## Poster sessions

### P5 - Friday, 17 Sep 2021 (10:00-11:00, 13:00-14:00, 16:00-17:00)

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_all times are in UTC_
1000-member ensemble forecasts for extreme events: the 2019 typhoon Hagibis and the July 2020 Kyushu heavy rain

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Abstract

Forecast performances of two extreme events (the 2019 typhoon Hagibis and the July 2020 Kyushu heavy rain) have been revisited with the aim of improving the forecasts for these events. Our approach is to better quantify forecast uncertainties by running data assimilation systems with 1000 ensemble members to produce ensemble analyses. The two data assimilation methods to be used are the four-dimensional local ensemble transform Kalman filter 4D-LETKF and the hybrid variational-ensemble assimilation 4D-EnVAR. Verifications show that the resulting forecasts outperform the operational forecasts both in deterministic and probabilistic forecasts.

Keywords: ensemble forecast, 1000 members, typhoon Hagibis, heavy rain

∗Speaker
A Deep Learning approach for error correction of numerical weather prediction simulation data

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Abstract

Meteorological data are produced in various spatial and time sizes, depending on the application they will be used. The data are the result of Numerical Weather Prediction (NWP) simulations, e.g. the solution of mass & energy balance equations, concerning the fluids of the atmosphere. The uncertainty of the solution (time-series of domain) becomes higher as the prediction goes further to the future, thus, limiting the applicability of hour per hour resolution of such models, to 2 to 5 days ahead.

In the current study, a deep learning approach, based on convolutional autoencoders (CAEs), is explored in order to effectively correct the error of the simulation result, hence performing a result similar to statistical downscaling methods. The global seasonal forecast (6 month ahead) Meteo France Seasonal data was used for the Greece area, alongside the reanalysis dataset NCEP FNL, that incorporates observations, satellite imaging etc and it has better spatial resolution. During the training of the model, external information is used as evidence transfer, concerning the time conditions (month, day, season) and the simulation characteristics (initialization of simulation). The study was performed for the temperature variable at 2m from the ground and it was found that the CAEs help improve the resolution of the seasonal data and successfully correct the error of NWP data for 6 month ahead forecasting. Interestingly, the season evidence yields the best results which indicates a seasonal (winter, spring, summer, autumn) dependence of the performance.

Keywords: deep learning, convolutional neural networks, autoencoders, evidence transfer, error correction

∗Speaker
Accelerating Climate Model Computation by Neural Networks: A Comparative Study

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Abstract

In the era of modern science, scientists have developed numerical models to predict and understand the weather and ocean phenomena based on fluid dynamics. While these models have shown high accuracy at kilometer scales, they are operated with massive computer resources because of their computational complexity. In recent years, new approaches to solve these models based on machine learning have been put forward. The results suggested that it be possible to reduce the computational complexity by Neural Networks (NNs) instead of classical numerical simulations. In this project, we aim to shed light upon different ways to accelerating physical models using NNs. We test two approaches: Data-Driven Statistical Model (DDSM) and Hybrid Physical-Statistical Model (HPSM) and compare their performance to the classical Process-Driven Physical Model (PDPM). DDSM emulates the physical model by a NN. The HPSM, also known as super-resolution, uses a low-resolution version of the physical model and maps its outputs to the original high-resolution domain via a NN. To evaluate these two methods, we measured their accuracy and their computation time. Our results of idealized experiments with a quasi-geostrophic model show that HPSM reduces the computation time by a factor of 3 and it is capable to predict the output of the physical model at high accuracy up to 9.25 days. The DDSM, however, reduces the computation time by a factor of 4 and can predict the physical model output with an acceptable accuracy only within 2 days. These first results are promising and imply the possibility of bringing complex physical models into real time systems with lower-cost computer resources in the future.

Keywords: Weather Forecasting, Neural Networks, Model Acceleration

∗Speaker
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Assimilation of solar reflectances in a pre-operational online system with a local ensemble Kalman filter

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Abstract

Since spring 2021, the convection-permitting ensemble data assimilation system (ICON-D2 KENDA) of Germany’s National Weather Service (DWD) assimilates solar reflectances from the SEVIRI 0.6 micron channel inside the pre-operational SINFONY system for seamless prediction from nowcasting to NWP. Assimilating solar reflectances allows for deeper insight into the physical dynamics of atmospheric radiation and microphysical processes. Better tracking of clouds and convective processes may also improve the skills of short-term NWP, especially for precipitation.

