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Flow dependent SPP perturbations for C-LAEF

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Motivation

Can a stochastic perturbation pattern in SPP be adjusted to reflect the state of the flow, i.e., to generate the noise in the areas of high uncertainty? The idea was first proposed in Wastl *et al*. (2019) who writes: "At the moment the perturbation field is created randomly without any consideration of the weather or flow situation. Accordingly, it occurs that strong perturbations are applied in very stable areas (e.g., high pressure areas) without any effect, while on the other hand perturbations are not added in sensible areas with strong convection or near frontal zones. Hence it would be much more reasonable to restrict the perturbations to areas with large uncertainties." Following this line of thought, this work will formulate a new type of SPP – flow dependent SPP.

Introduction

In total, there are 6 physics schemes that are affected by SPP in C-LAEF. In this work, we will only concentrate on microphysics. Microphysics generally governs cloud particle formation, growth, and dissipation on very small scales. In microphysics SPP, there are 4 namelist switches for 5 parameters which are perturbed. Those are:

1. ZRDEPSRED – snow reduction factor (LPERT_ZRDEPRED)
2. ZRDEPGRED – graupel reduction factor (LPERT_ZRDEPRED)
3. RCRIAUTI – snow autoconversion threshold (LERT_RCRIAUTI)
4. RCRIAUTC – rain autoconversion threshold (LERT_RCRIAUTC)
5. PSIGQSAT – saturation limit sensitivity (LPERT_PSIGQSAT)

Following Ollinaho *et al.* (2017), in C-LAEF, SPP-perturbed parameters $\hat{P}$ are obtained:

$$\hat{P} = P\, e^{c+w\varphi} \tag{1}$$

Where P is the original constant parameter, φ is normally distributed stochastic perturbation pattern and *c* and *w* are some constants. This results in a log-normal distribution for $\hat{P}$ which has a nice consequence that perturbed parameters will not change the sign. The stochastic perturbation pattern φ varies in space and time independently for each parameter and ensemble member. After the perturbations are applied according to (1), each parameter is clipped to remain inside its physical limits. Additionally, impact of φ can be tuned for each parameter separately by adjusting *c*, *w* or its clipping values. Increasing (decreasing) *w* will increase (decrease) the magnitude of the applied perturbations and increasing (decreasing) *c* will move the log-normal distribution to the right (left) resulting in shifting all the perturbations in positive (negative) direction.

Methodology

In this work, the pattern generator will not be changed, and all its settings will remain the same. Instead, the approach taken here is based on modifying the existing pattern by some weights. The idea is to diagnose which areas in the model are the most unstable for each parameter and then to modify the pattern so that it perturbs more in those areas. The weights are then added to the perturbation field as w in (1), i.e., they multiply the pattern. One can wonder why the weights are not added so that they multiply P directly. The reason is that if weights are greater (lesser) than 1, then all the perturbations are moved to the positive (negative) direction. This means that the magnitude of perturbations can be lowered and that is not what we want. The goal here is to always increase the perturbations in the targeted regions and that can be achieved by applying weights as in (1).

The question now remains how to find which areas of the domain to target, i.e., how to determine the magnitude and the spatial distribution of weights? For microphysics, several options were explored. First, all moist variables (except water vapor) were considered (cloud water, rain water, pristine ice, snow/aggregate and graupel/hail), i.e., their mixing ratios from the model time step t – dt. They were all summed up and aggregated over all vertical levels, the resulting field is shown on Figure 1. We can see that a nice field where those variables make an impact is obtained. If we add water vapor, the whole domain will be affected and that is the reason it is left out. It looks like that this field is a good candidate for our weights, except that there is a small problem. It is not trivial to convert this field to weights (for example, to between 0 and 1) because we cannot normalize it easily as we do not have the access to the whole field as it is spread between the processors. For this reason, another field was found – cloud fraction. This field is already in fractions – between 0 and 1 so it is almost ready to be used as weights! First, as this field is given for all model levels separately, it needs to be summed up over all model levels. Then, this new field, let's call it w', is slightly modified:

$$w = \left(\frac{w'}{N_l} \times N\right) + 1 \quad (2)$$

Where N_l is the number of vertical levels in the model, N is some arbitrary real number and w are the final weights. The division by N_l is done to normalize the values (go to 0-1) because N_l is the maximum value in w'. We multiply by a factor of N=1.5 to increase the impact. Lastly, 1 is added to transform the values from 0-N to 1-N as this is what is needed since the w is multiplying the stochastic pattern (1). If that wasn't done, then all the parts of the domain where there are no clouds, would multiply the pattern by 0 and we wouldn't have any perturbations there. It may seem that big part of the domain is now affected, but at most of locations, w has small values because it is proportional to the cloud amount.

