



Seamless probabilistic analysis and forecasting: from minutes to days ahead

Wang, Atencia, Awan, Bica, Dabernig, Kann, Kemetmüller, Meier, Schicker, Tüchler, Wastl and Wittmann

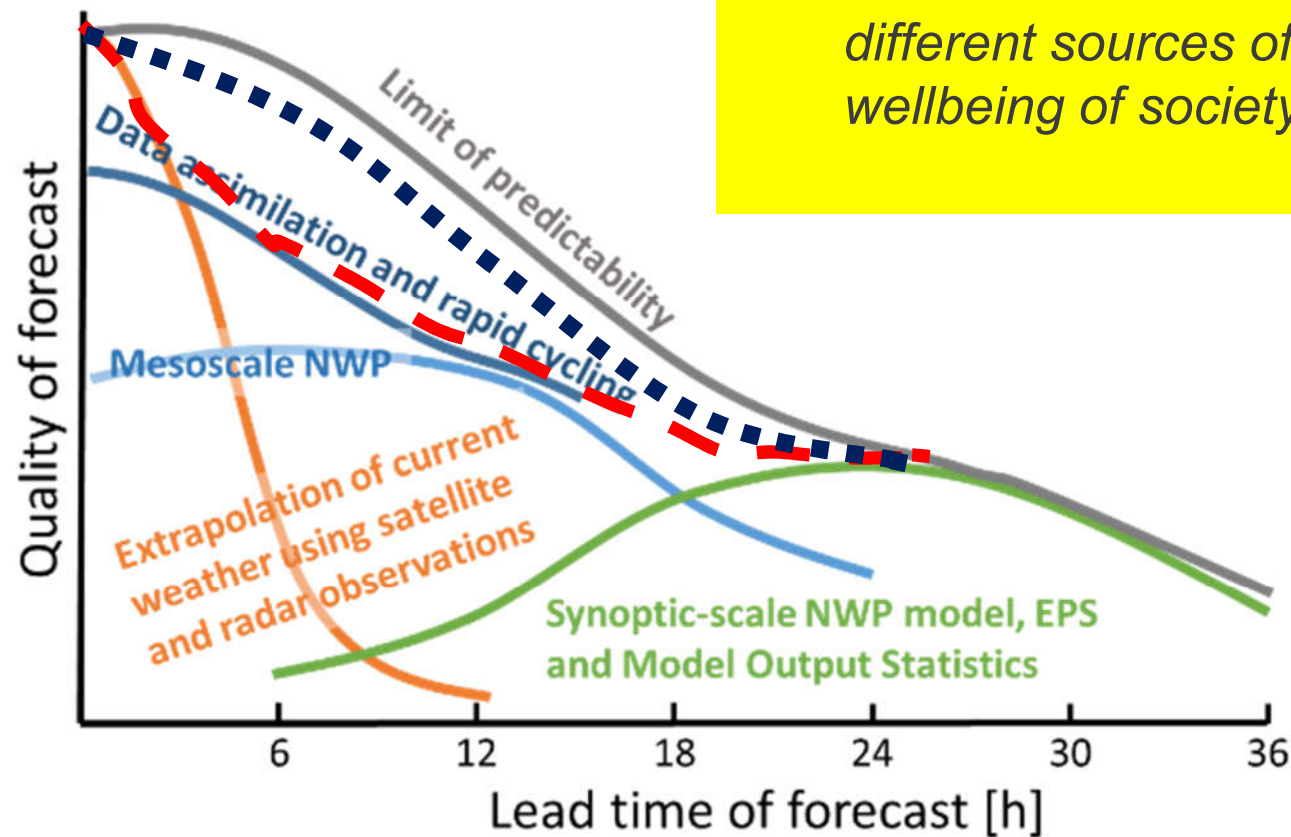


ZAMG
Zentralanstalt für
Meteorologie und
Geodynamik

The seamless vision for forecasting



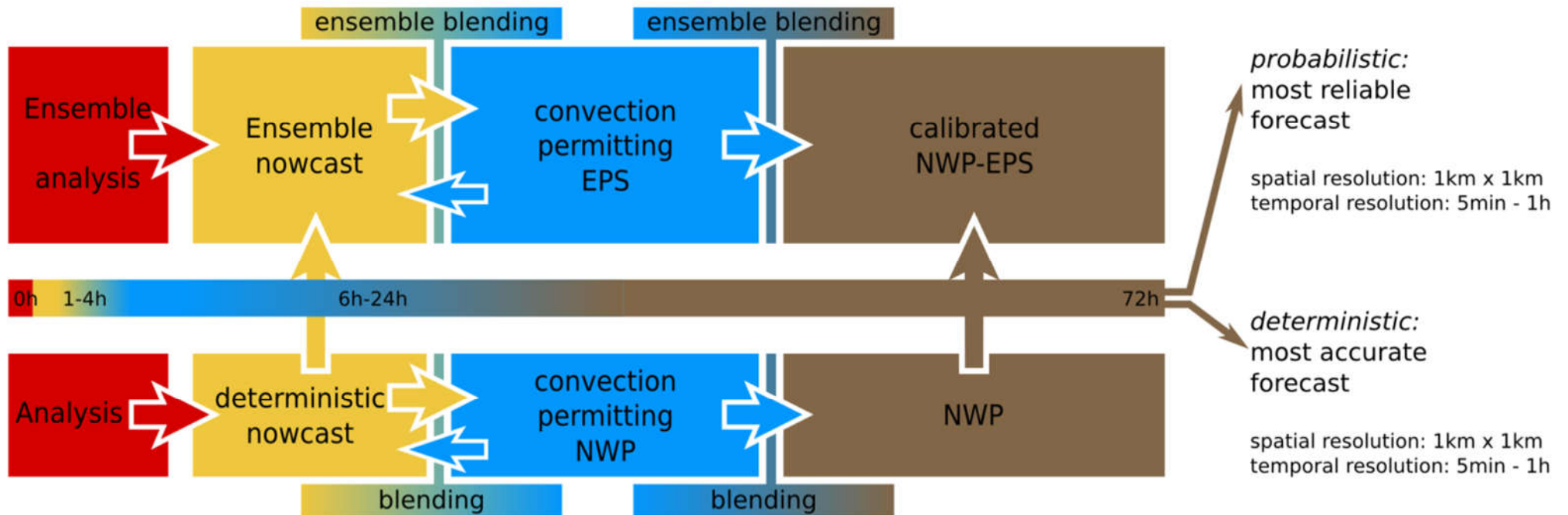
*“We are entering a new era in technological innovation and in use and **integration** of different sources of information for the wellbeing of society”*



The quality of weather forecasts defined as a function of lead time for different forecasting methods. The figure is highly schematic and the quality of forecast is a qualitative accuracy of the different performance. This figure is based on a previous one originally created by Browning (1980).

SAPHIR system design

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Expectation: output



- Seamless forecast 0-72h
- Resolution: 1km x 1km horizontal, 100m vertical up to 4km
- Update cycle: 5min – 1h
- Deterministic and probabilistic
- Application oriented: T, Q, U, V, RR (amount and type), T_{2m} , RH_{2m} , $V_{10m/100m}$, T_{surf} , cloudiness, global radiation, visibility, snowlines, wind gust, icing potential

