain and orography of the AROME model as run operationally at the Hungarian Meteorological Service.

The aim of this paper is to present recent developments of the AROME model performed at HMS regarding dynamics, physical parameterizations, and ensemble prediction. In Section 2, the dynamical core of the model is briefly described and developments related to horizontal diffusion are presented. In Section 3, an overview of the physical parameterizations applied in AROME is given, together with the description of certain developments related to the turbulence parameterization and surface processes. Section 4 presents new developments regarding non-hydrostatic probabilistic forecasting. Finally, results are summarized in Section 5.

2. Dynamics

At horizontal mesh sizes at or below two kilometers, vertical accelerations could be of the order of the gravitational acceleration (g) and cannot be neglected any more, thus the hydrostatic approach is not recommended. Consequently, a new equation has to be carried for the vertical momentum in the non-hydrostatic dynamical cores. The advantage of this approach is that certain atmospheric phenomena (like deep convection or orographic gravity waves) are resolved explicitly by the model, therefore no parameterization of these processes is required. The AROME model uses the non-hydrostatic dynamical core which was developed by the ALADIN consortium (*Bubnová et al*., 1995).

The application of high resolution atmospheric models is a computationally demanding task, due to the increased number of grid points, the additional equation for vertical momentum in the dynamical core, and the increased complexity of certain parameterization schemes (e.g., microphysics). These requirements are only partly compensated by the fact that the deep convection scheme could be switched off in the model. In the case of the AROME model, this high computational demand is tackled by the application of advanced and efficient numerical schemes. AROME is a spectral model, which means that in the dynamical part of the model, the prognostic equations are handled in spectral space, which enables a fast computation of horizontal derivatives. Regarding the time integration, a very efficient semi-implicit, semi-Lagrangian time integration scheme is applied in AROME. This scheme permits a rather long time step even at fine horizontal resolutions. In the current operational version at the HMS, a time step of 60 s is used in AROME at 2.5 km horizontal resolution. This is approximately five times larger than the time step applied in other widely used non-hydrostatic models.

2.1. Horizontal diffusion

In current mesoscale NWP models, one dimensional physical parameterizations are applied. The reason for this is that above 1 km horizontal resolution, vertical gradients of meteorological variables are much larger than the horizontal gradients. However, due to numerical stability constraints, it is necessary to ensure a horizontal communication of grid cells. Apart from advection, this can be realized by the application of a numerical horizontal diffusion filter operator. In the case of the ALADIN/AROME model family, there are two main options for numerical horizontal diffusion. The first one is the spectral diffusion which is calculated in spectral space and consequently acts on the full model domain. The second option is the semi-Lagrangian horizontal diffusion (SLHD, *Vána et al.*, 2008), which is calculated in grid point space as a function of wind deformation, hence it has a physically based and more local effect. It is important to note that in the AROME model, SLHD is used in combination with the spectral diffusion. In fact, next to SLHD, two other spectral diffusion operators are used: a fourth order spectral diffusion which acts mainly at the upper part of the model domain to prevent the reflection of gravity waves from the model top and a sixth order spectral diffusion to filter noise due to orography.

At HMS, several experiments have been done in connection with SLHD. The main goal of these experiments was to tackle some known deficiencies of the AROME model during convective conditions (e.g., too strong updrafts, too high precipitation peaks in the cells, too strong gust fronts). In the original configuration, SLHD is applied to all (falling and non-falling) hydrometeors. The experiment presented here is based on the work of *Bengtsson et al*. (2010). SLHD is applied only to non-falling hydrometeors, and additionally it is also applied to the dynamical fields (wind, temperature, and humidity) and turbulent kinetic energy (TKE). Characteristics of the fourth order spectral diffusion have also been changed: while in the original configuration spectral diffusion acts on all levels (although with increasing intensity upwards), in the experiments spectral diffusion was only applied above 100 hPa. *Fig. 2* presents the impact of SLHD changes on a convective event. With the new SLHD configuration, the AROME simulation is closer to observations: the intensity of convective precipitation is reduced, convective wind gusts are weaker and the number of convective cells is decreasing. Apart from case studies, the new SLHD settings were tested on longer summer and winter periods, and the forecasts were compared against the surface (SYNOP) observations and radar-based precipitation data. Verification scores against SYNOP data show a clear improvement in the wind speed, wind gust, and cloudiness forecast, while the impact on temperature and humidity is neutral (*Fig. 3*). The diurnal cycle of convective precipitation is also improved, as the overestimation in the late afternoon is decreased (*Fig. 4*).

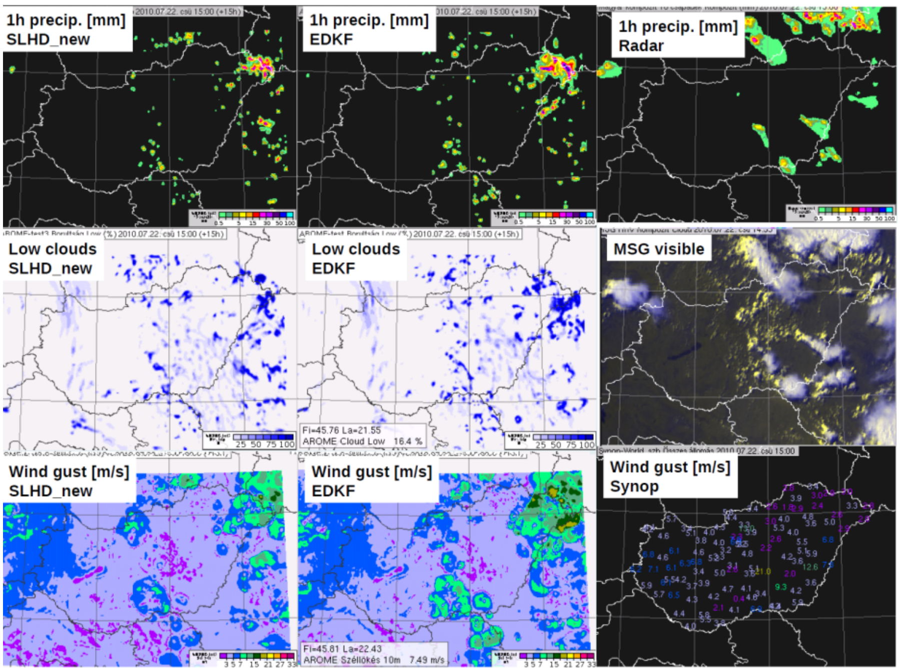

Fig. 2. Forecasted fields of two AROME experiments and measurements for July 22, 2010, at 15 UTC (+15 h forecasts). Left column: AROME with new SLHD settings, middle column: AROME with original SLHD settings, right column: measurements. First row: hourly precipitation, second row: low cloud cover, third row: hourly maximum wind gust.

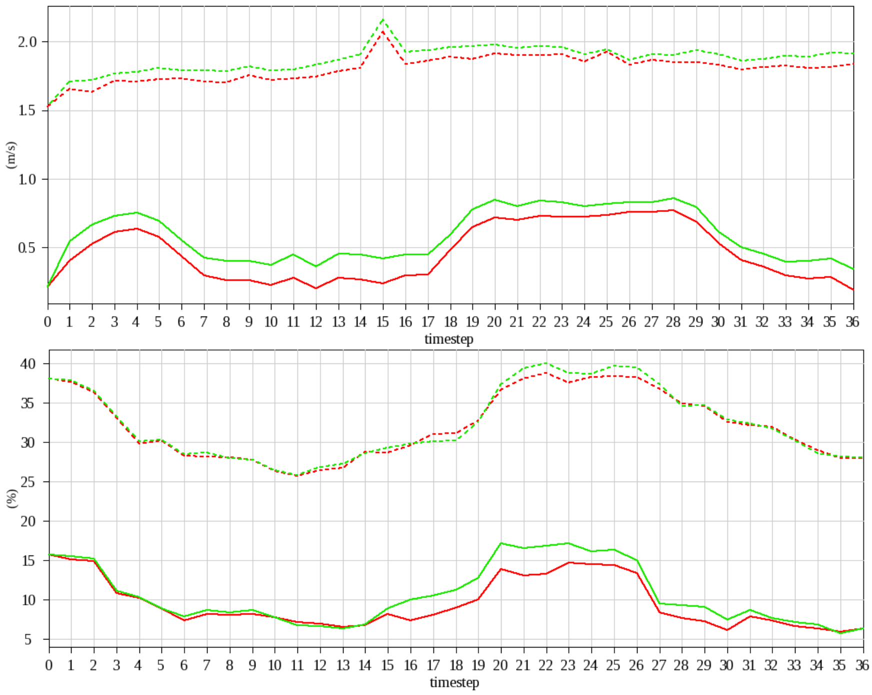

Fig. 3. Verification scores for the period between May 1, and June 1, 2013 as a function of lead time (in hours). Upper panel: 10-meter wind speed, lower panel: cloudiness. Green line: original SLHD settings, red line: new SLHD settings. Dashed line: root mean square error, solid line: bias. Always the 00 UTC forecasts were verified against low-altitude (station altitude below 400 m) SYNOP observations above sea level on the operational AROME domain.