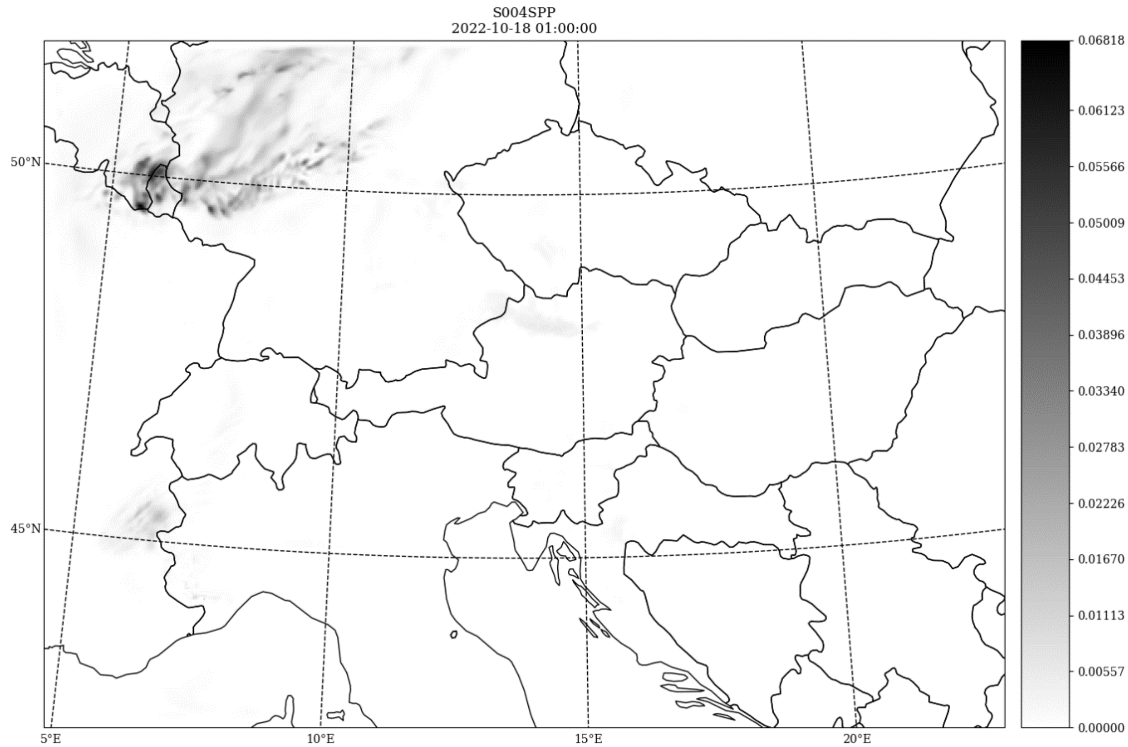

Figure 1. Moist variables mixing ratios (except water vapor) summed up and aggregated over all vertical levels.

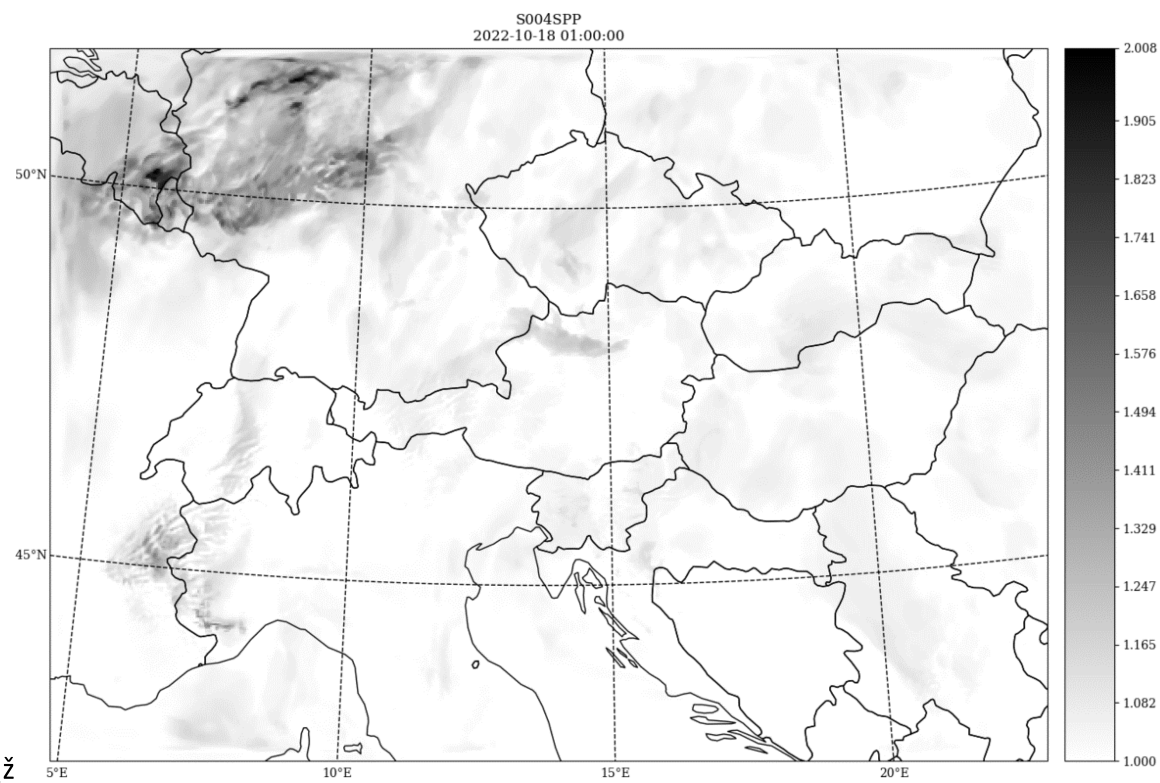

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Figure 2. Final weights based on cloud fraction field.