This work is based on the incorporation of the fast and accurate forward operator for solar reflectances MFASIS into the NWP system at DWD. Data assimilation of these reflectances further demands careful study of the underlying biases introduced by both model and forward operator. We therefore give an overview of the steps undertaken during the development of this system as observational error modelling, quality control and an adaptive bias correction. Extensive case studies and impact experiments in different seasonal conditions show that data assimilation of solar reflectances reduces the forecast error of cloud and precipitation, precipitation intensity, global radiation and screen-level variables.

Keywords: SEVIRI, solar reflectance, VIS, MFASIS, RTTOV, data assimilation, regional model, convective scale, ICON, LAM

∗Speaker
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Enhancement of Variational Assimilation of High-Frequency and High-Resolution Radial Winds

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Abstract

This study is aimed at effectively utilizing radial winds from Doppler radars densely distributed in time and space in data assimilation to initialize a forecast model. An appropriate handling of the observation error correlation is firstly important to consistently assimilate high-resolution data without applying severe thinning. Handling of detailed flow-dependency in data assimilation scheme is also essential to extract information from the high-resolution observations as a time evolution in line with the model dynamics. A hybrid 4D-Var equipped with an observation error of radial wind correlated in time and space is implemented based on the former operational Meso-scale Analysis of Japan Meteorological Agency applying the JNoVA 4D-Var (JMA 2019, Honda et al. 2005), introducing the flow-dependent background error generated by the Ensemble of Data Assimilation (EDA; Isaksen et al. 2010) with extended control variables. A case study shows the flow-dependent background error along with the correlated observation error contributes to give promising results lasting into forecast. Investigation is carried out on sensitivity of the flow-dependent background error to the EDA perturbations, including uncertainties from the random sampling of perturbations added to observations. An enhancement of the ensemble control variables also is tried to take into account the scale dependent profile of the background error.

Keywords: observation error correlation, flow dependent background error, hybrid 4DVar, radial wind

*Speaker
Exploring the potential of nested EnVAR in the global-to-regional ensemble system at DWD

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Abstract

The German Weather Service (DWD) operationally runs ensemble predictions systems for the global and regional Numerical Weather Prediction (NWP). The global system deploys the NWP model ICON with an EnVAR+LETKF (Ensemble variational + localized Ensemble Transform Kalman Filter) data assimilation at a resolution of 40 km for the ensemble and 13 km for the deterministic run. The global setup is run with a two-way nest in central Europe (ICON-EU). This provides the lateral boundary conditions for the regional system which consists of ICON-LAM (ICON Limited Area Mode) run at a resolution of 2.1 km (model configuration ICON-D2) and a 4D-LETKF scheme called KENDA (Kilometre-scale Ensemble Data Assimilation). We are investigating a number of different setups for creating a regional EnVAR analysis for the deterministic forecast. The model is ICON-LAM, but the ensemble members for the ensemble covariance matrix and the boundary conditions for the deterministic run originate from different resolutions of the ICON model, e.g. ICON-D2, ICON-EU or ICON global. We focus on a EnVAR data assimilation based on the KENDA ensemble to improve the forecasts on the convective scale.

Keywords: EnVAR, convective scale, LETKF, DWD, KENDA, data assimilation, ICON

∗Speaker
Forecast Evaluation of a Deep Convection Case During Relampago Assimilating Conventional and Satellite Observations with the WRF-GSI-LETKF System

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Abstract

We present forecast evaluation results from the first attempt to use the WRF-GSI-LETKF system in Argentina. The impact of assimilating high-resolution surface networks and satellite observations on a forecast from the analyses is evaluated. This study also represents the first steps to assimilate satellite radiances in a regional context in South America. We focus on a case study corresponding to a huge mesoscale convective system (MCS) developed over central and north-eastern Argentina during November, 22th, 2018.

Analyses with 10-km horizontal grid spacing were produced assimilating observations every hour from 11/20 18Z to 11/23 12Z. We used a 60-members ensemble which at the first assimilation cycle is initialized from the deterministic GFS run adding random perturbations with climatological covariance. A multiphysics approach is also used to represent model errors, using different physics configurations. Four assimilation experiments were conducted using increasing sets of observations: CONV assimilates conventional observations from prepBUFR, AUT uses CONV observations plus automatic stations, SATWND add satellite-derived winds and RAD also includes satellite radiances from AMSU, HIRS, MHS, ATMS, AIRS and IASI.