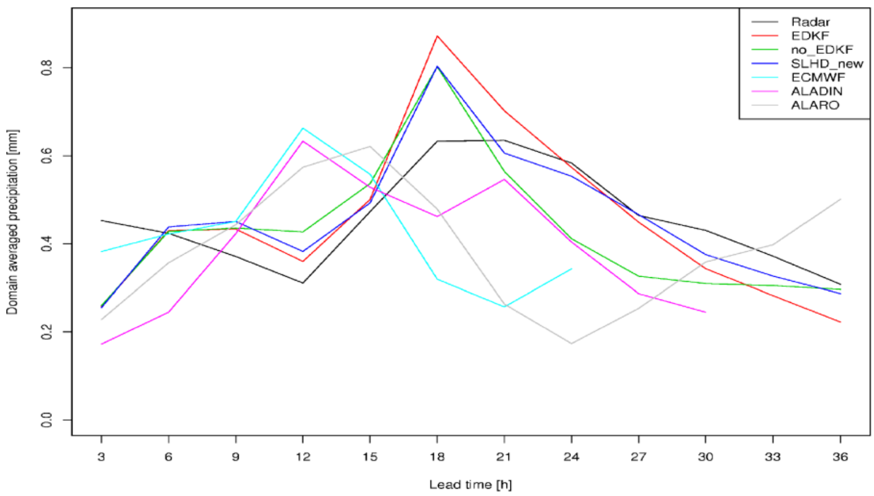

Fig. 4. Observed (radar) and predicted diurnal cycle of convective precipitation (area averaged precipitation on the AROME domain) for the period between July 17 and August 17, 2010. AROME experiments mentioned in the text: green: without EDKF parameterization and original SLHD settings; red: with EDKF parameterization and original SLHD settings; blue: with EDKF parameterization and new SLHD settings. Forecasts of the 8 km resolution limited area regional model run at the Hungarian Meteorological Service with two different physical parameterizations (ALADIN and ALARO) and of the ECMWF model are also indicated.

3. Physical parameterizations

Numerical weather prediction models are not able to resolve explicitly those processes which are smaller than the grid scale of the model, thus these processes have to be parameterized. Parameterization means the description of the overall effect of a given subgrid scale process on the grid scale values, using the given grid scale variables. The AROME model uses the physical parameterizations of the Meso-NH French research model. In the following, an overview is given on the components of this physical parameterization package, and the corresponding developments performed at HMS are described.

3.1. Microphysics

Phase changes occurring in clouds are described by the microphysical parameterization. In convection permitting NWP models, the choice of the microphysical scheme is of great importance. As these models do not apply a deep convection parameterization, the convective cloud should explicitly be simulated by the model, and thus the non-hydrostatic dynamical core and the microphysical parameterization play a crucial role. Consequently, the microphysical scheme has to be rather sophisticated to be able to simulate all the relevant processes during a lifetime of a convective cloud.

In AROME, the so-called ICE3 scheme (*Pinty* and *Jabouille*, 1998) is used, which carries six prognostic microphysical variables (vapor, cloud water, cloud ice, rain, snow, graupel), and describes the phase change processes among these variables. In the AROME model this means 35 processes: warm-cloud and mixed-phase processes are distinguished. Warm-cloud processes are autoconversion, accretion, evaporation, sedimentation, while mixed-phase processes are nucleation, ice-crystal autoconversion, aggregation, raindrop contact freezing, riming, melting, deposition, Bergeron-Findeisen effect, and ice-crystal sedimentation. The ICE3 scheme is a bulk one-moment scheme. This means that the mixing ratio of each hydrometeor is written as the third momentum of the size distribution of the given hydrometeor. The advantage of this approach is that the microphysical processes become analytically resolved processes. It has to be noted that a new two-moment microphysical scheme is currently under development in Meso-NH and is planned to be available in AROME soon. Next to the mixing ratios, this scheme handles the number concentration of hydrometeors prognostically as well.

Several tests were performed in connection with the initialization of the hydrometeor fields in the microphysics parameterization at the Hungarian Meteorological Service. The problem regarding hydrometeors is that these variables are not measured regularly, thus it is not possible to initialize these model fields based on measurements in an operational setting. In the early years of AROME development, it was considered that the formation of hydrometeors is a relatively fast process, and consequently, it is possible to initialize these fields with zero. It was assumed that if the initial temperature and humidity fields are correct, then the hydrometeors would form within a couple of time steps. As a contrary to this assumption, case studies showed that if the hydrometeors are initialized with zero, then precipitation events could be missed by AROME in the early hours of the forecast. To overcome this problem, the following procedure was applied: the hydrometeors are "cycled" from the previous run, so, e.g., the initial hydrometeor fields of an AROME forecast starting at 06 UTC are the +6 h forecasted hydrometeor fields of the 00 UTC AROME forecast. With this approach, several previously missed precipitation objects could be well simulated by AROME (*Fig. 5*).

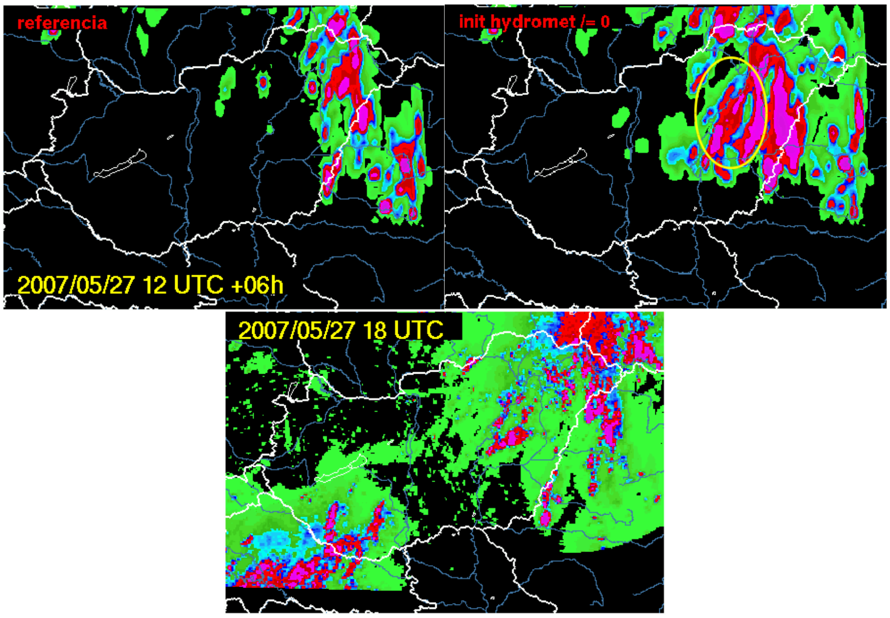

Fig. 5. Impact of hydrometeor initialization on the AROME forecast. Left: hydrometeors are initialized with zero; middle: hydrometeors are initialized from the 6 hour forecast of the previous run; right: hourly accumulated radar precipitation. A +6 h forecast of hourly precipitation is shown valid for 12 UTC, May 27, 2007.

3.2. Turbulence and shallow convection

Shallow convection refers to the warm updrafts (thermals) which originate from the surface and reach the top of the planetary boundary layer (PBL). These thermals are usually indicated by small non-precipitating clouds (Cumulus humilis). Boundary layer turbulence refers to those eddies which are generated either by wind shear (mechanical turbulence generation) or buoyancy, with a characteristic size much smaller than the depth of the PBL. Until recently, shallow convection was parameterized separately from boundary layer turbulence in NWP models, however, nowadays these two processes are handled in a unified way in several schemes.

In the AROME model, the eddy diffusivity – mass flux (EDMF) approach is followed to parameterize turbulence and shallow convection. The eddy diffusivity part of the parameterization uses the CBR scheme (*Cuxart et al.*, 2000) to describe the effect of boundary layer turbulence. This is a 1.5 order closure which carries a prognostic equation for the turbulent kinetic energy. The diffusion coefficients are then calculated based on TKE, a turbulent length scale and stability functions. In the AROME model, the length scale formulation after *Bougeault* and *Lacarrere* (1989) is applied. Originally, the CBR scheme has both one and three dimensional versions, however, currently the one dimensional version is applied in AROME. Based on recent experiments, it is assumed that a three dimensional turbulence scheme is not necessary above 1 km horizontal resolution (*Yann Seity* and *Rachel Honnert*, personal communication). The main drawback of the CBR scheme is that it is a local scheme, which means that turbulent fluxes at a given vertical level are determined by the local vertical gradients of wind and temperature at that level. Consequently, with a local turbulence scheme, it is not possible to reproduce the correct behavior of the convective boundary layer, which has a strong non-local nature: thermals originating at the surface result in considerable vertical transport in the middle part of the PBL, where the local vertical gradients are very close to zero. To resolve this problem, in the EDMF framework a mass flux parameterization is applied next to the CBR scheme.