Results

Weights are added to (1) as *w* for the first 4 parameters listed above. For the 5th parameter, the cloud fraction field is not available, so this was left for a future study. The effect of applying weights on the perturbations can be seen on Figure 3 where perturbations are shown for the RCRIAUTC parameter. We can see that positive perturbations became more positive and negative became more negative in magnitude especially in the areas denoted by yellow circles. Figure 4 shows the difference between the two fields from Figure 3 to better see the difference. If one wishes to additionally increase the influence of weights, the factor 1.5 can be increased (2). Figure 5 shows impact on the 2 m temperature, relative humidity, zonal wind speed and hourly liquid precipitation after 24 h of run time. We can see that impact is quite measurable.

Finally, a one-day case study was run to assess the impact for a day when a cold front was moving in through the domain (Figure 6). Three different experiments were made. NO_SPP – no model perturbations are used, SPP_REF – default SPP is used, SPP_NEW – new flow dependent SPP is used. In the two SPP experiments, only microphysics is perturbed (the same 4 parameters). One C-LAEF (all 17 members) run was performed – 48-h integration started on 3 November 2022 at 00 UTC. No big differences are expected to be seen from this one integration, nevertheless, to better understand the nature of the new method and to see if it behaves correctly, it is worth to include it.

Figure 7 shows domain averaged spread for two SPP experiments with respect to NO_SPP and for different surface variables. The differences between the two experiments are small, but SPP_NEW has more spread for all variables. Furthermore, the differences are only occurring when clouds occupy significant part of the domain indicating that our new method is behaving expectedly. Figure 8 shows RMSE and spread for about 50 stations inside Croatia. Differences are only visible once clouds occupy significant part of Croatia, but they remain small. To additionally observe the propagation of differences with the incoming clouds, Figure 9 shows differences between the two SPP experiments for 2 m temperature and member 10. Notice, however, that no systematic differences are observed which indicates that no bias is introduced by the new method.

Future work

A new model perturbation method was introduced – flow dependent SPP. The method was implemented to C-LAEF (4 parameters in microphysics), it works technically and behaves expectedly. Next, it needs to be implemented for the rest of the perturbed parameters in other physics schemes. After that, a more comprehensive verification is needed. This includes a long-term evaluation and a few case studies (both winter and summer).

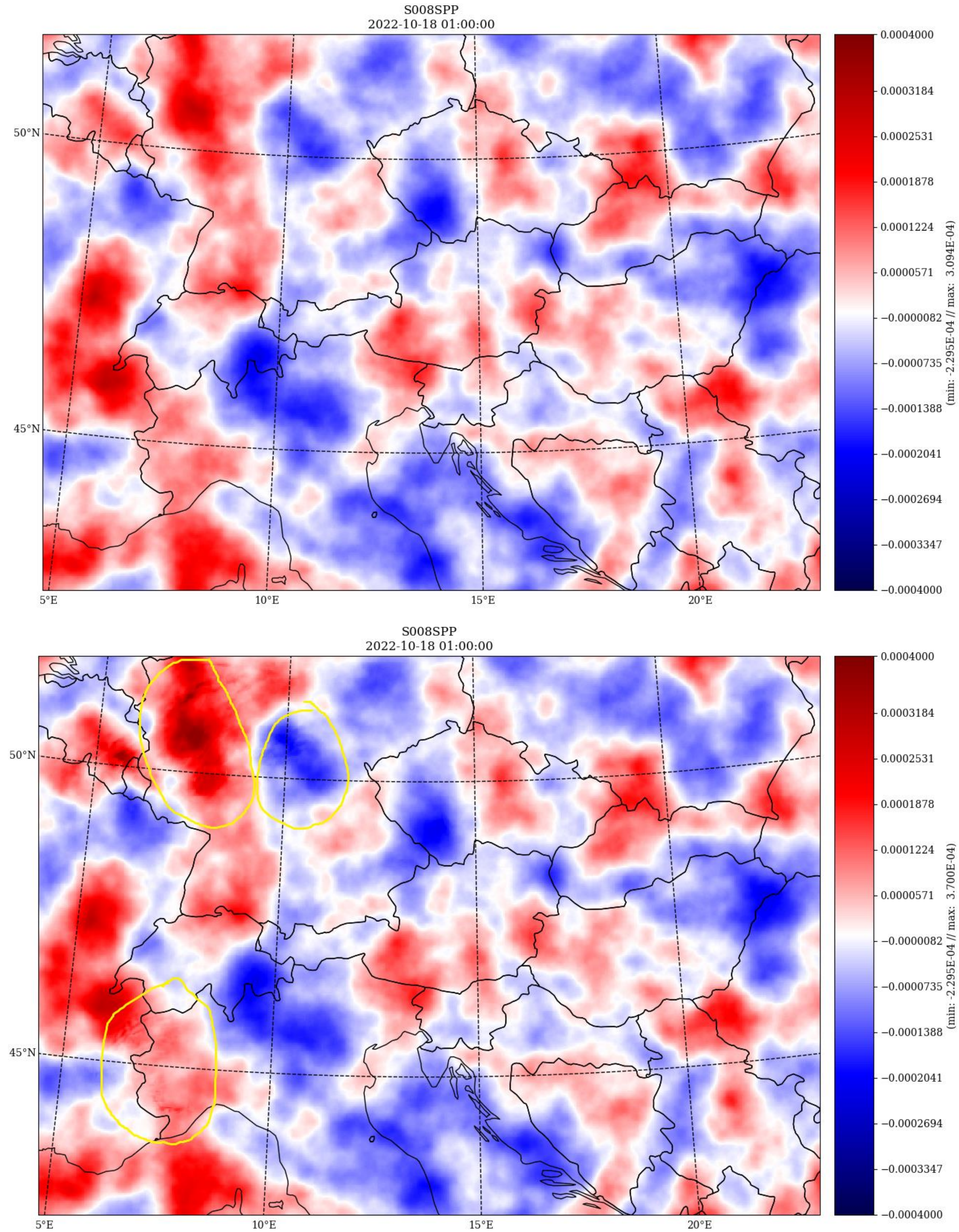

Figure 3. The final perturbations for the RCRIAUTC parameter before (up) and after (down).

