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Doktorska disertacija – Sažetak
D.Sc. Thesis – Extended abstract

MEZOSKALNA ASIMILACIJA PODATAKA U REGIONALNOM ATMOSFERSKOM NUMERIČKOM MODELU

Mesoscale data assimilation in regional numerical weather prediction model

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Sažetak: U prvom dijelu ovog rada opisan je sustav mezoskalne asimilacije podataka uspostavljen za regionalni numerički model atmosfere ALADIN-HR (operativna konfiguracija na Državnom hidrometeorološkom zavodu). Izrađena je validacija utjecaja asimilacijskog sustava na kvalitetu prognoze. Rezultati su pokazali da postoji doprinos kvaliteti prognoze temperature i relativne vlažnosti zraka na 2 m tijekom cijelog prognostičkog razdoblja, dok je za visinska polja on vidljiv za prve sate integracije modela. Promatranjem jedne vremenske epizode kada je zabilježena značajna količina oborine pokazalo se da je korištenjem asimilacije podataka dobivena realističnija struktura oborine. Drugi dio rada produbljuje razumijevanje utjecaja metode za procjenu matrice kovarijanci pogrešaka pretpostavljenog stanja (**B** matrica) na njena obilježja, na analizu i kvalitetu prognoze. Napravljen je proračun **B** matrice na tri načina: NMC metodom – NMC, ansambl metodom s perturbiranim bočnim rubnim uvjetima (BRU) – ENSLBC te ansambl metodom bez perturbacija BRU – ENS. Dijagnostička usporedba je pokazala da ansambl **B** matrice imaju uže horizontalne i vertikalne korelacije, manje standardne devijacije po vertikali, manje relativne doprinose varijanci na velikim skalama te pomak krivulje korelacije prema manjim skalama u odnosu na NMC **B** matricu. Perturbacije BRU kod ENSLBC **B** matrice utječu na povećanje relativnog doprinosa varijanci za velike skale, ali isto tako malo utječu na pogreške pretpostavljenog stanja specifične vlažnosti (veći utjecaj ima odabir metode). Eksperimenti s asimilacijom jednog mjerenja korištenjem NMC i ENSLBC **B** matrice pokazali su da se najveće razlike u strukturi inkremenata javljaju za specifičnu vlažnost. Također, najveća razlika i bitno veći inkrementi analize dobiveni su za specifičnu vlažnost kada je korištena NMC **B** matrica u odnosu na ENSLBC **B** matricu. Utjecaj **B** matrice na kvalitetu prognoze pokazao je da ENSLBC **B** matrica unaprjeđuje prognozu naoblake, oborine i srednjeg tlaka zraka na razini mora. Također, pozitivno utječe na prilagodbu modela na početne neravnoteže.
U zadnjem dijelu rada prikazane su mogućnosti poboljšanja prognoze korištenjem asimilacije radarskih mjerenja u modelu malog prostornog koraka za slučaj olujnog nevremena na području Hrvatske. Rezultati su pokazali da bez korištenja asimilacije podatka simulacija razvoja i kretanje oluje, ali također i odgovarajućih okolišnih uvjeta, nije bila zadovoljavajuća. Asimilacija površinskih mjerenja dala je odgovarajuću prostornu raspodjelu atmosferskih polja važnih za konvektivne procese. Bez toga, model malog koraka mreže, čak i uz korištenje asimilacije radarskih podataka, ne simulira dobro razvoj oluje. Najbolja simulacija dobivena je korištenjem asimilacije površinskih i radarskih mjerenja.

Extended abstract:

1. Introduction

Numerical weather prediction (NWP) models are the main source of information on the future state of the atmosphere. As NWP models are based on coupled nonlinear partial differential equations that describe the evolution of the state of the atmosphere, accurate knowledge of the initial conditions is essential. To address this problem, many methods and approaches have been developed and have become an important part of atmospheric science known as data assimilation (DA). DA methods were mainly developed in the global NWP model framework and were subsequently adopted in limited-area models (LAMs). DA combines different sources of information about the state of the atmosphere with the aim to obtain the best possible estimate of its true state. As all sources of information are imperfect, and to produce the optimal combination, the error statistics (of this information) must be estimated as accurately as possible.