Challenges

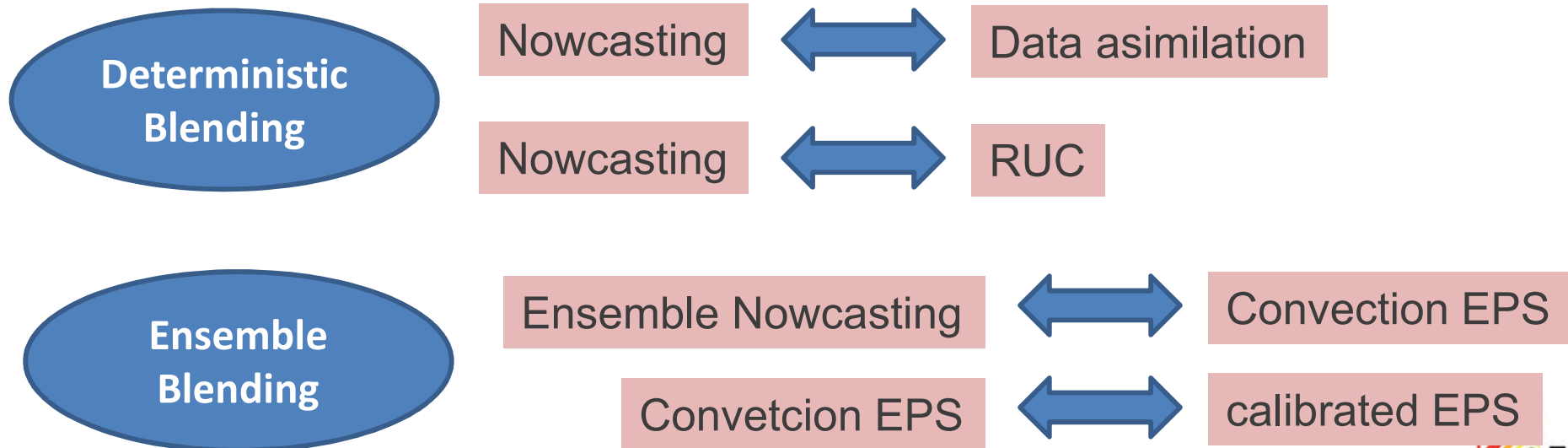


Observation integration: analysis and uncertainties quantification

Nowcasting: deterministic and ensemble

Data assimilation & RUC; convection permitting EPS

Post-processing: calibration and ensemble calibration



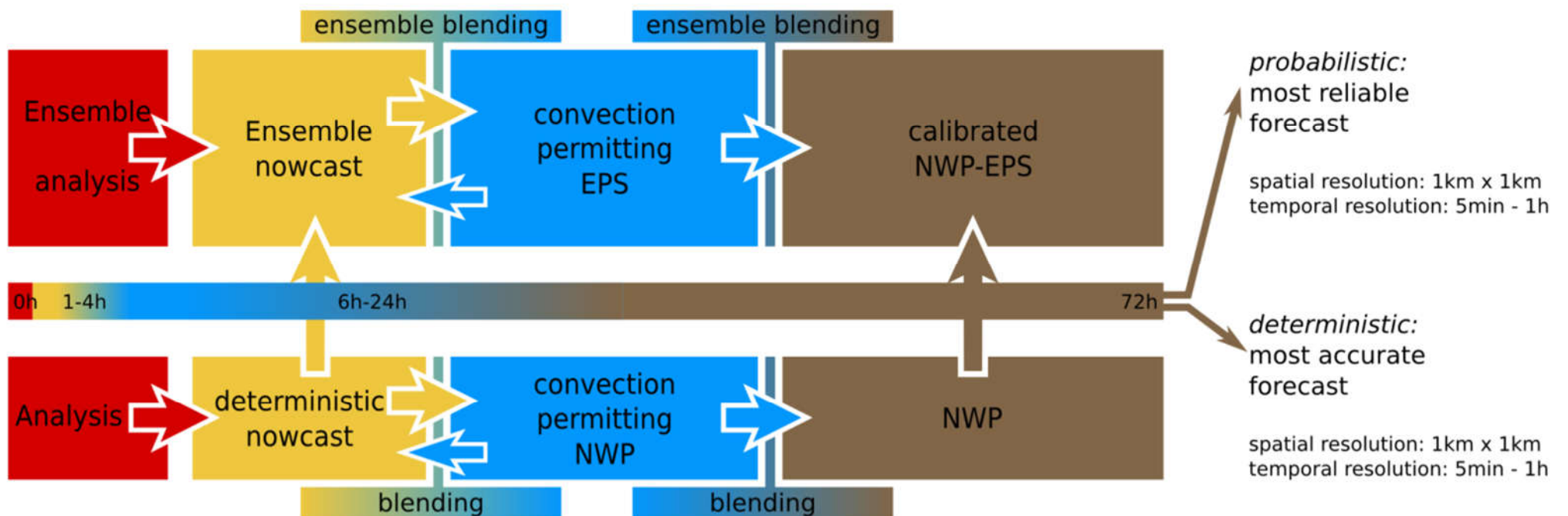