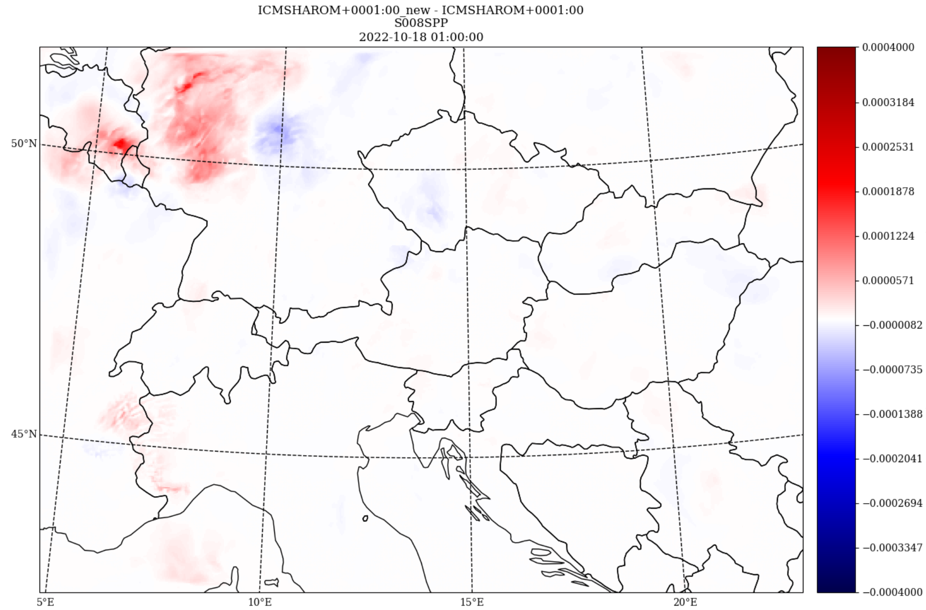

Figure 4. Difference plot for the two plots on Figure 3. Lower – upper.