We run two ensemble forecasts initialized from the analyses at 00Z and 06Z 11/22 to evaluate the impact of the different observing networks on forecasts. Comparing the forecasts with the observed precipitation (IMERG Final Run), the representation of precipitation is shown to improve for forecasts initialized from AUT, SATWND and RAD. Moreover, the impact continues for many hours after its initialisation. Complete results and conclusions from these experiments will be presented at the symposium.

Keywords: Regional data Assimilation, GSI, Satellite Data Assimilation, Ensemble Forecast

*Speaker
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Hydrometeor control variables in the
AROME-France 3DEnVar assimilation scheme

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Abstract

Initialization of variables related to condensed water is a topic of active research for convective-scale weather forecasting. We present in this talk the work that has been performed at Météo-France to add hydrometeors as control variables of a three-dimensional ensemble variational scheme (3DEnVar) for the regional model AROME-France. Hydrometeor variables are added in the forecast error covariance matrix $B$ estimated from an Ensemble of Data Assimilations. As a first approximation, no variable transform nor static hydrometeor covariance matrix are used. Common localization and Scale-Dependent Localization (SDL) are tested. Even without any direct assimilation of hydrometeor observations, hydrometeor analysis increments can be produced via covariances with observed variables in $B$.

Cycled forecast-analysis experiments in near-operational conditions have been performed over a 3-month summer period. Three configurations were compared, (i) a control experiment without hydrometeor control variables, (ii) a test experiment with hydrometeor control variables but without cycling the resulting forecasts, and (iii) an experiment with hydrometeors and cycled forecasts. Compared to the control experiment, both hydrometeor experiments show a positive impact in the first 7 hours of the forecast in terms of cloud cover, and in the first hour for precipitations. The forecasts display an extended short-term predictability window for precipitation, with skill scores decaying beyond a reference threshold after 1 h 14 min on average, instead of 1 h in the control experiment. The added value of hydrometeor control variables persists independently of the chosen localization method, thus confirming the robustness of the results.

Keywords: hydrometeor, control variables

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Improving dynamical balance and mass conservation in convective-scale data assimilation

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Abstract

An idealized framework for radar data assimilation has been developed based on the COSMO-KENDA system (Zeng et al. 2021a). It is shown that the data assimilation could cause significant biased increases in divergence and vorticity as well as in total specific mass of microphysical variables. To reduce the bias, two methods have been developed: First, a new integrated mass-flux adjustment filter, which uses the analyzed integrated mass-flux divergence field to correct the analyzed wind field (Zeng et al. 2021b). It is found that the new filter considerably diminishes spurious mass-flux divergence and the high surface pressure tendency and thus results in more dynamically balanced analysis states. Second, a weakly constrained LETKF on mass conservation and nonnegativity of microphysical variables, which improves the mass conservation property of microphysical variables of analyses (Zeng and Janjic 2021). Both methods lead to better forecasts.

Keywords: convective, scale, radar data assimilation, mass conservation, imbalance

*Speaker
Spin-up time from switching the microphysics scheme within the assimilation cycle and impacts on the precipitation forecast quality

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Abstract

The SINFONY project at DWD aims to produce seamless forecast products from minutes up to 12 h focusing on convective precipitation events. While the forecasts early on are typically produced from nowcasting procedures using radar data, numerical weather prediction (NWP) aims at forecasting longer time ranges. However, the latest available forecast is usually too old to merge with nowcasting data for reliable seamless predictions. At DWD, forecasts with lead times beyond 2 h are produced by a short-range numerical weather prediction system (SRNWP) using ICON. A continuous assimilation cycle is used with relatively long cutoff times and a 1-moment microphysics. To reduce differences in predicted precipitation and nowcasting, 3 actions are taken on the NWP side. First, we reduce the latency of forecasts by using short assimilation cycles with shorter data cutoff and increasing the frequency of forecasts. This is the Rapid Update Cycle (RUC). Second, the RUC uses new observation systems, e.g. radar or all-sky satellite data, to capture and represent strong convection. Third, we introduce a 2-moment microphysics scheme into ICON, improving the simulated radar reflectivities. To keep the model state similar to that of the SRNWP, the RUC branches off from the SRNWP assimilation cycle at several pre-defined times. The introduction of the 2-moment scheme leads to a spin-up affecting both assimilation cycle and short forecasts. The resulting effects are assessed by a comparison to the SRNWP with the 1-moment scheme. The results are compared regarding quality of precipitation forecast and other observations. It is shown how far the resulting improvements are related to the assimilation and microphysics scheme, or to the higher forecast frequency.