System design



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Seamless probabilistic Analysis and Prediction in very High Resolution



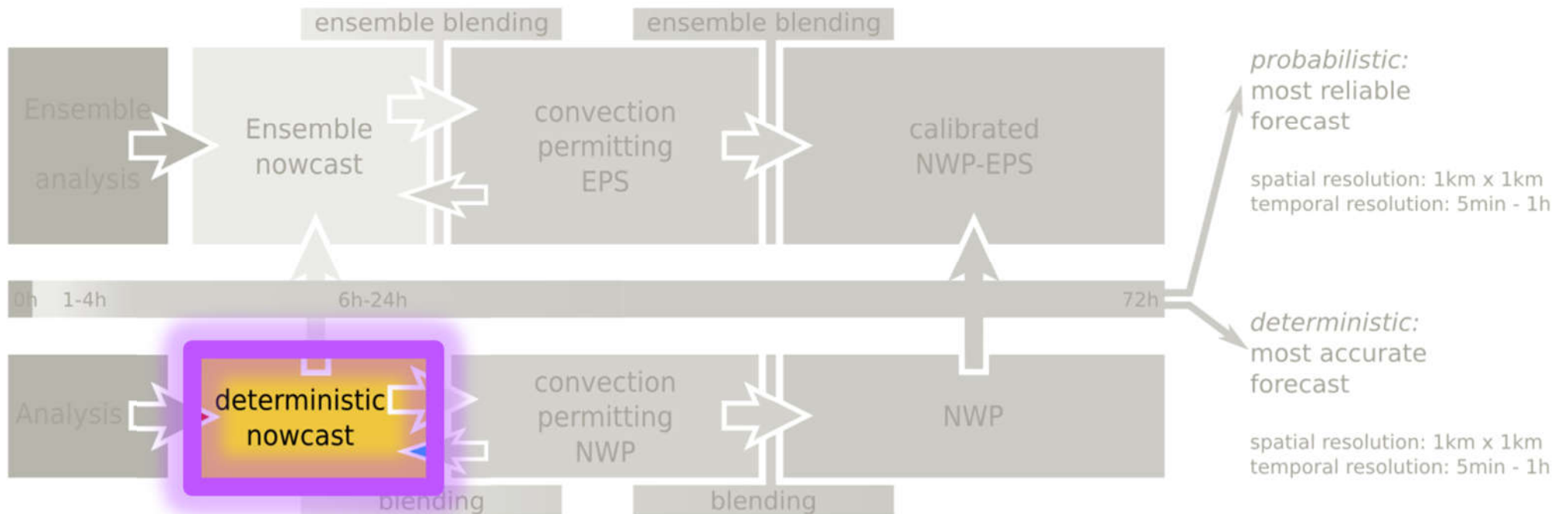
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Seamless probabilistic Analysis and Prediction in very High Resolution



