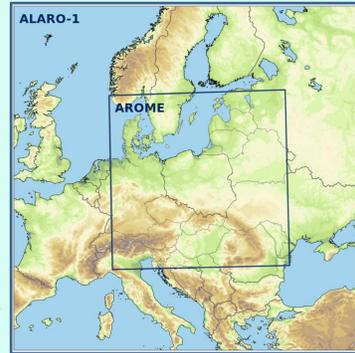


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Operational

ALARO-v1B NH (CY43T2) operational domain:

4km horizontal resolution, 789x789 grid points, 70 vertical model levels, on a Lambert projection with 3h coupling frequency and 1h output, coupling zone 16 points; Runs 4 times per day (00,06,12 and 18) with 102 hours forecast range; LBC from ARPEGE with 9.4km horizontal resolution; Time step 150s. In pre-operational mode CANARI surface assimilation with 6h cycling.



Computational domains of ALARO-1 (4.0km horizontal resolution) and AROME (2.0km horizontal resolution) nested models.

AROME (CY43T2) operational domain:

2km horizontal resolution, 799x799 grid points, 70 vertical model levels on a Lambert projection with 3h coupling frequency and 1h output. 4 runs per day (00, 06, 12 and 18UTC) with 42 hours forecast range; LBC from ALARO-1 4km; output every 1h – for LEADS system; Time step 50 s; 10min output for INCA Nowcasting System.

New operational machines - characteristics

SAWA (located in Warsaw) – 180 Dell R660 CPUs, 1 Pflap in total, each core 512 GB RAM, OS Rocky Linux, Debian, CentOS; KRAK (Kraków) – 45 Dell R660 CPU (250 Tflops), 3 Dell XE9680 GPU (750 Tflops). Each GPU core contains eight NVIDIA H100 cards.

Testing ALARO CY46T1

Preoperational tests with CY46T1 export version runs daily for ALARO CMC with horizontal resolution 2.45km. The four packages of code changes developed by Czech LACE team in Prague were included in the local model version. Timestep 90s, 70 vertical levels (later maybe more). Climatological files were prepared according to the procedure described in Jan Masek's report. Initially, model dynamics setup was set according to Petra Smolkova presentation, then some changes in namelists were introduced.



SAWA - new operational computer cluster

X-term treatment in vertical divergence variable

Methodology

In the dynamical core of the ACCORD system, the numerical stability of the time scheme depends on the choice of the model variable for the vertical motion in the linear part of the Iterative Centered Implicit scheme. It has been previously stated that the most stable option uses a modified vertical divergence which includes the so-called X-term. In the non-linear part of the ICI time scheme, vertical velocity is used instead of the modified vertical divergence, which imposes a requirement to convert between those two variables in each time step. The X-term can either be calculated from other variables or stored and transformed between grid-point and spectral space. While the latter ensures consistency and filtering, it is computationally expensive.

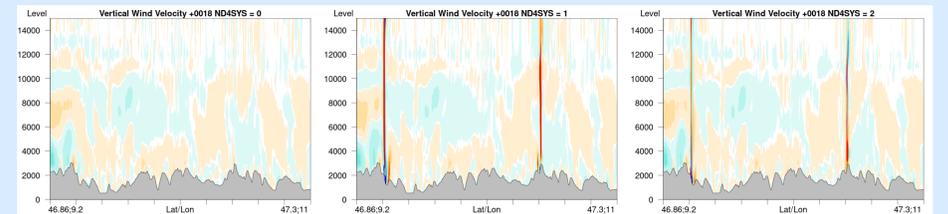


Figure 1. Vertical velocity field for ND4SYS=0, 1 and 2, respectively. For ND4SYS=0 (left) spurious chimneys over orographic obstacles disappear.

Results

In order to investigate whether the current treatment of the X-term is the best choice in terms of accuracy and numerical stability, the code was modified to enable the calculation of the X-term from model variables without the need to transform it to and from the spectral space. Avoiding this transformation, using the key ND4SYS=0, resulted in the reduced usage of the CPU time by around 7%, compared to previously used ND4SYS=1 and 2. The recalculation of the X-term also had a good impact on the results. Some of the spurious chimneys over orographic obstacles disappeared from the vertical velocity field (Fig. 1). Moreover, the time oscillations present in the solution observed in averaged spectral norms are removed (Fig. 2).