In the AROME model, the mass flux parameterization of a shallow convection thermal is divided to two parts (*Pergaud et al.*, 2009). On vertical levels below the shallow convective cloud base, the parameterization of *Lappen* and *Randall* (2001) is used. This scheme is closed with the surface sensible heat flux, consequently, the entire mass flux part of the EDMF parameterization is inactive if the surface sensible heat flux is negative (stable conditions). Above the cloud base, the *Kain* and *Fritsch* (1990) parameterization is applied (this is why the EDMF parameterization is mentioned as EDKF in connection with the AROME model). The closure of this scheme is performed by taking the mass flux at cloud base from the parameterization of the non-cloudy part of the thermal. The cloudy part uses a diagnostic cloud scheme where the cloud fraction at a given level is proportional to the area fraction of the updraft.

At the Hungarian Meteorological Service, the impact of the EDKF parameterization on the overall performance of the AROME model has been investigated before the operational introduction of the scheme. As the scheme is only active during unstable conditions, largest impact was expected for summer convective events. *Fig. 6* shows the impact of EDKF on a summer convective case. Here, two AROME simulations are compared; one with EDKF, and a second one which parameterized turbulence and shallow convection separately (with the CBR and Kain-Fritsch schemes, respectively). The run without EDKF significantly overestimates the number of convective cells during early afternoon, while during the evening it fails to simulate the heavy thunderstorms (not shown here). Also, convection itself is initiated too early (around 8 UTC) in this experiment (see also in *Fig. 4*), and consequently, convective wind gusts are overestimated until the early afternoon hours.

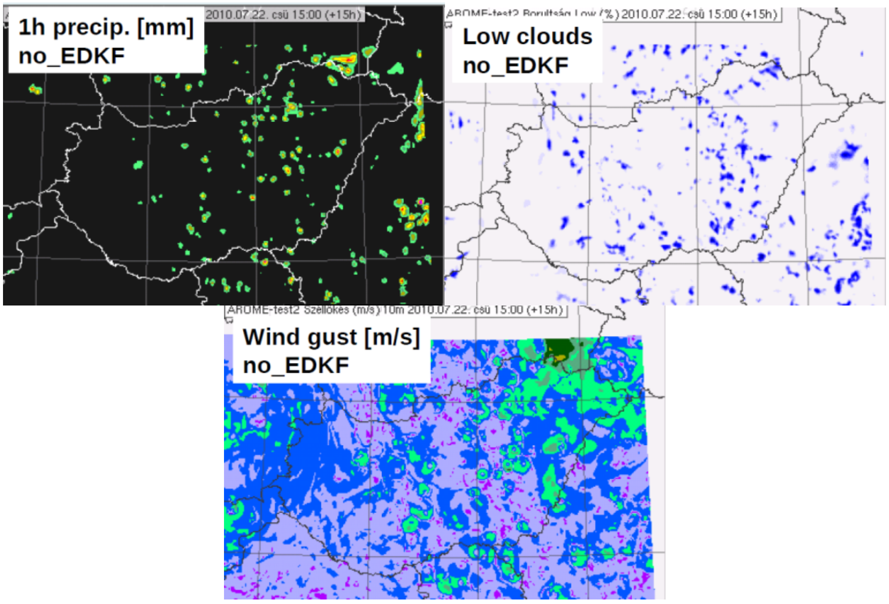

Fig. 6. Same AROME forecast of hourly precipitation, low clouds and wind gusts as in *Fig. 2*, but the EDKF parameterization is switched off, thus turbulence and shallow convection is parameterized separately (CBR scheme for turbulence and Kain-Fritsch scheme for shallow convection). Colour scales are the same as in *Fig. 2*.

3.3. Surface

Surface processes are calculated using the SURFEX (SURFace EXternalisée, *Le Moigne*, 2012) platform.

SURFEX uses the tiling approach: each grid point is divided into 4 different surface types (tiles): sea, inland water, town, and vegetated land. Each tile uses the same atmospheric forcing (air temperature, humidity, wind speed, long and shortwave radiation, pressure, precipitation), but the parameterizations are different and independent of each other. The resulting surface fluxes (momentum, sensible- and latent heat) are averaged according to the area fraction of the tiles and returned to the atmosphere. Surface parameters are determined by physiographic databases: GTOPO30 for orography, ECOCLIMAP for surface covers, and FAO for soil texture.

In the current operational version, over sea and inland water (lakes) SURFEX uses simple schemes: surface temperatures are kept constant, roughness length and fluxes are computed with the Charnock's approach. However, there is a more advanced scheme for lakes, FLAKE (Freshwater lake, *Mironov et al.*, 2010), in which lake temperature is a prognostic variable.

Over artificial surfaces, the TEB scheme (Town Energy Budget, *Masson,* 2000) is used. Towns are represented by the canyon concept: there is a single road with two buildings and a canyon between them. Each surface (road, wall, roof) consists of 3 layers and has a different temperature , while the temperature inside the buildingsis constant. The time evolution of the temperatures are calculated by heat conduction equations. In the radiative forcing, trapping and shadowing effects are also taken into account. The scheme also accounts for anthropogenic heat and water fluxes (traffic and industry).

Vegetated land surfaces are parameterized with the ISBA scheme (*Noilhan* and *Planton*, 1989; *Noilhan* and *Mahfouf,* 1996). The current operational version uses a 3-layer (surface, root zone, and deep soil) force-restore scheme. Over snow mantel, a one layer snow scheme (*Douville et al*. 1995) is used in which snow albedo and density are prognostic variables.

The 2 m temperature and 10 m wind are calculated by the Canopy scheme (*Masson* and *Seity*, 2009) ,which is a one dimensional vertical turbulence scheme in the surface boundary layer.

Vegetation is constant and determined from climatology databases. However, a more advanced version of the ISBA scheme, called ISBA-A-gs (*Calvet et al.* 1998), uses a simplified photosynthesis model which is able to describe the evolution of vegetation. In this model version, biomass is a prognostic variable. Growing of the active biomass is due to assimilation of CO_2 (photosynthesis), while the decline (or mortality) can be due to soil moisture stress, senescence, or transport of organic molecules from active biomass to structural one. Since the photosynthesis process depends on the vegetation type, the vegetated land tile in SURFEX is further divided into 12 patches according to the vegetation or surface type, like grass, crops, trees, etc. Beside the prognostic treatment of the vegetation, the scheme also calculates the carbon fluxes (assimilation and soil respiration).

In the framework of the Geoland2 EU-FP7 project, the task of the Hungarian Meteorological Service was to simulate the natural carbon fluxes and the evolution of vegetation over Hungary. SURFEX was used in offline mode (no influence on the atmosphere) with the ISBA-A-gs photosynthesis model. To improve the accuracy of the initial soil moisture and biomass fields, assimilation of satellite observations (surface wetness index and leaf area index) was developed and used. Results have shown that the model is able to describe the seasonal cycle of the vegetation and the natural carbon fluxes, and that assimilation of the above mentioned satellite observations (SWI and LAI) gives some improvement in spring (*Fig. 7*).

The Hungarian Meteorological Service also takes part in the IMAGINES EU-FP7 project. Our task – besides the simulation of vegetation and carbon fluxes – is the development of the model to be able to assimilate surface albedo from new generation Proba-V satellite observations and to calculate agricultural indicators like drought indices.

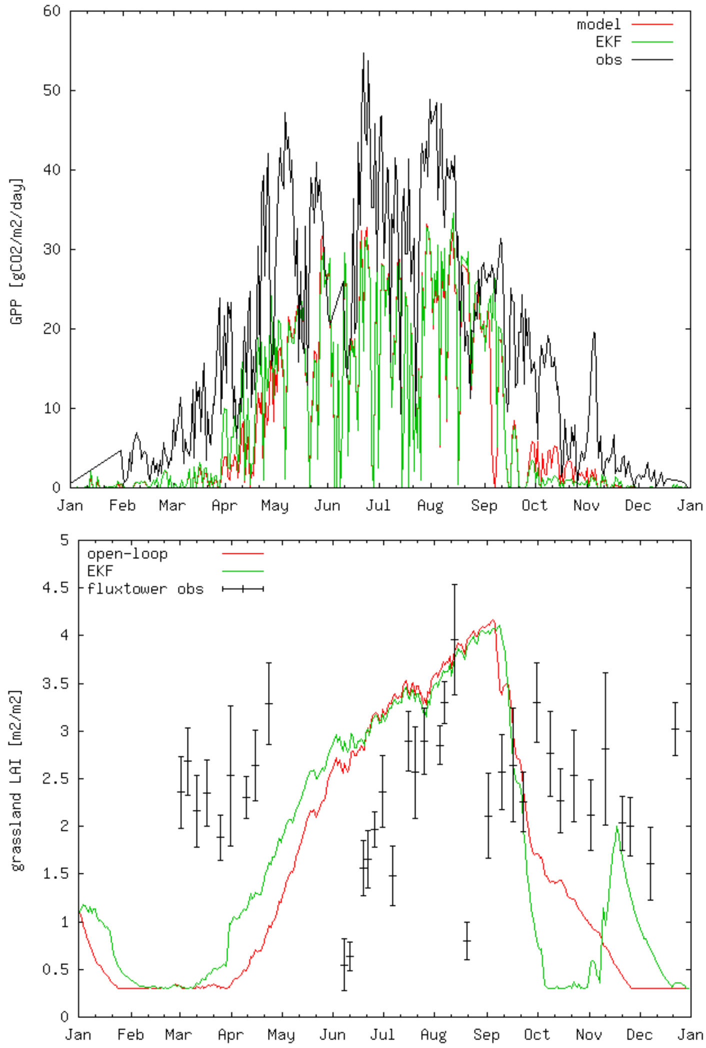

Fig. 7. Simulated and measured carbon flux (up) and leaf area index, LAI (down). Black line is observation, red line is without and green line is with assimilation.