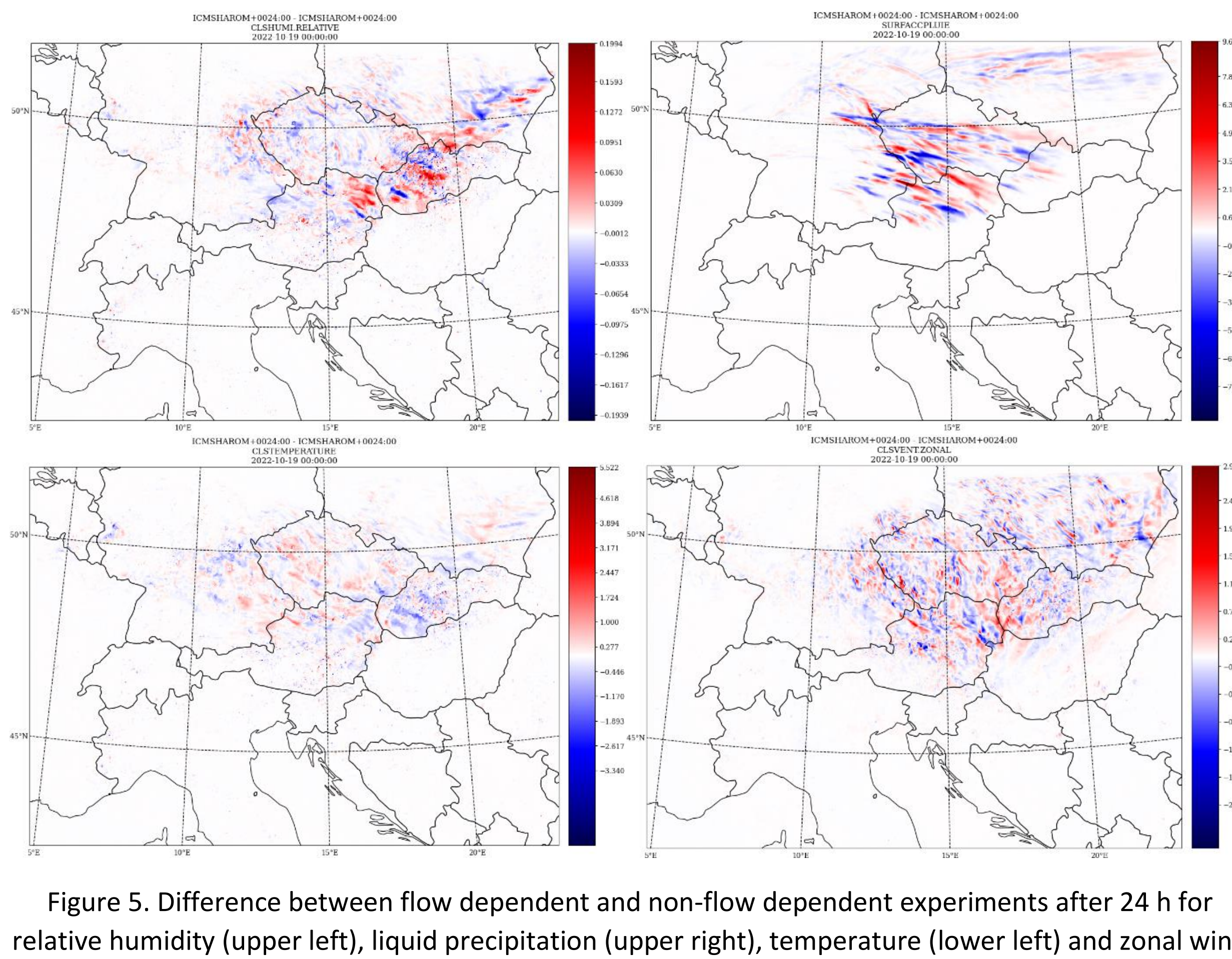

Figure 5. Difference between flow dependent and non-flow dependent experiments after 24 h for relative humidity (upper left), liquid precipitation (upper right), temperature (lower left) and zonal wind speed (lower right).

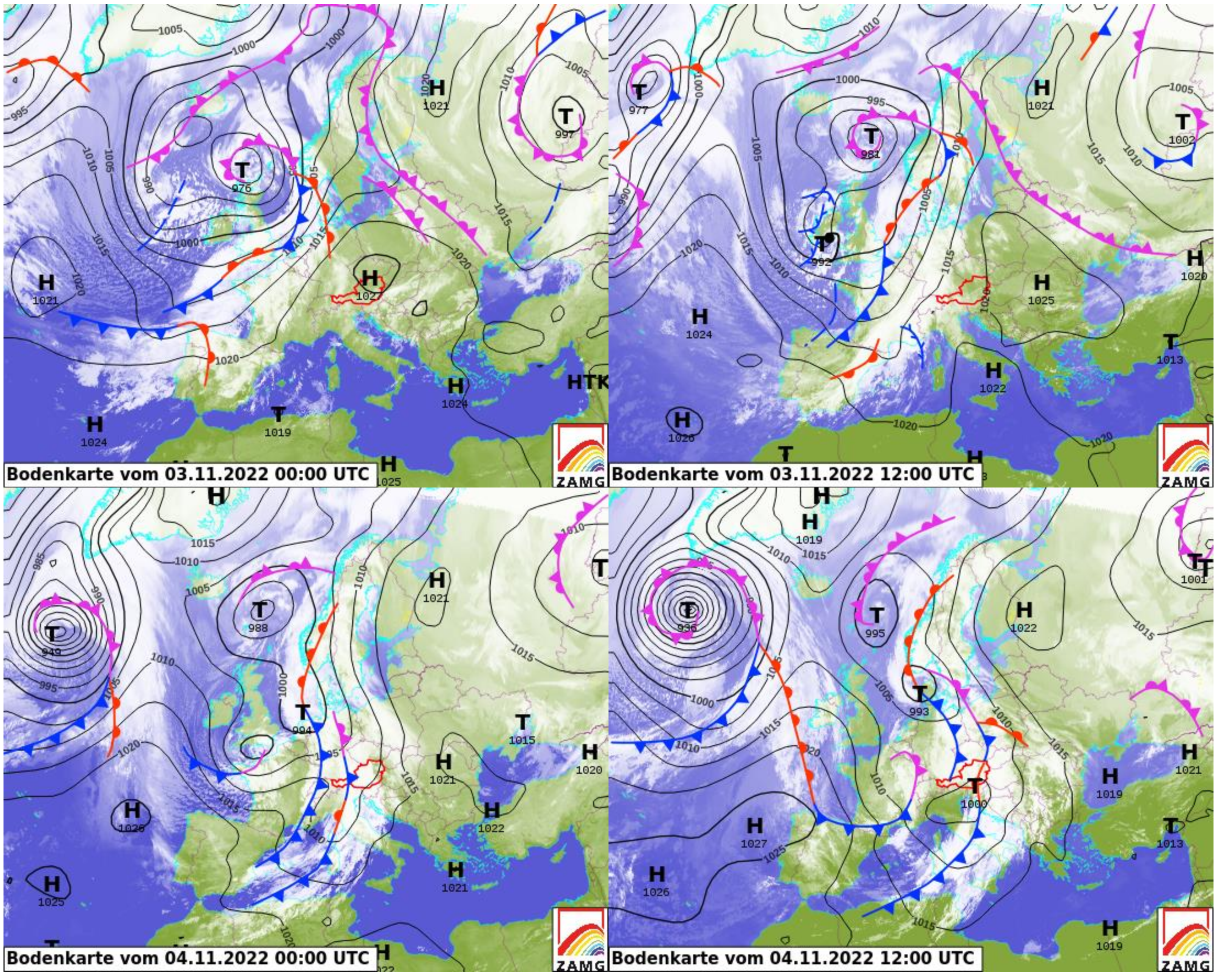

Figure 6. Synoptic situation for the dates written in the bottom-left on each figure.