Today, mainly two sources of information are used: observations and background (which is usually a short-range NWP model forecast). The main equation of linear analysis (Bouttier and Courtier, 2002) is given by Equation 1, page 2 where analysis is shown as a linear combination of a background state and a correction which depends on the gain matrix (**K**) and innovation (departure of the model from observations). Due to the large dimensions of the problem, some simplification is necessary to compute the analysis. One of the methods to solve the analysis problem is optimal interpolation and it assumes that, for each model variable, only a few nearby observations are important for the analysis. This approach reduces the size of **K**; thus, explicit inversion can be performed. Another approach is the variational approach which seeks analysis by minimizing the cost function that measures the distance of the control vector from the background and the observations (Eq. 3, page 2). The variational approach provides a global analysis and makes it possible to use observations with more-complex observation operators. However, there is a problem with the large dimension of background-error covariance matrix (**B** matrix) for practical implementation because its inversion is needed so still some simplifications are necessary.

1.1. Motivation and goals

Results from previous research suggest that implementation of DA in LAM enhances the quality of the forecast. Implementation of three-dimensional variational assimilation (3D-Var) for upper air fields in ALADIN model resulted in better precipitation forecast (Fischer et al., 2005), or in another example, better forecast of upper air fields, 2 m air temperature and precipitation (Bölöni, 2006). On the other hand, looking at the assimilated data, benefits of radar data assimilation were found in previous studies where it was shown that initialization of convective-scale numerical models with high-resolution radar data is beneficial for forecasting convective storm development and for improving precipitation forecasts (Sun, 2005; Seity et al., 2011). Thus, the implementation of DA in LAM could be beneficial for the model forecast quality. Today, there is also a tendency for high-resolution LAM implementations (e.g., grid spacing 2 km) and to refresh forecast frequently (e.g., every hour) so for that purpose having DA system for LAM is almost essential. For frequent assimilation on high-resolution grids, measurements with high spatial and temporal density are of great importance (e.g., radar data). With this motivation, the goal for setting up an assimilation system at the Croatian Meteorological and Hydrological Service (DHMZ) was made.

At DHMZ, a limited area model ALADIN-HR (Aire Limiteé Adaptation Dynamique dévelopement InterNational; ALADIN International Team, 1997) in its several configurations is used for operational forecasting. First step needed for DA is implementation of DA cycle which is a sequence of short-range (3 h or 6 h) forecasts and analysis as shown in Figure 1, page 6. One step of DA cycle consists of several parts: update of sea surface temperature (SST), surface assimilation and the upper air assimilation, Figure 2, page 11. One of the most important parts of the upper-air assimilation is **B** matrix. It influences the analysis field because it determines the weight of the background field with respect to the observations and determines how the information from observations is spread spatially and temporally to the model grid-point space. Additionally, in multivariate formulation, the **B** matrix spreads the information from one to the other model variables.

In theory, to be able to estimate a background error, the true state of the atmosphere should be known. As this is not fully possible, one seeks an appropriate surrogate of the background error that should have similar statistical properties, and presently, forecast differences are typically used. One of the methods for obtaining these forecast differences is National Meteorological Center (NMC) method (Parrish and Derber, The National Meteorological Center's spectral statistical-interpolation analysis system, 1992) which seeks a surrogate of the background error as a difference between the forecast valid at the same time but initialized at different times. Another approach is to use forecast differences from an ensemble of perturbed assimilation cycles (Fisher, 2003; Pereira and Berre, 2006). In this method, explicit perturbation of measurements is used with implicit perturbation of background. Additionally, lateral boundary conditions (LBC) can be perturbed by coupling each member of the perturbed assimilation cycle with the corresponding member of the global model ensemble system.

Previous research has shown that, except using different sampling strategies, **B** matrix characteristics are also influenced by (i) the model resolution (Ştefănescu et al., 2011), (ii) the geographical location (the location of the model domain) (Pereira and Berre, 2006) and (iii) the weather regime during the sampling period (the seasonal dependency) (Monteiro and Berre, 2010).