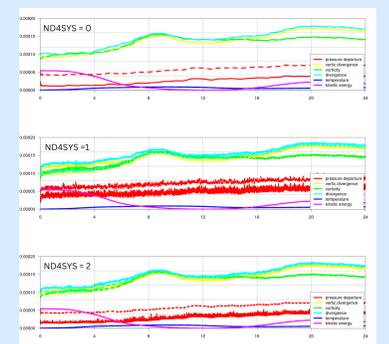


Figure 2. Averaged spectral norms for ND4SYS=0, 1 and 2. For ND4SYS=0 (top) time oscillations are removed.

Testing the Cascading Ensemble Method

Model information

FourCastNet is a data-driven global weather forecasting model. It was trained on ERA5 reanalysis data, spanning years 1979-2015. It can forecast 20 atmospheric variables, 5 of which are on the surface level. Timestep between each forecast is 6 hours, with a 0.25° spatial resolution, and the result is a 720x1440 grid point map of predicted values for each variable.

The model used in this project is a modified version of FourCastNet, installed on the ACK Cyfronet computing center supercomputer Athena. It creates an ensemble forecast, and the number of ensembles rises with the number of timesteps. For n timesteps, the final ensemble count is 2 to the n -th power.

The Cascading Ensemble Method (further also referred to as CEM) is a new method of creating ensemble weather forecasts. It proposes adding new members of any type of ensemble forecasts, not at the beginning of the forecast as it is usually done, but during the computations of forecasts, when the uncertainty of forecasts starts to grow. Its aim is to achieve similar or better results compared to the traditional methods, but at a lesser computational cost and less storage usage.

Methodology and data

We evaluated the scores of spread, bias, RMSE and CRPS of the original ensemble forecasting method (here called ENS) with CEM by running a month of forecasts using Nvidia's AI-driven global model FourCastNet and then comparing them to global data from WMO synoptic stations. The testing period was January 2023, with each run starting at 00:00 UTC and lasting 120 hours or 20 timesteps. CEM has the ensemble count increase from 1 to 256, doubling up until timestep 8. In ENS, the model maintains the same number of ensembles through the entire forecast (256 ensembles). Two variables were chosen for consideration: air temperature at 2m height (for which the graphics are presented here), and pressure at sea level.

Results

The CEM method has consistently rising spread values throughout the entire run, resulting in spread bigger than ENS for every timestep but the first (Fig. 1). For bias and RMSE the most notable difference is the varying amplitudes between the methods. Errors are most likely tied to the diurnal cycle of the variable. For example, bias reaches maximum around local noon and minimum around local 6 am (Fig. 2). This amplitude of values is larger for the ENS method, while for CEM the diurnal cycle of the errors has less extreme oscillations and the run smooths out over time, which leads to the difference between methods growing between timesteps (Fig.1).

Lastly CRPS sees a great difference in growth between the methods (Fig. 2). The ENS run has rapid growth for the first 6 timesteps before slowing down. For CEM, the values grow slowly and consistently without the initial jump, leading to a much lower CRPS overall.

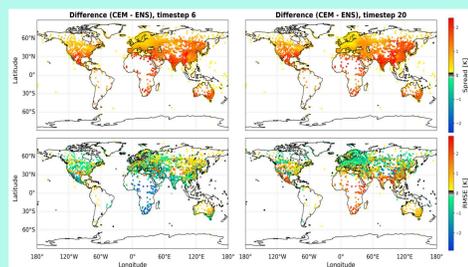


Figure 1. Difference maps of both methods for spread and RMSE.

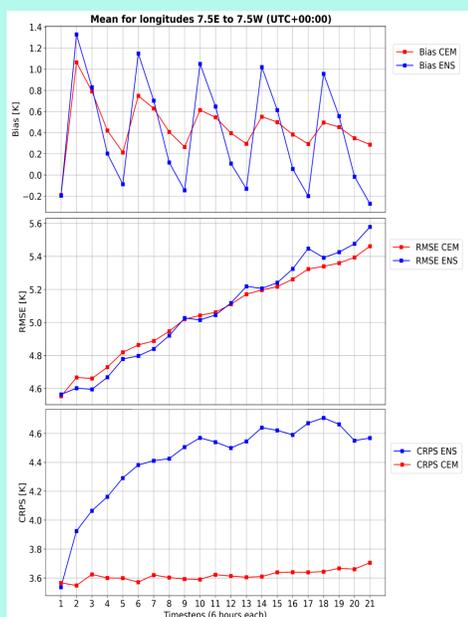


Figure 2. Mean bias, RMSE and CRPS progression through timesteps for a 15 deg wide area.