Keywords: rapid update cycle, assimilation, 2, moment, microphysics

∗Speaker
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The predictability of the moist convection over different mountain sizes and environmental flow conditions

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Abstract

The predictability of moist convection and the accompanying rainfall is limited to a few hours since the high nonlinearity of moist convective processes could lead to rapid initial error growth. On the other hand, the topography is considered to decrease the nonlinearity of the atmosphere and increase the predictability by providing a stationary forcing. It has been shown that topography can increase the predictability of rainfall from a practical perspective. However, the impact of topography on intrinsic predictability hasn’t been well investigated. By addressing the impact of topography on the initial error growth of moist convection, it is expected to be helpful in improving the weather prediction and data assimilation strategy in areas affected by topography.

Here, identical twin experiments with different single Gaussian shape mountains and vertical wind shear are conducted with the Weather Research and Forecasting (WRF) model in an idealized framework. The initial error growth is evaluated by a metric referred to as moist difference total energy (MDTE), which considers the differences in horizontal wind, temperature, water vapor, and surface pressure between the two simulations. Comparing to the experiment without the mountain, the initial error growth estimated by the MDTE is smaller for the moist convection occurring over the mountain in the morning. The reduction effect of the mountain on the error growth is more distinct in the water vapor than in the horizontal wind or temperature. When the mountain slope is steeper, the effect also becomes more pronounced. It also shows a sensitivity to the stability and different flow conditions of the environment.

Keywords: initial error growth, moist convection, topography
Timely allocation of resources after natural disasters: deep learning as a tool for damage assessment and saliency mapping

Thomas Chen

Abstract

Natural disasters ravage the world’s cities, valleys, and shores on a monthly basis. Having precise and efficient mechanisms for assessing infrastructure damage is essential to channel resources and minimize the loss of life. Using a dataset that includes labeled pre- and post-disaster satellite imagery, the xBD dataset, we train multiple convolutional neural networks to assess building damage on a per-building basis. In order to investigate how to best classify building damage, we present a highly interpretable deep-learning methodology that seeks to explicitly convey the most useful information required to train an accurate classification model. We also delve into which loss functions best optimize these models. Our findings include that ordinal-cross entropy loss is the most optimal loss function to use and that including the type of disaster that caused the damage in combination with a pre- and post-disaster image best predicts the level of damage caused. The highest accuracy percentage on the testing set that we achieve is 74.6%; the non-optimal nature of this is largely attributed to the limited discernibility between the major and minor damage categories. We also make progress in the realm of qualitative representations of which parts of the images that the model is using to predict damage levels, through gradient class-activation maps. Our research seeks to computationally contribute to aiding in this ongoing and growing humanitarian crisis, heightened by climate change. Specifically, it advances more interpretable machine learning models, which were lacking in previous literature.

Keywords: machine learning, computer vision, climate change, disaster relief, natural disasters
Towards Developing Radio Occultation Machine Learning Forward Operators

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Abstract

Spire Global is a space-to-cloud data and analytics company that generates highly impactful earth observations and weather forecasts. Currently, Spire collects \( \sim 10,000 \) radio occultation soundings a day globally via the company’s large nanosat constellation; these soundings, along with other data, are assimilated into a global weather model to produce the Spire operational forecast. Our main goal of developing machine learning (ML) forward operators is to improve the skill of our data assimilation analyses and subsequent weather forecasts by enhancing the impact of the radio occultation profiles. More precisely, we plan to improve over existing physics-based operators by using more accurate implicit data driven interpolation operators, and superior handling of data biases. We developed two ML operators based on the random forest and deep neural network (DNN) methods. The random forest model is used as an exploratory tool for feature importance to deal with the large number of predictors obtained from numerical weather prediction forecasts and radio occultation profiles. The first implementation of the DNN model employs a reduced number of features and takes advantage of an embedding layer to differentiate between various satellites sources characterized by categorical information. The next step is to make use of all geophysical variables as required by the data assimilation scheme and implement DNNs equipped with either a convolutional or SVD layer. Bending angles resulting from the ML forward operators will be compared against the physics-based 1D operator ROPP outcomes. The performance will be assessed based on statistics of departures from the real measurements.