The overall goal of this study is to set up DA system for ALADIN-HR. More specific goals include estimation of **B** matrix with the aim to provide additional further insights into differences between NMC and ensemble-based **B** matrices (calculated for the samples of the same size and obtained over the same period). The influence of those **B** matrices on analysis and quality of forecast will be assessed, same as the influence of the whole DA system on quality of the forecast. At the end, the influence of DA (with conventional and radar data) and model grid spacing on a prediction of severe storm will be inspected.

2. Data assimilation system

In this study, LAM ALADIN (Aire Limiteé Adaptation Dynamique dévelopement InterNational; ALADIN International Team, 1997) was used. At the DHMZ there are several configurations of this model of which two of them were used here: ALADIN-HR8 (8 km horizontal grid spacing) and ALADIN-HR4 (4 km horizontal grid spacing). In practice to set up DA system one must first set up DA cycle (Fig. 1, page 6). One step of DA cycle consists of several parts (Fig. 2, page 11). First is an update of sea surface temperature (SST) which is done simply by copying SST from the global model as SST analysis is not implemented at the DHMZ. The second step is surface assimilation where soil variables are updated and at the end upper-air assimilation where and upper-air fields are corrected.

The goal of surface assimilation is to correct soil variables with information obtained from measurements. As there is a small number of direct measurements of soil variables available, 2 m temperature (T2m) and 2 m relative humidity (RH2m) measurements are used. In the first step, T2m and RH2m measurements are combined with background through optimal interpolation (OI) procedure to obtain an analysis of these fields. Then analysis increments of T2m and RH2m are calculated and propagated to the soil using empirically determined transfer coefficients as shown in Equation 4, page 14. Soil can influence forecast of 2 m parameters up to few days and it was shown that the most important impact has the amount of water in the soil which can be quantified by calculating soil wetness index (SWI; Eq. 5, page 14). One example of the influence of surface DA on the evolution of soil state is demonstrated by examining changes of soil state of the background, the analysis, and the global model analysis for one model point (Fig. 4, page 17; Fig. 5, page 18). Results indicate that smoother evolution of soil state is in the global model than in ALADIN-HR model. The reason for this is biases in T2m and RH2m present in ALADIN-HR8 model. The changes in the soil triggered by these biases could be beneficial for the forecast of 2 m parameters, but this could also result in unrealistic drying or moistening of soil.

For the upper-air DA, the 3D-Var method which seeks analysis by minimizing cost function (Fig. 6, page 20) is used. A number of different observations that pass quality control is used in this process (Tab. 1, page 21; Fig. 7, page 21). At the end of upper-air DA, analysis is obtained, and it is used as initial conditions for the subsequent forecast. This analysis can also be used as the first LBC in the so-called space consistent coupling scheme which decreases unbalances at the edges of the domain (which would be present because there is a discrepancy between analysis and global model LBC).

The influence of DA was assessed by comparing forecast from ALADIN-HR8 configuration with DA (ASSIM) and ALADIN-HR8 configuration that did not use DA (NO_ASSIM) with surface and upper-air measurements during an almost 10-months period. Results demonstrate that for a surface better quality of forecast is obtained ASSIM experiment for T2m and RH2m (Fig. 8, page 23). For 10 m wind speed and direction results are neutral.

For upper-air fields (Fig. 8, page 23) result indicates that better fit to measurements was during the first 6–12 h of the forecast. Best results were obtained for relative humidity and temperature in lower parts of the atmosphere where positive impact can also be seen for longer lead times. Additionally, simulation of one heavy precipitation event measured during IOP of the HYdrological cycle in the Mediterranean EXperiment (HyMeX) was done with ALADIN-HR8 model configuration that used initial condition from global model and the configuration that used initial condition form DA cycle. Results demonstrate (Fig. 9, page 26) that run with DA has precipitation structures that are in better agreement with measurements. The verification measures (Tab. 2, page 27) show that the simulation with data assimilation produced slightly better results. The scores (e.g., critical success index – CSI) for the entirety of Croatia show that the strong precipitation category results were improved for the operational run (CSI = 0.28) compared to the run without data assimilation (CSI = 0.23). In addition, polychoric correlation coefficient (PCC) indicates that the model and observations for the run with data assimilation were better associated. The impact of data assimilation for this case is rather small, but it yielded an improvement in the 24 h precipitation forecast. One of the reasons for the small impact could be relatively large model grid spacing, so using a model of smaller grid spacing could enhance the simulation of such events. For such model, DA should include high-resolution measurements (e.g., radar data) and one example of this path is given in the last section. Another enhancement could include better estimation of **B** matrix and this is explored in the following chapter.