3.4. General performance of the AROME model

As a result of the developments described in the previous sections, the AROME model has become a robust and reliable operational NWP model at HMS. The quality of AROME forecasts is comparable to that of other operational models used at HMS. In this section we show verification scores of a longer period, where the performance of AROME is compared to two operational hydrostatic models: the IFS global model run at ECMWF at 16 km horizontal resolution and the ALADIN regional model run at HMS at 8 km resolution.

The time period for the comparison was chosen in a way that no major changes should be applied in any of the three models. According to this criteria the period between September 16, 2013 and July 2, 2014 was selected. In this period, AROME was running with the model cycle 36, and the 3DVAR data assimilation system was operational using conventional upper air observations.

In the following, verification scores for screen and surface level variables (using SYNOP stations) as well as upper level variables (using radiosounding stations) are presented. Only forecasts with 00 UTC initial time were verified, and the verification scores were investigated as a function of lead time.

Regarding temperature and dew point at 2 meters, performance of AROME is comparable with the ECMWF model, while these two models outperform the ALADIN model for these variables (*Figs. 8a* and *8b*). The model bias has a diurnal dependency, daytime temperatures are underestimated, while nighttime temperatures are overestimated in AROME. Wind speed and wind gusts at 10 meters are generally overestimated by all three models (*Figs. 9a* and *9b*). For wind speed, ECMWF gives the best forecasts followed by AROME and ALADIN. Wind gusts are best captured by AROME, while ALADIN and ECMWF have similar performance for this variable.

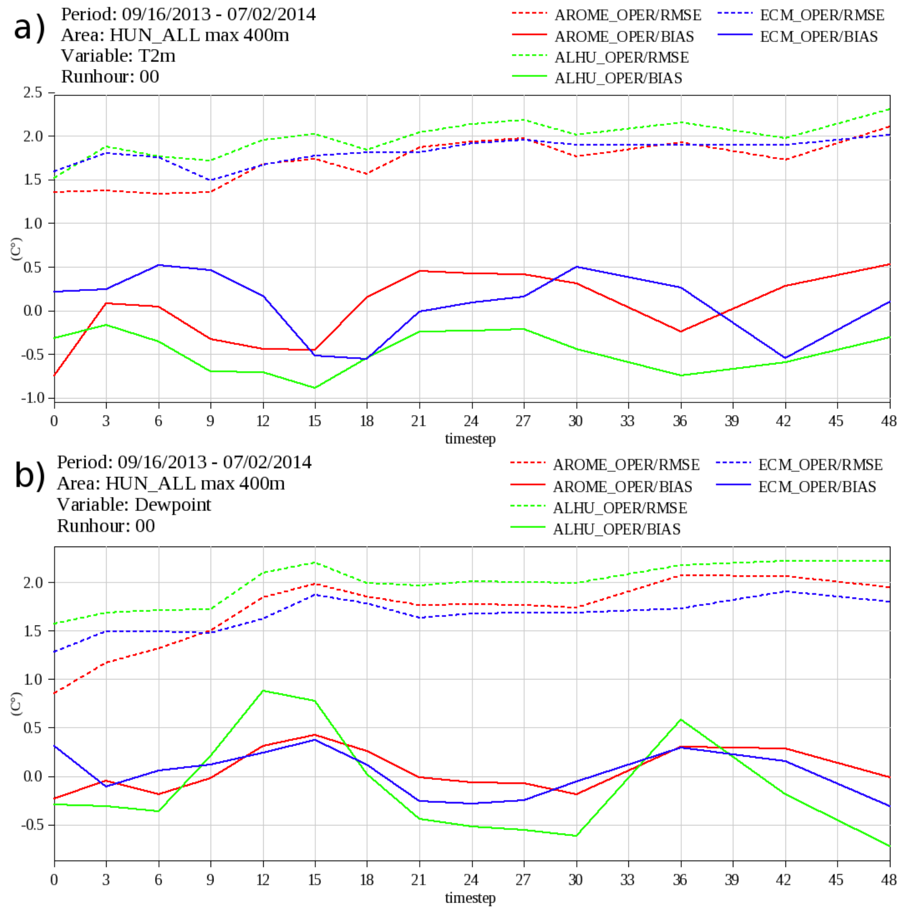

Fig. 8. Verification scores as a function of forecast lead time for temperature (a) and dew point (b) at 2 meters for operational NWP models at HMS between September 16, 2013 and July 2, 2014. Red: AROME, green: ALADIN, blue: IFS; dashed line: root mean square error, solid line: bias.

High resolution non-hydrostatic models are mainly applied for the forecasting of severe weather events, thus it is important to assess the quality of forecast performance for heavy precipitation. *Fig. 10* presents the symmetric extremal dependence index (SEDI), which is often used to verify high threshold events and the frequency bias for forecasted 12 hourly precipitation amounts. The SEDI score shows that for higher thresholds, the AROME model gives the best precipitation forecasts out of the three operational models. However, the frequency bias score points out a serious problem of AROME, namely that the model tends to forecast intensive convective cells more often than in reality. This erroneous model behavior is currently investigated at HMS.

Model performance at upper levels is mainly important for aviation forecasting. Based on the investigation of geopotential, temperature, wind, and humidity at several vertical levels, it can be concluded that the three models have similar performance, and the AROME model has usually a low bias but somewhat higher RMSE scores than the other two models (*Figs. 11a* and *11b*).

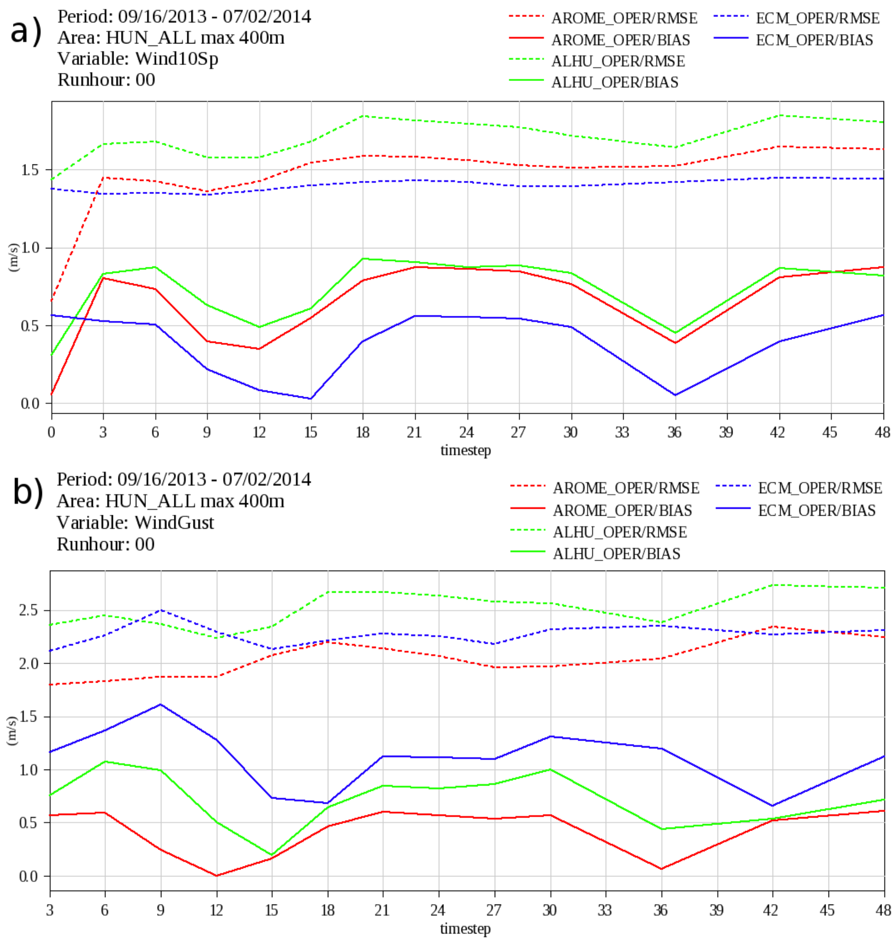

Fig. 9. Same as *Fig. 8* but for wind speed (a) and wind gusts (b) at 10 meters.