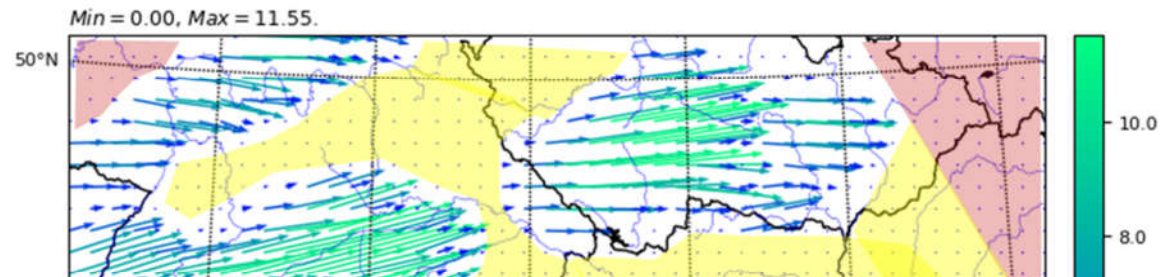
Optical Flow (OF) equation (methodology **Farnebäck**¹: Dense OF working on all grid points)

$$\frac{\partial P}{\partial x} \frac{\partial x}{\partial t} + \frac{\partial P}{\partial y} \frac{\partial y}{\partial t} + \frac{\partial P}{\partial t} = 0$$

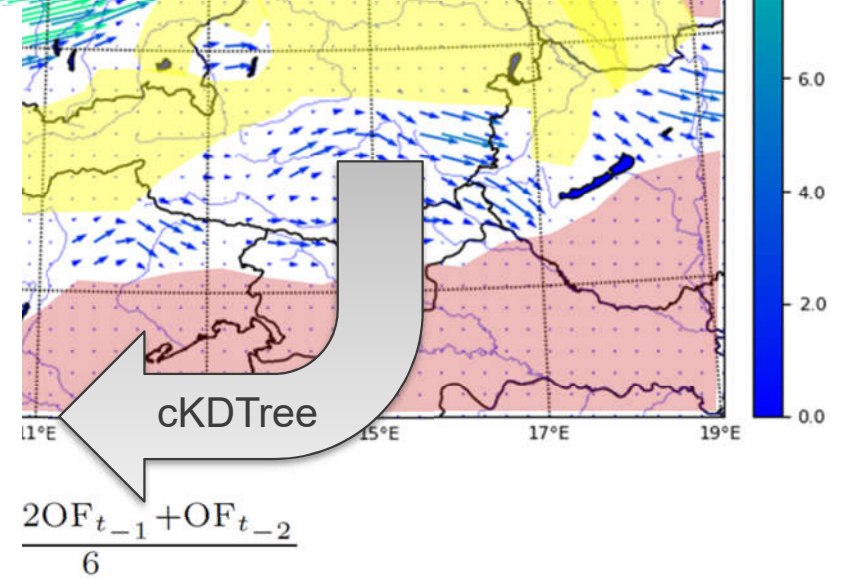
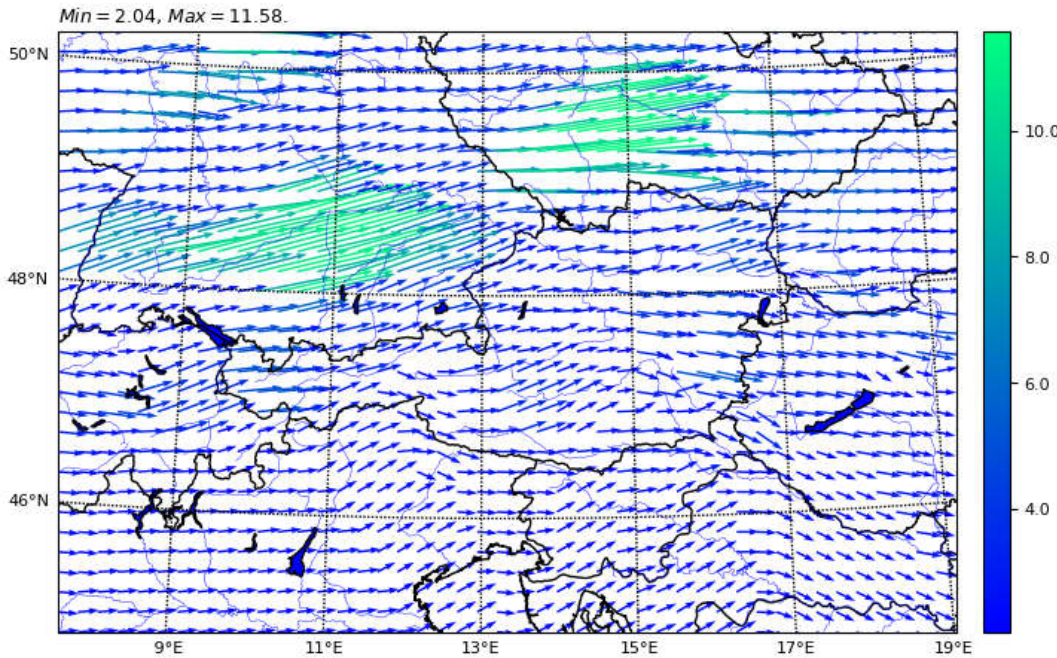
$$u \frac{\partial P}{\partial x} + v \frac{\partial P}{\partial y} + \frac{\partial P}{\partial t} = 0$$