3. **B** matrix

As mentioned in the Introduction, the **B** matrix is one of the most important parts of variational DA. It can be expressed as the difference between background and the true state of the atmosphere (Eq. 9, page 28). As the ensemble method for estimating the **B** matrix has advantages over the NMC method and with the aim to provide additional further insights into differences between NMC and ensemble-based **B** matrices, three **B** matrices were estimated for the ALADIN-HR4 model, the first using the standard NMC method and the two latter ones using different ensemble-based methods. Forecast differences were computed over the same period to consider the seasonal/weather regime influence on the **B** matrix characteristics. Also, to have the same sample size as for NMC, only two ensemble members were used. Such a comparison in the LAM framework differed from most of the other studies in the field in several aspects. First, the NMC and ensemble **B** matrix were sampled over the same period. Second, the **B** matrix was estimated for the NWP model with 4 km horizontal grid spacing. Third, the **B** matrix was estimated for the domain that covered a geographically diverse areas of southern Europe, including the Mediterranean Sea, several mountain chains (the Alps, Dinaric Alps, and the Apennines), and several plains and lowlands, and these topographical features have an important influence on the weather conditions specific to this area and pose challenges to optimal data assimilation. This is likely to result in some differences compared to the studies performed in other regions. Fourth, this study used a somewhat smaller domain for the calculation of the **B** matrix compared to most of the other studies. Because of the small horizontal domain of the model, the influence of LBC perturbation on the characteristics of the ensemble-based **B** matrix could be enhanced.

3.1. NMC method

The first set of forecast differences was calculated using the standard NMC method, where the existing archive of ALADIN-HR4 operational forecasts was used. The samples were calculated as the difference between the 36 h forecast and the 12 h forecast of the subsequent day, and this procedure was performed for the model forecasts initialized at 00:00, 06:00, 12:00, and 18:00 UTC during the period of 10 December 2016–27 February 2017, which resulted in 316 samples. The main characteristics of this method are much longer forecast ranges (36 h and 12 h) and usage of analysis increments in analysis step representation (Eq. 13, page 33). This sample and the **B** matrix estimated from it are denoted with NMC in the following text.

3.2. Ensemble method

The ensemble-based **B** matrices were estimated from a 2-member ensemble of perturbed assimilation cycles of the ALADIN-HR4 model (EDA). The first EDA setup used the same LBCs for all members while in the other setup perturbed LBCs from the global ensemble were used. Although neglecting the LBC errors led to an unrealistic setup, this approach aimed to test the influence of the LBC perturbations on the characteristics of the **B** matrix for a relatively small LAM domain (the influence of the LBCs could be substantial). For both EDA systems, the assumption of a perfect model was used. The samples were obtained by calculating the differences between the 6 h forecasts for the two ensemble members every 6 h. The EDA was started on 20 November 2016 from the same background field for all ensemble members.

Before the analysis step, two different observation vectors were obtained by perturbing the real observations vector. This was done by adding perturbations that had a Gaussian distribution with a zero mean and standard deviation corresponding to the estimated observation error standard deviations. Using this procedure, the two perturbed analysis and a subsequent two perturbed 6 h forecast (the new backgrounds) were obtained. For the computation of the statistics the period from 11 December 2016, 12:00 UTC to 28 February 2017, 06:00 UTC was used to be consistent with the NMC sampling strategy, thus providing a sample of 316 differences for estimating the **B** matrix. Equation 18, page 35 shows that forecast differences are the result of explicit perturbations of observations, and implicit perturbations of background. Also, in one sample, LBCs are also perturbed. Sample of forecast differences obtained from EDA with or without LBC perturbations and **B** matrix estimated from it are denoted with ENSLBC and ENS, respectively in the following text.