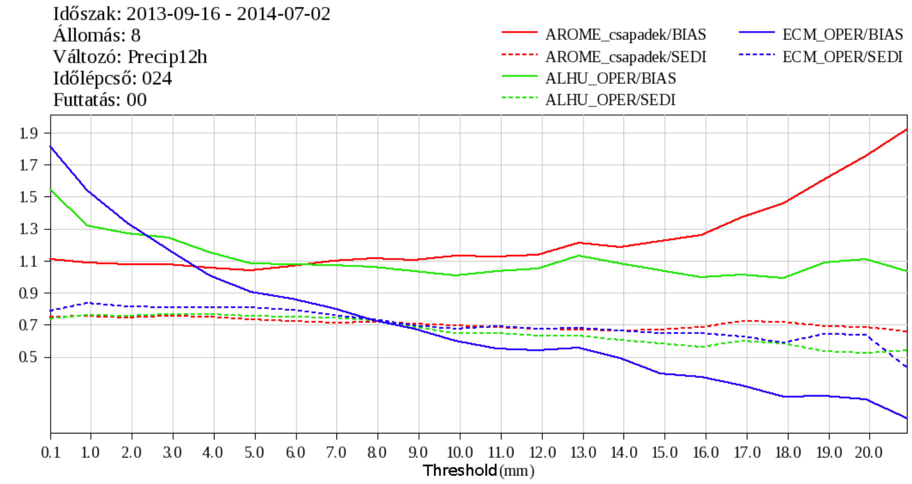

Fig. 10. Verification scores for 12 hourly accumulated precipitation for operational NWP models at HMS between September 16, 2013 and July 2, 2014. Red: AROME, green: ALADIN, blue: IFS; dashed line: SEDI, solid line: frequency bias.

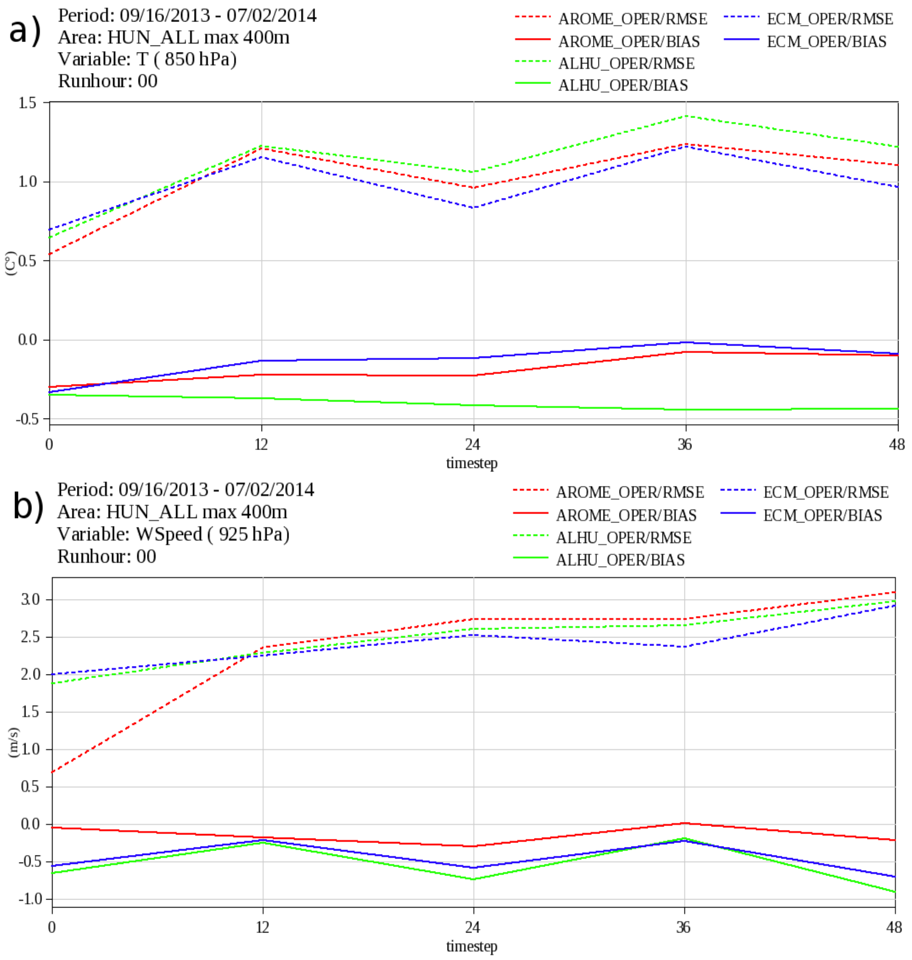

Fig. 11. Same as *Fig. 8* but for temperature at 850 hPa (a) and wind speed at 925 hPa (b).

4. Ensemble prediction system with AROME model

4.1. Motivation for a convection-permitting EPS

The uncertainty of numerical weather predictions is usually thought to originate from two main sources (*Palmer* and *Tibaldi*, 1988):
– Initial condition (IC) errors which evolve with time in the models due to the chaotic nature of the non-linear atmospheric system;
– Model errors which are based on limited human knowledge about atmospheric processes and finite resolution and representation possibilities of our models.
In reality, these errors can not be absolutely separated and they evolve together with time in the numerical models. Instead of giving a single-value as a forecast of a meteorological variable, it is more correct to give a probability density function (PDF) of it which contains information about forecast uncertainty. Until now, ensemble prediction systems (EPS) have been the only feasible and widely used tools to estimate such PDF. The main idea behind EPS is to run not only a single-forecast but an ensemble of numerical integrations where members can differ from each other in various aspects. These differences are defined by the perturbation generation methods which are designed to address different sources of error, so basically IC perturbation methods and model error representation can be separated.

The first ensemble prediction systems (EPS) were implemented in the early 90's with global models of ECMWF and NCEP (*Buizza et al*., 1993; *Toth* and *Kalnay*, 1997). These global systems described synoptic-scale motions on medium-range. Consequently, their error is dominated by the chaotic growth of IC error, and that is why early methods focused on IC perturbations (singular vector and breeding methods). Later it was realized that classic methods can not always ensure sufficient spread at the early stage of the forecast, so new methods were implemented, which aim is usually to identify the most uncertain parts of analysis fields where bigger initial spread is needed. One possible way is to run an ensemble of data assimilation cycles (EDA) with perturbed observations. This method has been successfully used for example in ECMWF's EPS or in Meteo-France's global ensemble, called PEARP (*Desroziers et al*., 2009; *Vié et al*., 2011).

In the improving ensemble systems, it was recognized that the representation of model error is also a very important challenge, so the perturbation of the model formulations is also necessary. Generally, it is assumed that model physics is more uncertain than dynamics because of the fluctuation of sub-grid scale processes and the bigger error of the parametrization methods. For that purpose, ensemble members can run with different parametrization schemes (multi-physics approach, used e.g., in PEARP) or with slightly different parameter settings in physics (parameter perturbations). Another possible way of representing model error is the stochastic perturbation of the total tendencies coming from the physics. Such a method is the so-called stochastically perturbed parameterized tendencies (SPPT) which was first implemented at ECMWF (*Buizza et.al*., 1999).

Limited area ensemble prediction systems (LAMEPS) have become also popular tools to refine global probabilistic forecasts on a shorter time range and for a smaller domain. LAMEPS have to be coupled to global EPS, which results in some additional challenges. Global perturbations have to be taken into account through the interpolated lateral boundary conditions (LBC) of the perturbed members. The potential benefit of LAMEPS motivated the HMS to start its own researches on that field and established an operational system in 2008. This EPS uses the hydrostatic ALADIN model and runs with 8 km horizontal resolution. It has 11 members which are the simple dynamical downscaling of the control and the first 10 perturbed members of the 18 UTC run of the Prevision Ensemble ARPege (PEARP). While no local perturbation or data assimilation have been implemented yet, its quality depends highly on PEARP, and the impact of the changes in global system can be also measured in the LAMEPS. The slightly positive impact of a simple EDA implementation was shown, where only near-surface observations were perturbed in an ensemble of surface optimal interpolations (*Horanyi et al.,* 2011).

The quality of numerical weather prediction has been improving for the previous decades because of the better model formulations and the finer resolution which was enabled by the growing computer capacity. As it has been already mentioned in Section 2, at around 2 km resolution, models become non-hydrostatic and they can resolve such small-scale phenomena like deep convection. This way, finer structures can be produced and more realistic fields can appear. Unfortunately, this type of improvement is not necessarily associated with better scores, because resolving smaller scales can cause more uncertainty in model results (e.g., localization problems can lead to double-penalty effect). To overcome this problem, more and more national meteorological services in Europe started to develop non-hydrostatic model based ensemble systems. This new generation of EPS is also referred to as convection-permitting EPS. The introduction of such systems has already happened at Deutscher Wetterdienst (DWD) with COSMO-DE which has 20 members and runs with 2.8 km resolution (*Gebhardt et.al*., 2008). Met Office has also started its operational convection-permitting EPS based on the 1.5 km resolution version of Unified Model (*Migliorini et.al.,* 2011). Météo-France has also joined the bigger services and runs its 12-member EPS with AROME model (*Vié et al.,* 2011).