$$\vec{v} \cdot \nabla P + \dot{P} = 0$$

Optical Flow 23.04.2018 14:30 UTC



Optical Flow 23.04.2018 14:30 UTC



¹ Farnebäck, 2003: Two-Frame Motion Estimation Based on Polynomial Expansion

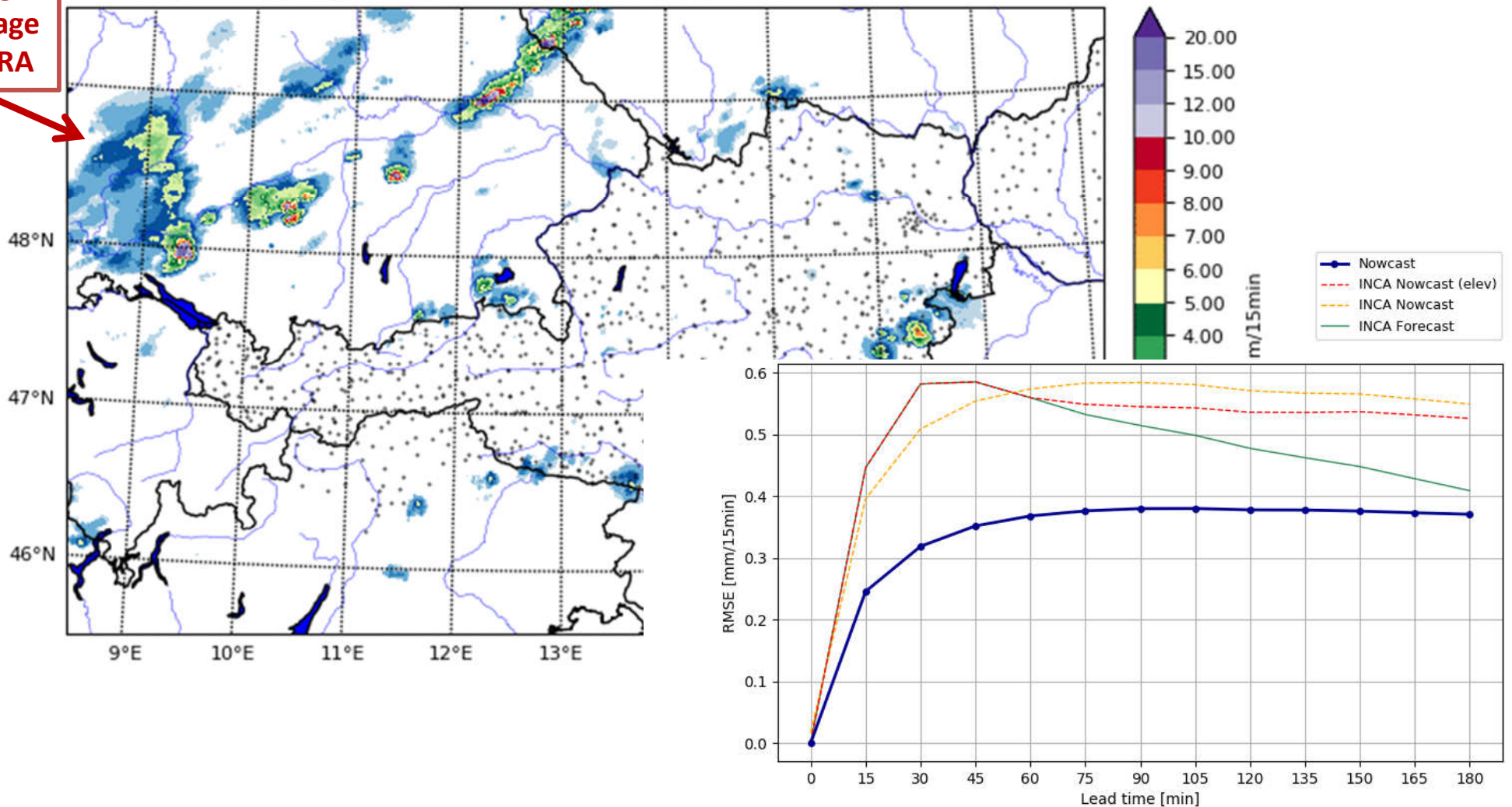
Introduction of Optical Flow and cKDTree in INCA

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Taking advantage of OPERA

Analysis D2 23.04.2018 12:30 UTC (-15min)

Min = 0.00, Max = 23.31, $\mu = 0.06$, $\sigma = 0.49$. $\Delta = 1000m$, Obs = 951.