3.3. Diagnostic comparison

To address the characteristics of the estimated **B** matrices, the standard deviations (STD) in the grid-point space were computed and compared. On Figure 10, page 38 the normalized STD for the surface pressure and specific humidity at level 34 (approximately 500 hPa) of the samples used in **B** matrix estimation are plotted. Results show that neglecting LBC perturbations lead to unrealistically small standard deviations near the domain boundaries. It also shows that for the specific humidity, the smallest differences are between the ENS and ENSLBC experiments, which suggest that the humidity field is more sensitive to the method used to sample the forecast error than to LBC perturbations. For the other variables, especially for the surface pressure and temperature, a notable influence on the standard deviation amplitude comes from the LBC perturbations. More importantly, this influence spreads over a significant portion of the relatively small ALADIN-HR4 domain. Considering that the **B** matrix was estimated from temporal and the domain averages, the influence of the LBC perturbations could dominate other sources of background errors.

The horizontal correlation spectra were obtained by normalizing the variance spectra by the total variance to compare the contributions of the different horizontal scales to the correlation function shape for the different experiments (Fig. 11, page 41). Results show that the contribution of the large scales is the smallest for the ENS experiment, with ENSLBC in the middle and NMC having the largest amplitudes. Thus, LBC perturbations enhance large scale part of spectra. On the other hand, the shape of the correlation functions (for temperature and specific humidity) for ensemble **B** matrices is shifted to smaller scales compared to the NMC experiment. The inclusion of LBC perturbations in ENSLBC brings the shape of correlation closer to the one of NMC. The smallest difference between the correlation spectra of the ENSLBC and ENS experiments are found for the humidity. The ensemble **B** matrices were further characterized by smaller standard deviations

(Fig. 12, page 44), shorter horizontal length scales (Fig. 13, page 46), and sharper vertical correlations (Fig. 14, page 47) compared to the **B** matrix derived using the NMC method, which agrees with previous research results.

The diagnostic study suggests that the ensemble-based **B** matrix is better adapted for use in the LAM DA system because it emphasizes more on the small scales than the NMC **B** matrix. Reasons for this are longer forecast ranges and involvement of analysis increments in the NMC method instead of analysis errors as in the ensemble method. In order to assess the degree to which analysis increments and longer forecast ranges influence the NMC **B** matrix characteristics, two additional NMC **B** matrices were estimated, using 36 and 24 h forecast differences (NMC2436) and using 24 and 12 h forecast differences (NMC1224). Results (Fig. 15, page 49) indicate that for the standard deviation, length scale, and vertical correlation more pronounced differences among experiments are found for temperature and humidity than for vorticity and divergence. The largest differences for divergence and vorticity are found for the large-scale part of the horizontal correlation spectrum where the highest values are found for the NMC experiment. Overall results clearly show that accumulation of analysis increments influences statistics more than longer forecast ranges.

*3.4. Impact of **B** matrix on the analysis and quality of forecast*

For assessing the impact of using different **B** matrices on analysis and quality of forecast, two DA cycles were set up during June 2017 where one of them used ENSLBC **B** matrix and another NMC **B** matrix. Prior to this for each experiment, one month of cycling was done in order to tune **B** matrix using the method suggested by Desroziers et al. (2005).

The single-obs experiment (Fig. 16, page 51) shows that resulting increments for the two **B** matrices differ both in shape and spatial extent from the observation location. Sharper increments for the ENSLBC **B** matrix are clearly visible for all variables where the 0.5 contour lines differ by 50–200 km in extension for the two experiments. Except for the sharpness, the differences in the sign of the increment at certain places between the two experiments can be noticed in all figures. This is most pronounced for the humidity, where a strong negative increment is present near the observation point for the ENSLBC experiment, while it is completely missing in the NMC experiment. The shape of mean vertical increment computed for June 2017 and over the model domain (Fig. 17, page 52) for the temperature increments is similar for both experiments, but the warming (below 900 hPa, and between 400 and 200 hPa) and cooling (approximately 600 hPa) is more pronounced for the NMC experiment. The vorticity increments are also rather similar, with slight differences in the location and intensity of the extremes. Larger differences are found for the divergence between 600 and 200 hPa. The largest differences are for the humidity, where moistening is present in both experiments, but the shape of the mean vertical increment is quite different between the two experiments. To assess the degree of balance within the analyses produced using different **B** matrices, the mean and root-mean-square of the surface pressure tendency over the domain were calculated (Fig. 19, page 54). High values for both, the mean and root-mean-square, at the beginning of the forecasts indicate that the model is adjusting during the first three hours of forecasting in both experiments. Nevertheless, smaller values are found for the ENSLBC experiment compared to the NMC experiment, thus most probably showing more balanced initial conditions.