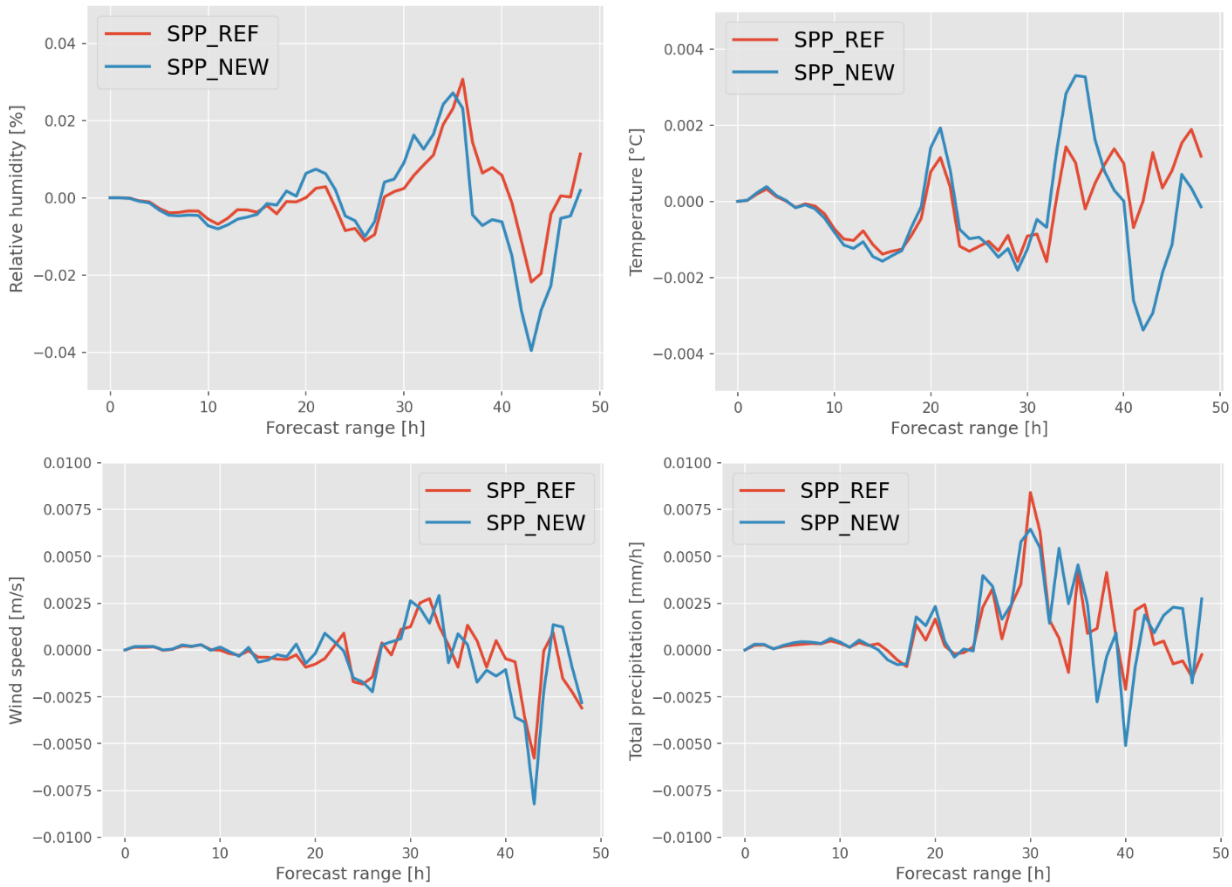

Figure 7. Domain averaged spread for two SPP experiments with respect to NO_SPP for 4 different variables as written on y-axis.