HMS started its own research around convection-permitting EPS in 2012, and many tests have been run since then. Some of the results will be presented in this chapter. In this paper, an 11-member test configuration is called as a reference, which is, similarly to the operational LAMEPS, the simple dynamical downscaling of the first 11 PEARP member. AROME model runs with very similar settings to what was detailed in previous parts for single-forecasts. The only notable difference was that the SLHD settings were not changed (cf. Section 2.1). In the following parts, the impact of two perturbation methods will be presented, which have been already mentioned as successfully used approaches in global EPS. The EDA method is addressed to IC error (see Section 4.2), while the SPPT method represents the model error (see Section 4.3).

4.2. Impact of Ensemble Data Assimilation Method

Modern data assimilation methods are based on complex algorithms which usually combine model forecasts as background fields and different types of observations. Similarly to the atmospheric models, these algorithms also have their limitations, while background fields and observations are also sources of additional errors. As a result of the above mentioned weaknesses, it has to be admitted that analysis fields are imperfect. A plausible way for handling this imperfection is to define the most uncertain areas of the analysis, which is possible with generating not only a single analysis field but running an ensemble of data assimilation cycles. This ensemble can provide flow dependent information about the accuracy of the background fields which is very useful to the data assimilation itself (*Brousseau et al*., 2006; *Desroziers et al*., 2009). From the aspect of an ensemble, it is even more important that more analysis fields are generated in EDA which can be the initial conditions of different ensemble members in an EPS.

The differences between the members of EDA originate usually from the perturbations which are added to the observations:

$$y'_j = y + \sigma(y) r_j \tag{1}$$

where it is assumed that observations y are imperfect but they are not biased and their uncertainty can be described by σ, which is estimation of the accuracy of the instrument. There is an r random number for the jth member, picked from a Gaussian-distribution, which has 0 mean, unit variance, and bounded in a [–3;3] interval. Observation perturbations can evolve in assimilation cycles, so in new steps there are always uncertainty information in the system which comes from the background fields. Additionally, LBCs are needed in LAM EDA during the model integration when background fields are generated. These LBCs are usually interpolated from different members of a global EPS, so they can be also sources of perturbations inside an EDA system.An EDA was implemented to construct better perturbed initial conditions for our test AROME-EPS compared to those obtained by simple downscaling of the global EPS. In this implementation of EDA (very similar to the EPS itself), different members were coupled to the different members of PEARP. The data assimilation methods are very similar to the operational AROME system of

HMS (*Mile et al.*, 2014). Conventional data (SYNOP, radiosonde, aircraft measurements) were used in a 3D-VAR data assimilation which generated atmospheric fields. Surface fields were simply interpolated from HMS's operational ALADIN model, where an optimal interpolation method is used to improve surface variables with observations.

In comparison with the reference, it is expected from the EDA based configuration that the quality of all members can be improved simply because of the positive impact of data assimilation itself. It is also expected that additional perturbations can increase the spread of the system. These two effects can result in a better relationship between the root mean square error (RMSE) of the ensemble mean and the system's spread. These expectations are verified on spread-skill relationship plots (*Figs. 12a, 12b, 12c, 12d*), where RMSE is smaller and spread is bigger in the early stage of the forecast. Later the difference between reference and EDA based version are smaller, because on such a small domain, the effect of LBC's become dominant quite fast. For total cloudiness scores, *Fig. 12c* underlines another advantage of EDA which is valid in AROME-EPS framework: hydrometeors can be initialized from background, which importance have been already mentioned in Section 3.1. In this paper, mainly near-surface scores are presented because of the big number and high frequency of independent SYNOP observations (*Figs. 12a. 12b, 12c*). ECMWF analysis was chosen as a reference for upper-air verification (*Fig. 12d*). It has to be noted that the remarkable resolution difference between AROME model (2.5 km) and reference analysis (16 km) can be questionable. Unfortunately, the short test period and the small domain resulted a very limited number of radiosonde measurements, what has not permitted to calculate atmospheric scores on higher level with observations.

a)

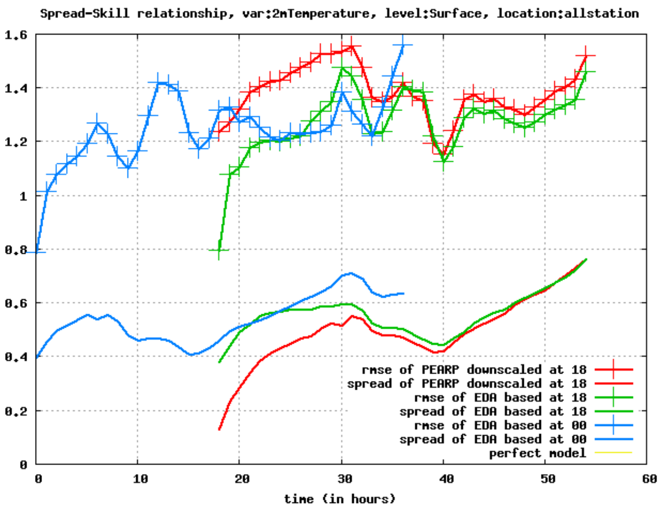

Fig. 12a. Spread-skill relationship of 2 meter temperature. Red is a simple PEARP downscaling as a reference; blue and green are the test versions where IC is generated in an EDA system. Scores are calculated for the period between December 26, 2011 and January 8, 2012.

b)

c)

d)

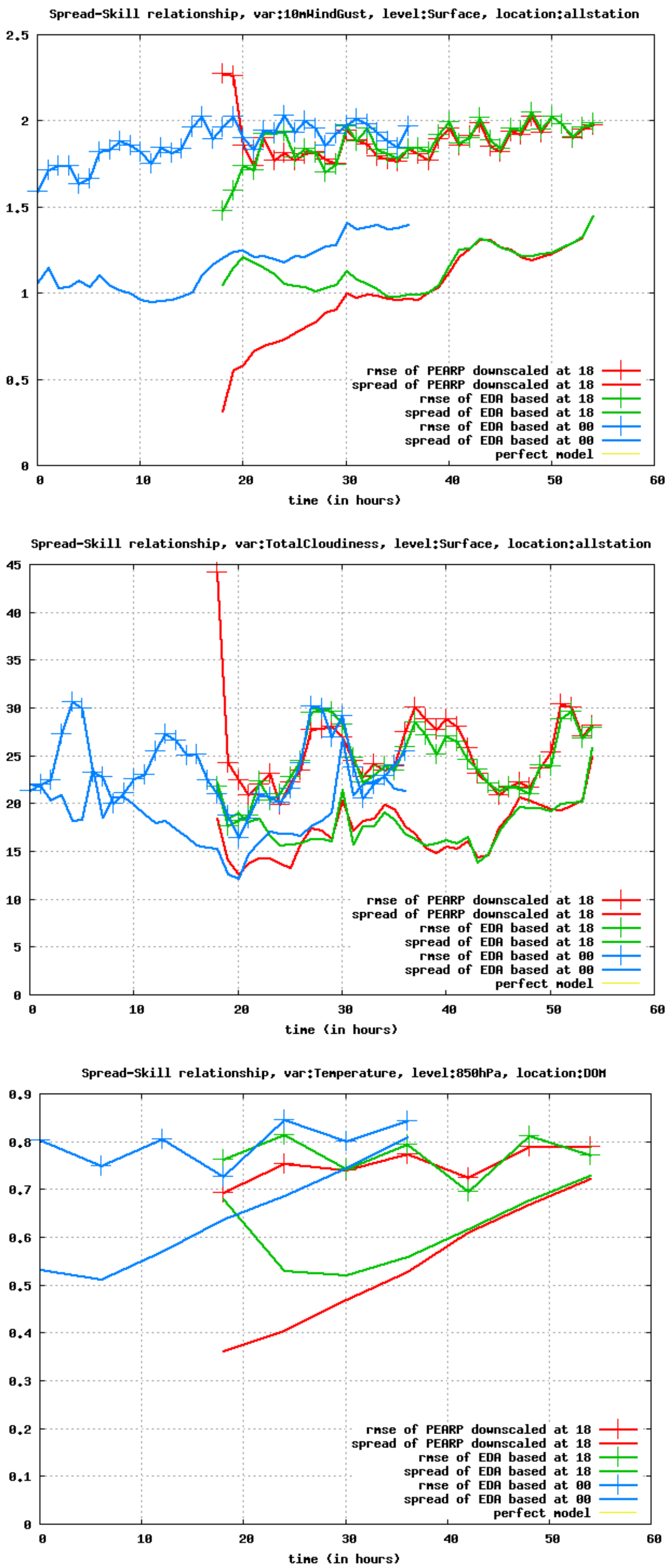

Fig. 12 b-d. Spread-skill relationship of 10 meter wind gust values (b), and total cloudiness (c), temperature on 850hPa pressure level Red is a simple PEARP downscaling as a reference; blue and green are the test versions where IC is generated in an EDA system. Scores are calculated for the period between December 26, 2011 and January 8, 2012.