Keywords: Radio Occultation, Machine Learning, Deep Neural Networks, Random Forest
Using a cost-effective approach to increase background ensemble size in EnVar to improve radar analyses and forecasts of convective systems

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Abstract

The valid time shifting (VTS) method is explored for the GSI-based EnVar system extended for convective scales with direct assimilation of radar reflectivity. VTS is a cost-efficient method to increase ensemble size or reduce current cost by including subensembles before and after the central analysis time. Additionally, VTS addresses common time and phase model error uncertainties within the ensemble. VTS is examined here in a HRRRE-like continuous hourly analysis system over UTC on 1-2 May 2019. The VTS application is compared against the 36-member control experiment (ENS-36) to increase ensemble size (3x36 VTS) and as a cost-savings method (3x12 VTS), with three time-shifting intervals t = 15, 30, and 45-min. The 3x36 VTS experiments increased the ensemble spread overall, with larger subjective benefits in early cycles during convective development. The 3x12 VTS experiments capture analysis with similar accuracy as ENS-36 by the third hourly analysis. Control forecasts launched from hourly EnVar analyses show skill increases in 1-h precipitation over ENS-36 out to hour 12 for 3x36 VTS experiments. Experiment VTS-3x12t45 captures similar level of skill to ENS-36 out to forecast hour 16, with at times subjectively better structure of the bowing line. The 3x36 VTS experiments add a computational cost of 35-56%, compared to the near tripling of costs when directly increasing ensemble size, while 3x12 VTS experiments save about 45-55% costs over ENS-36.

Keywords: ensemble, data assimilation, convective scale, convection, radar, envar, analysis, forecast

∗Speaker
Using a Neural Network to choose amplitude and anisotropy parameters of an adaptive background error covariance

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Abstract

As part of the development of the new 3D Real-Time Mesoscale Analysis (3D RTMA) we have developed a multigrid background covariance scheme using local superpositions of quasi-Gaussian numerical filters based on compact-support beta distributions. We plan to use a machine learning approach, specifically a neural network, to guide the optimal construction of the multigrid’s amplitude scale-weights, and anisotropy-determining aspect tensor, in response to smoothed diagnostics from terrain, background and ensemble, so that the analysis can be made dynamically adaptive. Given the tensorial characterization of anisotropy, we extract from the background and ensemble fields suitable tensor diagnostics which a neural network has only to combine additively. The quasi-Gaussian character of the covariance contributions allows some inter-observation covariances to be well approximated by direct evaluation. Thus, we construct a quadratic quality criterion measuring that covariance deviation from the corresponding sample innovation statistics that subsets of observation pairs provide, and train the neural network over multiple archived cases, to optimize the covariance parameters, and hence the analysis.
Using Machine learning techniques to switch background error distributions to improve data assimilation

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Abstract

With the development of non-Gaussian based data assimilation in the variational formulation, and the understanding that the underlying distribution can change dynamically, we need techniques that allow us to "switch" between the distributions to ensure a consistent background error model. To address this question, we have used different machine learning techniques with different criteria to determine if the behavior of the variable has switched between Gaussian and lognormal, but also back to Gaussian. In this presentation, we shall present results using a support vector machine technique to determine when the z component of the Lorenz 1963 model switches between Gaussian, lognormal, and back, through using skewness changing from 0 to determine this change and show that by switching between the distribution, the analysis error is improved compared to just assuming a Gaussian all the time. We shall also present results from the Lorenz 96 model as well.

Keywords: Variational data assimilation, support vector machine, Gaussian, lognormal

∗Speaker
Remote sensing data play a critical role in improving numerical weather prediction (NWP), especially for regions with no in situ observations available. However, the physical principles of radiation dictate that data voids often exist in physical space (e.g., subcloud area for satellite infrared radiance or no-precipitation region for radar reflectivity). Such data gaps undermine the accuracy of initial conditions from data assimilation, negatively impacting NWP. Here, we use the barotropic vorticity equation (BVE) to demonstrate the great potential of deep learning (DL) in augmenting data assimilation by reconstructing spatially complete observation fields from incomplete observations. The training dataset for deep learning is a long-term BVE simulation at a coarse resolution (T63). By training a convolutional autoencoder (CAE), we obtain a DL approximation of the ‘reconstruction operator,’ which maps spatially incomplete observations to a reconstructed model state with full spatial coverage. The operator is applied to the incomplete streamfunction field from a high-resolution (T85) simulation and exhibits satisfactory performance. We further evaluate the impact of DL reconstruction on assimilation and forecasting with four groups of observations from the T85 benchmark simulation, including those with full coverage (FullObs), incomplete observation (PartObs), DL reconstruction (RecObs), and a combination of PartObs and RecObs (MixObs). Data assimilation using MixObs generates significantly more accurate initial conditions than those based on PartObs and is similar to the accuracy of FullObs assimilation. Predictions based on the initial conditions from the DL-augmented data assimilation are also notably better than the predictions relying on spatially incomplete observations only.