The quality of the forecasts started from ALADIN-HR4 DA system using different **B** matrices was assessed by comparing the forecasts with in situ data from surface and radiosonde observations during June 2017. For the surface parameters, the differences between the experiments are negligible, except for the mean sea level pressure (MSLP) and total cloudiness (Fig. 20, page 55). The results show that the MSLP forecast is better in the first 6 h for the ENSLBC experiment, which is likely related to the higher degree of balance in the ENSLBC experiment. The total cloud cover is better for the ENSLBC experiment for the first 12 h of the forecast (only for two lead times it is not statistically significant). Upper-air field results show that there is no significant difference between the experiments. For the precipitation, the point-based verification where the model output was compared to the rain gauge measurements over the domain was computed and the verification statistics were calculated from contingency tables. The Wilson diagram demonstrates (Fig. 23, page 59) that for the two highest precipitation thresholds, better results are obtained for the ENSLBC experiment. Symmetric extremal dependence index (SEDI), which is base-rate-independent and thus suited for the verification of rare events, indicates that the ENSLBC experiment outperformed the NMC experiment to a certain extent. This is especially the case for higher precipitation thresholds. The threat score already shows the ENSLBC predominance for high precipitation event thresholds, but this result is important because the SEDI, unlike the threat score, is not a base-rate-dependent score. Therefore, it confirms the ENSLBC high precipitation event forecasting predominance independently on the underlying climatology.

4. Radar data assimilation

In this part sensitivity of numerical simulation of a severe convective storm in the Pannonian Basin with a cloud-scale numerical model to (1) horizontal grid spacing, (2) assimilation of conventional observations (SYNOP), and/or (3) assimilation of radar observations was evaluated. A case of interest is a severe thunderstorm that hit the north-western part of Croatia in the late afternoon and evening of 24 June 2008. Strong wind gusts and hail were observed, and there were even reports of a small tornado. Hail was the size of a hazelnut (~ 13 mm) or in some locations the size of an egg (~ 50 mm). The storm caused significant damage to crop, buildings, and cars. The storm was initiated near Graz in Austria and travelled southeast through Slovenia and Croatia reaching as far as Bosnia and Herzegovina (Fig. 24, page 63).

4.1.Methods

The Advanced Regional Prediction System (ARPS) high resolution non-hydrostatic numerical prediction model (Xue i sur., 1995; Xue i sur., 2000, 2001) was used in several configurations with 24, 8, and 2.5 km horizontal grid spacing and the same configuration of vertical levels (Fig. 26, page 64). A number of experiments were performed, and they are summarized in Table 3, page 65. In the first two experiments, ARPS model with 8 km horizontal grid spacing was initialized at 12:00 UTC 24 June 2008 using initial and LBC from ARPS24. Both of them provided 9 h forecast, but for one of them (ARPS8assim) hourly sequential DA of conventional data starting from 15:00 UTC until 18:00 UTC (Fig. 27, page 67) was incorporated. Assimilation of conventional data was performed in two steps. First analysis increments were calculated at full hour using as a background forecast from the previous cycle. For calculating analysis increments ADAS–ARPS Data Analysis System (Brewster, 1996) was used. In the second step analysis increments were added gradually to the background field during model run using the incremental analysis update (IAU) procedure (Bloom et al., 1996).

Radar data was assimilated in ARPS2.5_ex3 and ARPS2.5_ex4 sequentially at 18:00 and 18:15 UTC (Fig. 27, page 67). As a background for radar data assimilation at 18:00 UTC the ARPS8* (* denotes different DA configurations) forecast valid at same time and interpolated to ARPS2.5* grid was used. Assimilation of radar radial winds was performed using three-dimensional variational analysis – 3D-Var (Gao et al., 2004), while radar reflectivity data increments were calculated through a cloud analysis procedure where hydrometeors and cloud fields are defined, and adjustments to the in-cloud temperature and moisture fields are made (Brewster, 2002). Analysis increments were added to the background field during a 15 min model run and using IAU with a 15 min window. This 15 min forecast was used as a background field for calculating increments for 18:15 UTC analysis. Analysis increments were added to the background field using 15 min IAU during ARPS2.5* forecast that started at 18:15 UTC and ended at 21:00 UTC.