...continues the series of analyses more or less smoothly (Better performance)

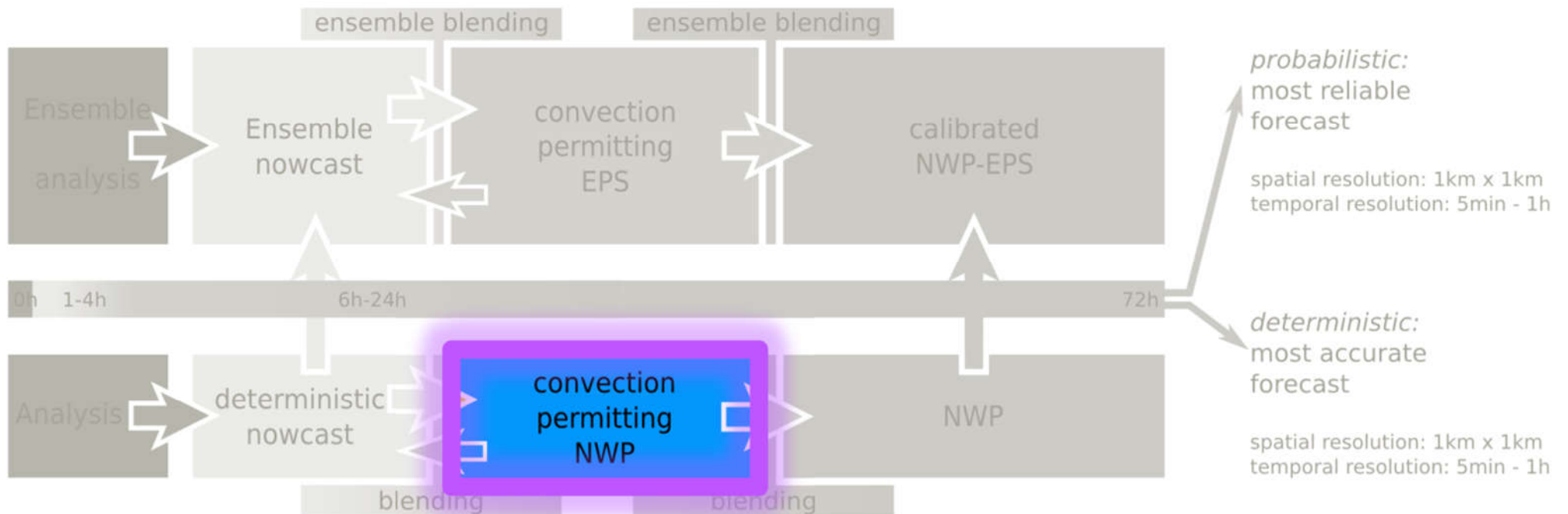
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Seamless probabilistic Analysis and Prediction in very High Resolution

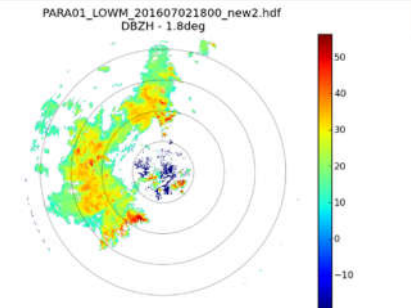


AROME-Nowcasting

Florian Meier
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classic DA

Nowcasting component



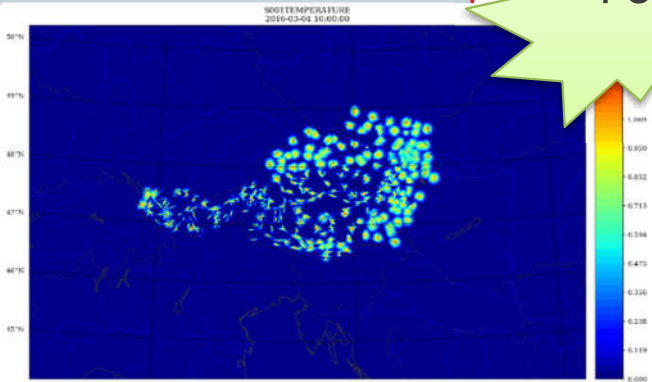
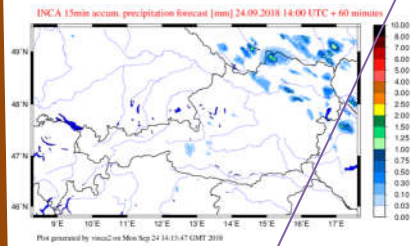
3D-VAR

SYNOP
Reflectivity
Doppler w.