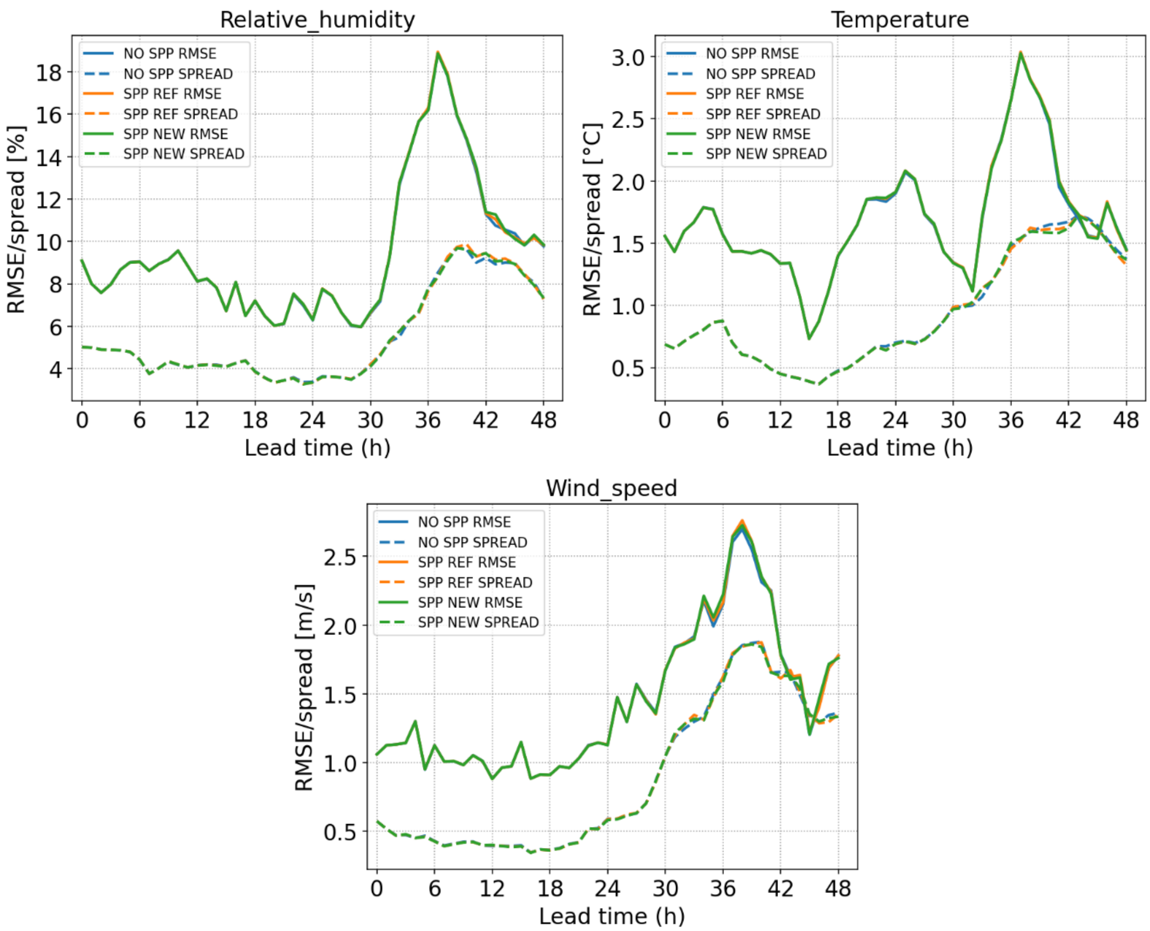

Figure 8. RMSE and spread for all three experiments and three variables as written in the title of each plot.

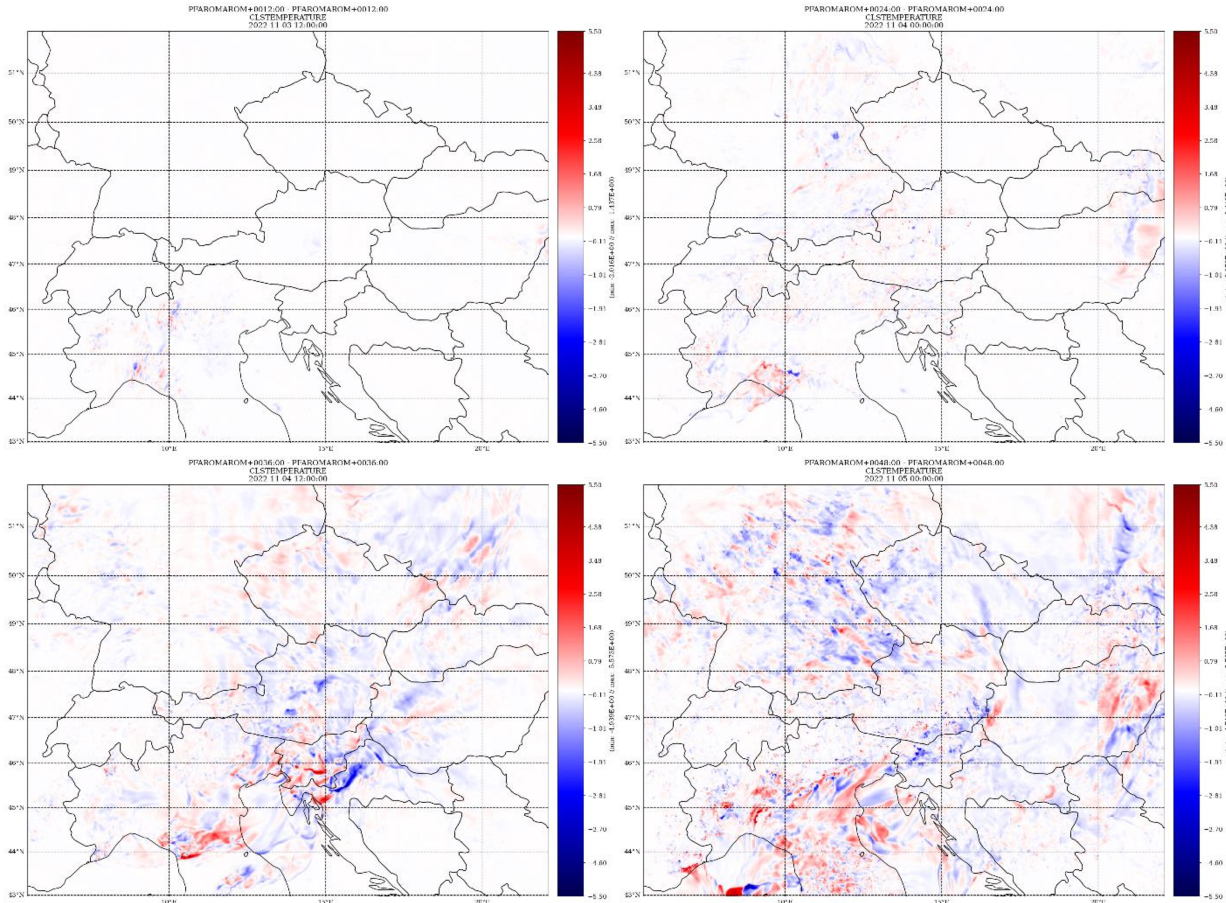

Figure 9. Difference plot (SPP_NEW – SPP_REF) for 2 m temperature and member 10 after 12 (upper left), 24 (upper right), 36 (lower left) and 48 (lower right) hours of integration.