4.3. Impact of Stochastically Perturbed Parametrized Tendencies

The original version of Stochastically Perturbed Parameterized Tendencies (SPPT) scheme was developed at ECMWF and called just as stochastic physics or BMP (*Buizza et al.*, 1999). Later it has been revised (*Palmer et al.*, 2009) and used as a successful tool to increase ensemble spread during the whole range of the forecast. It had positive impact even on the quality of single-model runs, especially in the tropical region.The concept can be expressed by the following equation:

$$e_j(T)=\int \{A(e_j;t)+P'(e_j;t)\}dt \quad , \tag{2}$$

where e is the model state of the jth member at time T, which can be simply evolved from the integration of two processes: A is the contribution of the resolved scales (model dynamics) and P is the total tendency coming from the parametrized processes (model physics). While model physics is assumed to be a more uncertain part, in SPPT (as in other methods representing model error), this term is perturbed and P' is calculated from the original P :

$$P'(e_j;t)=(1+\alpha r_j)P_j(e_j;t) , \tag{3}$$

where r is random number.

In the revised SPPT scheme, a spectral pattern generator is introduced, which provide horizontally smooth fields of r. Its horizontal structure is defined by an L horizontal correlation length parameter. The scheme has been implemented in AROME model (*Bouttier et al.,* 2012), where r is represented by biFourier functions and r' spectral coefficients are defined as first order auto-regressive processes:

$$(r')_{mn}(t+\Delta t)=\Phi(r')_{mn}(t)+\sigma_n\mu_{nm}(t) \quad , \tag{4}$$

where σ sets the size of the perturbation and μ is a random number picked from a Gaussian-distribution, which has 0 mean, 1 variance, bounded in interval [–2;2], and it is a white process in time. The correlation between time-steps is determined via a τ decorrelation time parameter:

$$\Phi=\exp(-\Delta t/\tau) \quad . \tag{5}$$

In Eq. (4) α is an attitude dependent number which varies on [0;1] interval and it has 0 value at the highest and the lowest model levels because of numerical stability reasons, and it is set to 1 in middle-troposphere.

In our AROME-EPS tests, SPPT was active in the case of perturbed members and inactive in the case of the control forecast. σ=0.5 and τ=2 hours settings were used and two different L parameters were applied: in the so-called 'SpptLong' test L=500 km and in the so-called 'SpptShort' test L=125 km. As it was in EDA related experiments, simple dynamical downscaling of PEARP is referred to as reference forecast. The impact of SPPT scheme is represented also via spread-skill relationship. This impact was found quite limited in this research: neither the RMSE of the ensemble mean has improved, nor the spread of the ensemble members has increased for the examined variables (*Fig. 13a*). The most sensitive parameter was the total cloudiness, but unfortunately, some model quality degradation in connection with the growth of the system's spread (*Fig. 13b*) was observed.Further examination is needed for better understanding of this limited impact. More tests are needed on summer periods, when a 'more active' atmosphere is expected to behave differently. The importance of control parameters (σ, τ, and L) also needs some additional clarification in our AROME model.

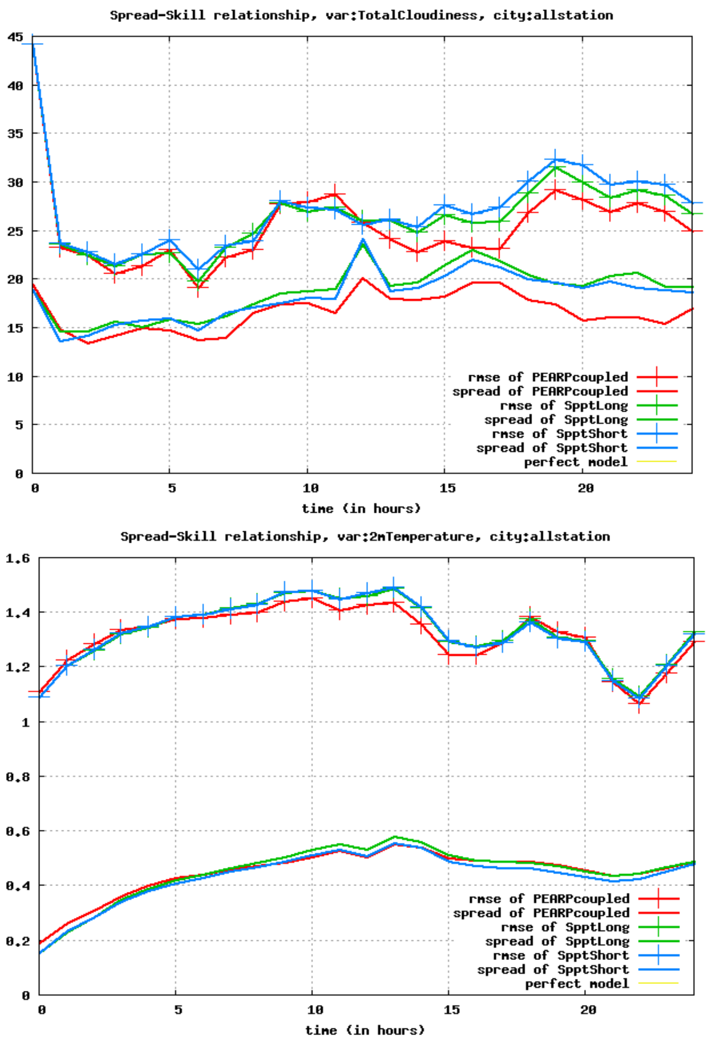

Fig. 13. Spread-skill relationship of 2 meter temperature (a) and total cloudiness (b). Red is a simple PEARP downscaling as a reference; blue and green are the test versions where SPPT scheme has been activated. Scores are calculated for the period between December 26, 2011 and January 8, 2012.

5. Summary and conclusions

In this paper, the AROME non-hydrostatic numerical weather prediction model as implemented at the Hungarian Meteorological Service was described with a focus on physical parameterizations and ensemble prediction. It was shown that high resolution NWP models are capable of predicting severe weather events. To achieve this, apart from increasing the horizontal and vertical resolution of the model, a non-hydrostatic dynamical core and advanced physical parameterizations have to be applied.

In connection with the dynamical core, aspects of horizontal diffusion in AROME were discussed. Recent developments regarding the semi Lagrangian horizontal diffusion scheme (SLHD) were described. It was shown that if SLHD is applied to all dynamical fields and not to falling hydrometeors then model performance – especially convective precipitation and wind gusts – could be improved.

The AROME model uses a state-of-the-art physical parameterization package, which was originally developed for the Meso-NH French research model. In this paper, some recent developments in connection with physical parameterizations performed at the Hungarian Meteorological Service were described. Regarding microphysics, the importance of the correct initialization of hydrometeor fields was highlighted. In connection with turbulence and shallow convection, the main ideas behind the eddy diffusivity – mass flux (EDMF) approach were discussed, and the positive impact of this parameterization on the resolved deep convection in the AROME model was shown. As the horizontal resolution of NWP models increases, surface processes are getting more and more important. In AROME, the SURFEX externalized surface model is utilized. Basic features of SURFEX were summarized as well as a recent development in connection with the prognostic treatment of vegetation.

To conclude the description of the deterministic AROME model, some verification scores were presented both for surface variables and upper levels. The performance of AROME was compared to other operational NWP models used at HMS. It was found that AROME has good performance for those meteorological variables (wind gusts and high precipitation amounts) which are linked to severe weather events.

As the horizontal resolution of NWP models is increasing, models are getting able to resolve even finer scales atmospheric phenomena. However, this not necessarily lead to better forecasts if forecast skill is measured locally (which is the case for most model applications). This is mainly related to localization problems in space and time. The application of the probabilistic approach could be a path to overcome this problem and handle the chaotic error growth in the model. In this paper, certain aspects of convection-permitting ensemble forecasts were highlighted and their impact was demonstrated using ensemble forecasts based on the AROME model. First, the ensemble data assimilation (EDA) method was described, which aims at the correct determination of perturbed initial conditions for ensemble members. Secondly, one possible solution for the representation of model errors, namely, the stochastically perturbed parametrized tendencies (SPPT) approach was described. Based on the experiments performed with the AROME-EPS, it can be concluded that the EDA approach could significantly improve the high resolution ensemble forecasts, while the SPPT scheme has limited impact in its current configuration.

Acknowledgements: Useful discussions in the framework of the COST ES0905 project ('Basic concepts for convection parameterization in weather forecast and climate models') which contributed to the sections about dynamics and physics are greatly acknowledged. The authors are thankful to *Filip Vana* and *Lisa Bengtsson* for discussions about the SLHD scheme. The work about prognostic vegetation with the SURFEX model was carried out in the frameworks of the Geoland2 and ImagineS EU FP7 projects. AROME-EPS related tests were realized in the framework of an ECMWF's special project, called 'Continental winter weather prediction with the AROME ensemble prediction system', where HMS participate together with Météo France. We are really grateful to the project partners, and personally to *Francois Bouttier*. Remarks of the anonymous reviewer which lead to an improvement of the manuscript are greatly acknowledged.