Examining timestep dependence of snowmelt in D95 in SURFEX

Methodology and data

D95 is a simple one-layer snow scheme available in SURFEX. It is used operationally, e.g., in the global ARPEGE model. In the scheme, the melting rate M [$\text{kg}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$] is given as:

$$M = p_{sn} \frac{T_n - T_0}{C_s L_f \Delta t}$$

where: p_{sn} – snow fraction, T_n – intermediate surface temperature, T_0 – water freezing point (0°C), C_s – snow heat capacity, L_f – latent heat of fusion.

However, in the model code (subroutine ISBA_FLUXES) the equation is slightly modified – a bottom limit for the model timestep was introduced. Thus, the model timestep Δt is replaced by a condition $\text{MAX}(X\text{TAU_SMELT}, \Delta t)$, where XTAU_SMELT is a namelist-defined parameter, equal by default to 300 s. The modification had already existed in the ISBA surface scheme in the global APREGE, before SURFEX was invented. Its main goal is to prevent timestep dependence of snowmelt. However, not denying the necessity of stable snowmelt regardless of timestep, the modification results in artificial inhibition of melting for $\Delta t < 300$ s. The smaller Δt , the greater underestimation occurs.

An offline experiment was performed to examine timestep dependence of snowmelt and the impact of XTAU_SMELT. The experiment spans the whole winter season 2023/2024 (from 1st November to 30th April). The forecasts were cycled (i.e., the output from the previous forecast was used as initial conditions for the next forecast). Other major SURFEX settings are given in Table 1. As snow in the lowlands is rare in Poland nowadays, plots concern a mountainous station, Hala Gąsienicowa (1523 m a.s.l.).

Table 1. SURFEX setup used in the experiment.

run mode	offline
forcing model	AROME (2.5 km)
forcing frequency	1h
forecast length	24h
forecast timestep	900/300/180/90
NPATCH	1
CISBA	2-L
TEB	on
CSNOW	D95
data assimilation	off

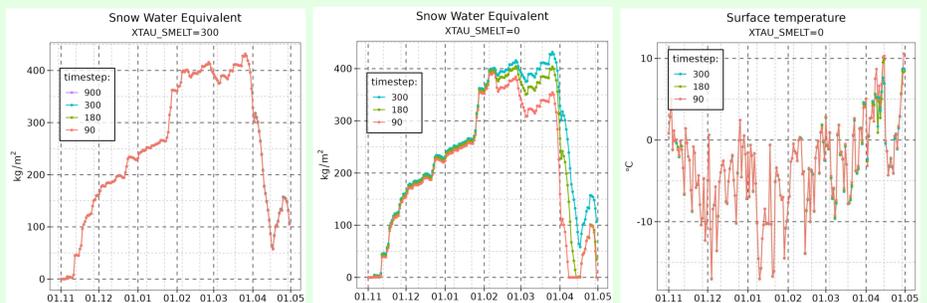


Figure 3. Forecasted snow water equivalent (left and middle) and surface temperature (right) for different timesteps and values of XTAU_SMELT in a winter season 2023/2024

Results and conclusions

With the default value of XTAU_SMELT, the lines completely overlap regardless of the timestep value (left chart). Therefore, the reproducibility of the results is assured and no timestep dependence is observed. However, if we set XTAU_SMELT=0 so that it is always the model timestep that is used to calculate melting rate, the results differ (middle chart). While in the beginning of the season, when snow accumulation prevails, the differences are negligible, they diverge in spring when melting occurs. It is important note that for $\Delta t = 300$ s. the results are just like for the default settings. The variability occurs only for smaller timesteps. The melting is more pronounced and consequently, snowpack is reduced faster. After intense melting in the beginning of April, the differences rise to around 100 kg/m^2 for $\Delta t = 180$ s. and around 200 kg/m^2 for $\Delta t = 90$ s. Obviously, such discrepancies will not appear if data assimilation is deployed. However, during a single 24-hour forecast in conditions of intense melting, the differences in reduction of SWE may rise to 12 kg/m^2 for $\Delta t = 180$ s and 25 for $\Delta t = 90$ s. Considering a known issue of snowpack overestimation in D95, this casts a new light on this problem. Nevertheless, prior to it, one has to understand the source of timestep dependence and run experiments in coupled mode to assess its impact on atmospheric fields.