Appendix

The perturbation field for parameter XCMF in shallow convection scheme was not properly optimized (CMPERT_XCMF) as perturbations required clipping too often (Figure A1). We propose a new value CMPERT_XCMF=0.12.

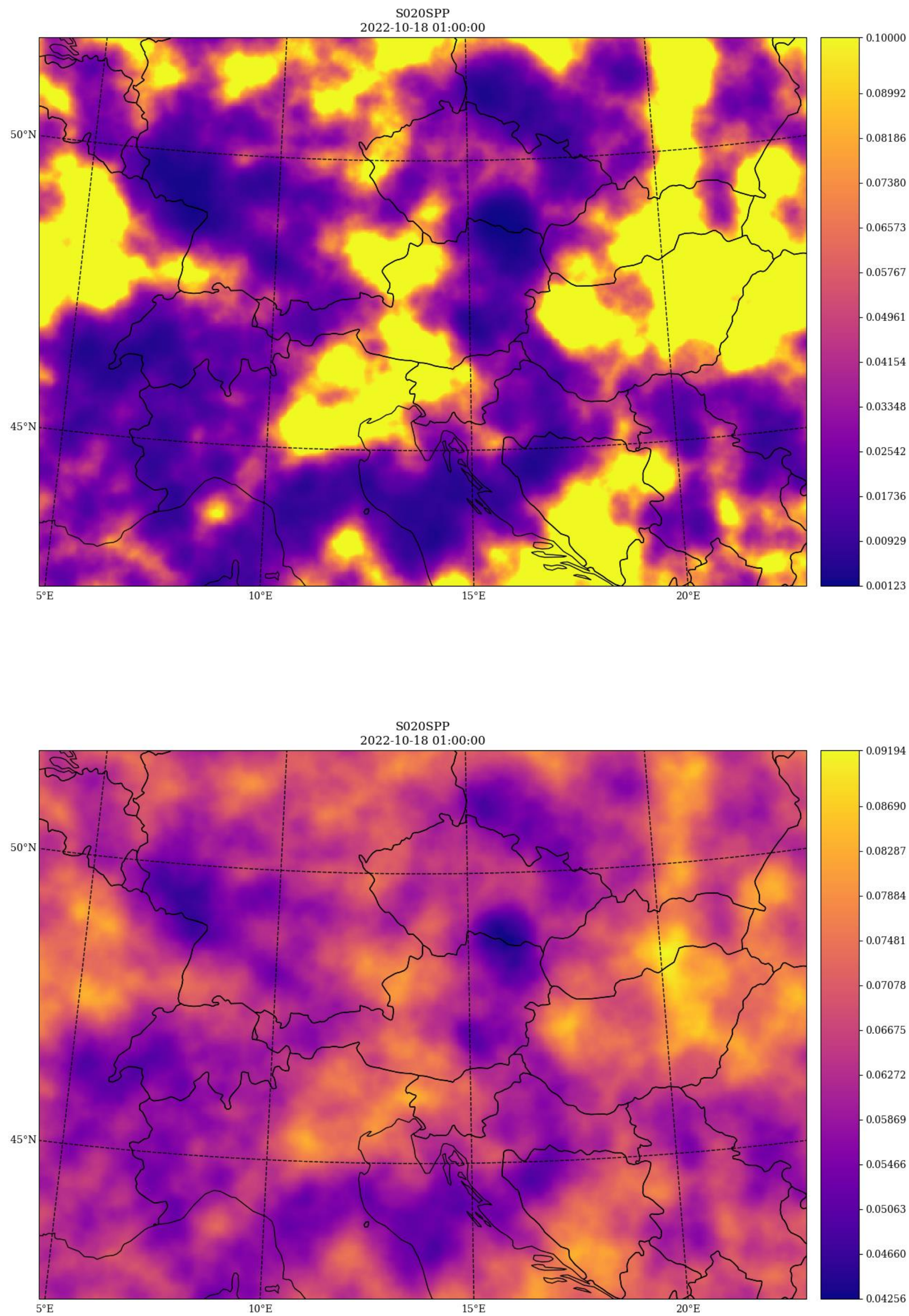

Figure A1. The perturbation field for XCMF before (up) and after (down).

References

Ollinaho, P., Lock, S.-J., Leutbecher, M., Bechtold, P., Beljaars, A., Bozzo, A., Forbes, R.M., Haiden, T., Hogan, R.J. and Sandu, I. (2017). Towards process-level representation of model uncertainties: stochastically perturbed parametrizations in the ECMWF ensemble. *Q.J.R. Meteorol. Soc.*, **143**: 408-422. https://doi.org/10.1002/qj.2931

Wastl, C., Wang, Y., Atencia, A., and Wittmann, C. (2019). A Hybrid Stochastically Perturbed Parametrization Scheme in a Convection-Permitting Ensemble. *Monthly Weather Review* **147**, 6, 2217-2230. https://doi.org/10.1175/MWR-D-18-0415.1