TEMP
AMDAR
MODE-S
GNSS
Satellite

INCA-LHN

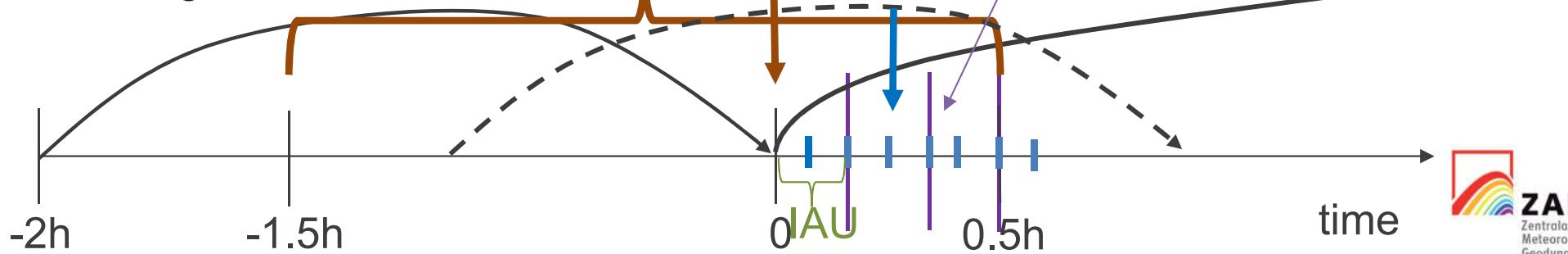


TWS-Nudging

LBC from
Last AROME-OPEI

First guess -2h RUC

12h-forecast



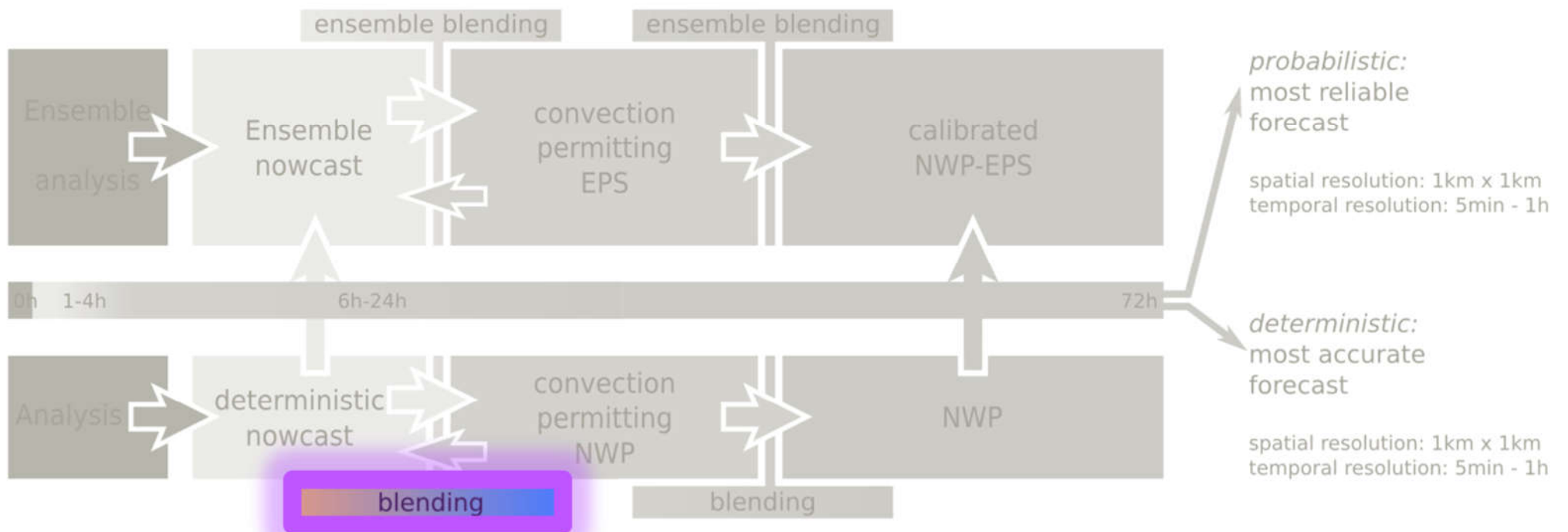
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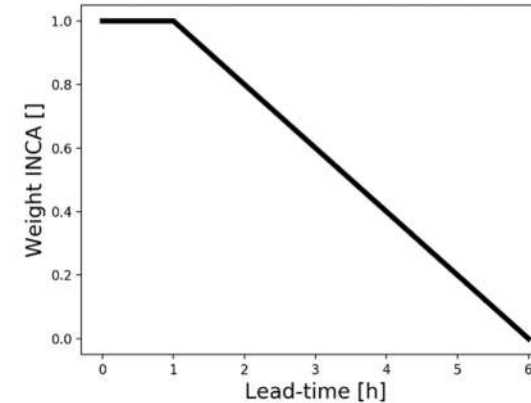
Possible improvements of the blending methodology



- The blending's weight are for a given lead-time $\rightarrow w(lt)$.