References

Benard, P., Vivoda, J., Masek, J., Smolikova, P., Yessad, K., Smith, C., Brozkova , R., and *Geleyn, J.-F.,* 2010: Dynamical kernel of the Aladin-NH spectral limited-area model: Revised formulation and sensitivity experiments. *Q. J. Roy. Meteor. Soc., 136*, 155–169.

Bengtsson, L., Tijm, S., Váňa, F., and *Svensson, G.,* 2012: Impact of Flow-Dependent Horizontal Diffusion on Resolved Convection in AROME. *J. Appl. Meteor. Climatol. 51*, 54–67.

Bougeault, P. and *Lacarrere, P.,* 1989: Parameterization of orography-induced turbulence in a meso-beta-scale model. *Mon. Weather Rev. 117*, 1870–1888.

Bouttier, F., Vié, B., Nuissier, O., and *Raynaud, L.,* 2012: Impact of Stochastic Physics in a Convection-Permitting Ensemble. *Mon. Weather Rev., 140*, 3706–3721.

Bölöni, G., 2006: Development of a variational data assimilation system for a limited area model at the Hungarian Meteorological Service. *Időjárás 110*, 309–327.

Brousseau, P., Berre, L., Bouttier, F., and *Desroziers, G.,* 2011: Background-error covariances for a convective scale data-assimilation system: Arome-France 3D-Var. *Q. J. Roy. Meteor. Soc. 137,* 409–422.

Bubnová, R., Hello, G., Bénard, P., and *Geleyn, J.-F.,* 1995: Integration of the fully elastic equations cast in the hydrostatic pressure terrain-following in the framework of the ARPEGE/ALADIN NWP system. *Mon. Weather Rev. 123*, 515–535.

Buizza, R., Tribbia, J., Molteni, F., and *Palmer, T.,* 1993: Computation of optimal unstable structures for a numerical weather prediction model. *Tellus 45A*, 388–407.

Buizza, R.,. Miller, M., and *Palmer, T.N.,* 1999: Stochastic representation of model uncertainties in the ECMWF Ensemble Prediction System, *Q. J. Roy. Meteorol. Soc. 125,* 2887–2908.

Calvet, J.C., Noilhan, J., Roujean, J.L., Bessemoulin, P., Cabelguenne, M., Olioso, A., and *Wigneron, J.P.,* 1998: An interactive vegetation svat model tested against data from six contrasting sites. *Agr. Forest Meteorol. 92,* 73–95.

Cuxart, J., Bougeault, P., and *Redelsberger, J.-L.,* 2000: A turbulence scheme allowing for mesoscale and large-eddy simulations. *Q. J. Roy. Meteor. Soc. 126*, 1–30.

Desroziers, G., Berre, L., Chabot, V., and *Chapnik, B.,* 2009: A posteriori diagnostics in an ensemble of perturbed analyses. *Mon. Weather Rev. 137,* 3420–3436

Douville, H., Royer, J.-F., and *Mahfouf, J.-F.,* 1995: A new snow parameterization for the French community climate model. Part I: Validation in stand-alone experiments, *Clim. Dynam., 12,* 21–35.

Fischer, C., Montmerle, T., Berre, L., Auger, L., and *Stefanescu, S.E.,* 2005: An overview of the variational assimilation in the Aladin/FranceNWP system. *Q. J. Roy. Meteor. Soc. 131,* 3477–3492.

Gebhardt, C., Theis, S., Krahe, P. and *Renner, V.,* 2008: Experimental ensemble forecasts of precipitation based on a convection-resolving model. *Atmos. Sci. Lett. 9,* 67–72.

Horányi A., Ihász I. and *Radnóti G.,* 1996: ARPEGE/ALADIN: A numerical weather prediction model for Central-Europe with the participation of the HMS. *Időjárás 100,* 277–301.

Horányi A., Mile M., and *Szűcs M.*, 2011: Latest developments around the ALADIN operational short-range ensemble prediction system in Hungary, *Tellus 63A*, 642–651.

Kain, J.S., and Fritsch, J.M., 1990: A one-dimensional entraining/detraining plume model and its application in convective parameterizations. *J. Atmos. Sci.* 47, 2784–2802.

Lafore, J.-P., Stein, J., Asencio, N., Bougeault, P., Ducrocq, V., Duron, J., Fischer, C., Héreil, P., Mascart, P., Masson, V., Pinty, J. P. , Redelsperger, J. L. , Richard, E. and Vilà-Guerau de Arellano J.,, 1998: The Meso-NH atmospheric simulation system. Part I: Adiabatic formulation and control simulations. *Ann. Geophys., 16*, 90–109.

Lappen, C.L. and *Randall, D. A.,* 2001: Toward a unified parameterization of the boundary layer and moist convection, Part 2: lateral mass exchanges and subplume-scale fluxes. *J. Atmos. Sci. 58,* 2037–2051.

Masson, V., 2000: A physically-based scheme for the urban energy budget in atmospheric models, *Bound.-Lay. Meteorol. 94*, 357–397.

Masson, V. and *Seity, Y.*, 2009: Including atmospheric layers in vegetation and urban offline surface schemes, *J. Appl. Meteorol. Clim. 48*, 1377–1397.

Migliorini, S., Dixon, M., Bannister, R., and *Ballard, S.,* 2011: Ensemble prediction for nowcasting with a convection-permitting model. I: Description of the system and the impact of radar-derived surface precipitation rates. *Tellus 63A*, 468–496.

Mile, M., Bölöni, G., Randriamampianina, R., Steib, R., and *Kucukkaraca, E.,* 2015: Overview of mesoscale data assimilation developments at the Hungarian Meteorological Service. *Időjárás 119*, 215–239.

Mironov, D., Heise, E., Kourzeneva, E., Ritter, B., Schneider, N., and *Terzhevik, A.,* 2010: Implementation of the lake parameterisation scheme flake into the numerical weather prediction model COSMO. *Boreal Env. Res. 15,* 218–230.

Le Moigne, P., 2012: SURFEX scientific documentation. Note de centre du Groupe de Météorologie a Moyenne Echelle, 87, Météo-France, CNRM, Toulouse, France, on-line available at: http://www.cnrm.meteo.fr/surfex/

Noilhan, J., and *Planton, S.*, 1989: A simple parameterization of land surface processes for meteorological models, *Mon. Weather Rev. 117*, 536–549.

Noilhan, J., and *Mahfouf, J.-F.,* 1996: The ISBA land parameterization scheme, *Global Planet. Change 13,* 145–159.

Pergaud, J., Masson, V., Malardel, S., and *Couvreux, F.,*2009: A parameterization of dry thermals and shallow cumuli for mesoscale numerical weather prediction, *Bound.-Lay. Meteor., 132,* 83–106.

Randriamampianina, R., 2006: Impact of high resolution observations in the ALADIN/HU model, *Időjárás 110*, 329–349.

Palmer, T.N., and *Tibaldi, S.*, 1988: On the prediction of forecast skill, *Mon. Weather Rev. 166*, 245.

Palmer, T., Buizza, R., Doblas-Reyes, F., Jung, T., Leutbecher, M., Shutts, G., Steinheimer, M., and *Weisheimer, A.,* 2009: Stochastic parametrization and model uncertainty. *Tech. Rep., ECMWF Tech. Memo. 598.* Available online at http://www.ecmwf.int/publications/.

Pinty, J.-P., and *Jabouille*, *P.,* 1998: A mixed-phased cloud parameterization for use in a mesoscale non-hydrostatic model: Simulations of a squall line and of orographic precipitation. *Preprints, Conf. on Cloud Physics, Everett, WA, Amer. Meteor. Soc.*, 217–220.

Seity, Y., Brousseau, P., Malardel, S., Hello, G., Bénard, P., Bouttier, F., Lac, C., and *Masson, V.,* 2011: The AROME-France Convective-Scale Operational Model. *Mon. Weather Rev. 139*, 976–991.

Toth, Z. and *Kalnay, E.,* 1997: Ensemble forecasting at NCEP and the breeding method. *Mon. Weather Rev. 127*, 3297–3318.

Vána, F., Bénard, P., Geleyn, J.-F., Simon, A., and *Seity, Y.,* 2008: Semi-Lagrangian advection scheme with controlled damping: An alternative to nonlinear horizontal diffusion in a numerical weather prediction model. *Q. J. Roy. Meteor. Soc. 134,* 523–537.

Vié, B., Nuissier, O., and *Ducrocq, V.,* 2011: Cloud-resolving ensemble simulations of Mediterranean heavy precipitating events: Uncertainty on initial conditions and lateral boundary conditions. *Mon. Weather Rev. 139,* 403–423.