4.2.Results

Results for ARPS8* runs are shown in Figure 28, page 68 and Figure 29, page 69. Comparison with the radar observations shows that at 18:00 UTC ARPS8 has a weak storm located north of the location of the observed storm while ARPS8assim has a well-developed storm at the proper location. The movement of the storm system is better described with the ARPS8assim run as it started to move southeast 1 h before ARPS8, in accordance with the radar observation. The simulated reflectivity at 2 km is stronger in the ARPS8assim run compared to ARPS8, and this is also in better agreement with radar observations. The movement of the storm in both runs can be explained using surface patterns (Fig. 30, page 70) and vertical wind shear. Broad areas of high values of CAPE covering Slovenia and northern parts of Croatia in ARPS8asssim on one side and larger values of CIN over Hungary on the other side resulted in a south-eastward storm motion which is comparable with radar observations. It seems that assimilation of surface observations provided proper low-level ingredients (surface moisture, convergence lines) needed for convection initiation and further storm propagation.

To further improve the simulation of storm development and to test the influence of model horizontal grid spacing, two high resolution runs ARPS2.5_ex1 and ARPS2.5_ex2 were performed where for initial and boundary conditions respectively ARPS8 and ARPS8assim were used. In both runs, the initial storm near the border of Austria and Slovenia is rapidly enhanced compared to the ARPS8 runs and the movement and location of the convective system in both runs closely follow that of the outer mesoscale model (Fig. 31, page 72; Fig. 32, page 73). Still, in the high-resolution simulation, the original storm is decomposed in several smaller ones which is more pronounced in ARPS2.5_ex2 simulation. At the end of simulation, there is a much better agreement with the observed radar image in the ARPS2.5_ex2 run, where three main storms are in the middle of northern Croatia. Nevertheless, the location is far north from the observed one and some spurious storm cells are present over the NE part of Slovenia. Also, the structure of the storm is not well captured as small values of observed reflectivity over Hungary are not simulated.

To improve the initialization of the high-resolution simulation, radar data assimilation was applied to ARPS2.5* simulations. Radar data assimilation leads to generation of an additional storm located south-east for ARPS2.5_ex3 and a bit north for ARPS2.5_ex4 from the one present in the background state (Fig. 33, page 75; Fig. 34, page 76). For ARPS2.5_ex3 those two storms are developing almost independently one of other until 19:00 UTC when the original storm encounters an area affected by the passage of the newly generated storm. After that radar data assimilation newly generated storm is soon decomposed into a number of smaller storm cells but eventually most of them decay leaving the one dominant storm cell that moves SE until the end of the simulation. For ARPS2.5_ex4 those two storm cells interact forming a wide band of high reflectivity and it continues to move SE until the end of the simulation. At 19:15 UTC the main storm cell is located near the town of Varaždin, very close to the observed one but about 15 min late. At the end of simulation main cell is located at a similar location as in the ARPS2.5_ex2 experiment but with a better storm structure having low reflectivity in the part extending over Hungary and thus providing the best results from all simulations performed.

To go beyond the rather subjective verification based on the comparison of model simulated reflectivity and observed radar CAPPIs an objective verification was performed. Results (Fig. 35, page 77) show that the highest scores for all thresholds were obtained for the ARPS2.5_ex4 experiment.

5. Summary

In this study data assimilation system implemented at DHMZ was described. Special focus was given to the estimation of the **B** matrix and study of its characteristics depending on the method used for estimation. The influence of the LBC perturbations was also assessed. Influence on analysis and quality of forecast confirmed that, showing that the ensemble **B** matrix has a positive influence on initial model balances and quality of the model forecast. The influence of radar data assimilation was evaluated for a severe convective storm that hit the northern part of Croatia. Results demonstrated the importance of data assimilation of radar, but also conventional data.

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