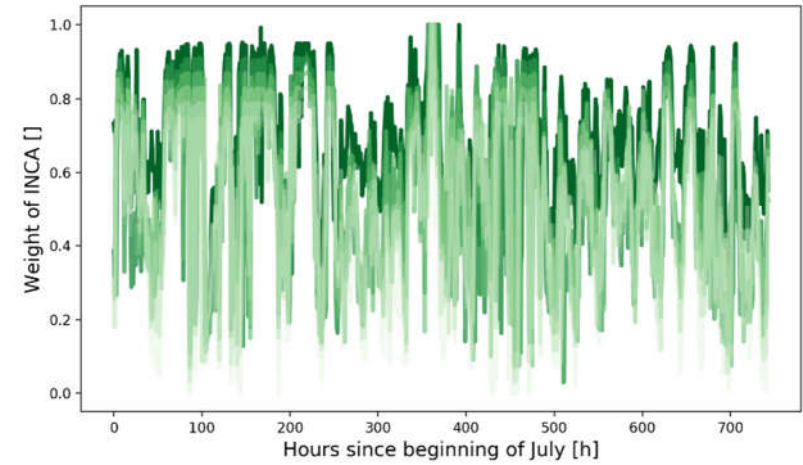
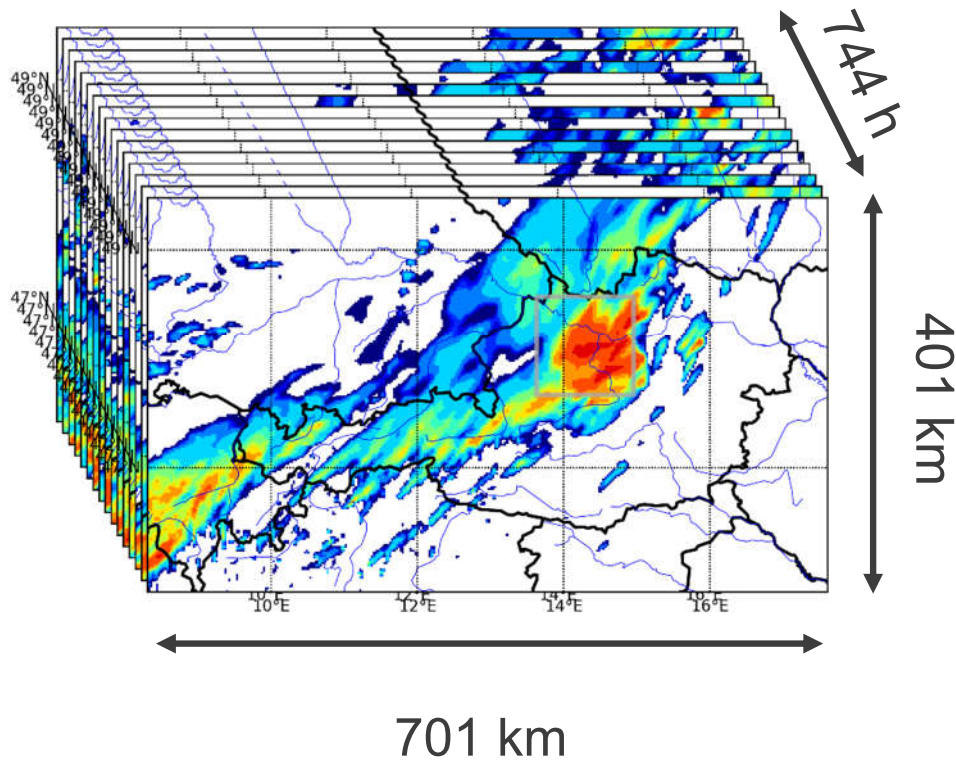
$$w_{inca} = \begin{cases} 0 & \text{Lead-time} > 6 \text{ h} \\ \frac{(6 - \text{leadtime})}{6 - 1} & \text{Lead-time} \leq 6 \text{ h} \end{cases}$$

$$w_{AROME} = 1 - w_{inca}$$



Possible improvements of the blending method

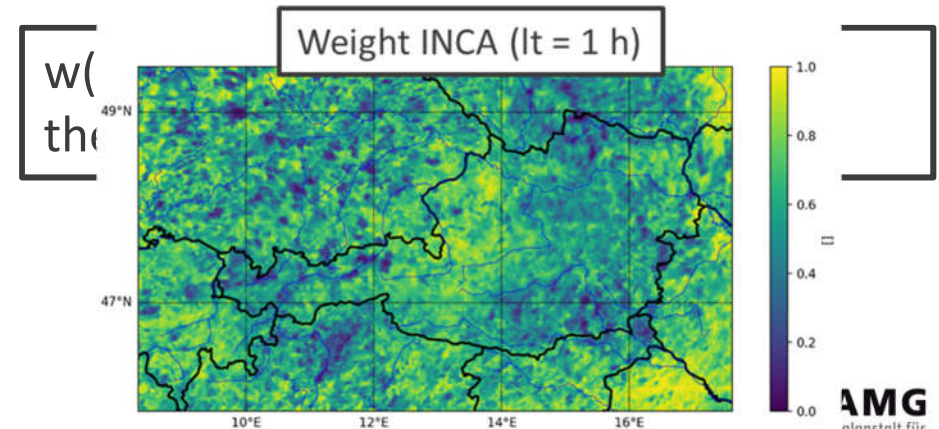
- The blending's weight are for a given lead-time $\rightarrow w(lt)$.
- However, the dataset used to compute the optimal blend (field $\times 24 \times 31$ [time of the month]) = (lt, x, y, t) .



Flow dependency

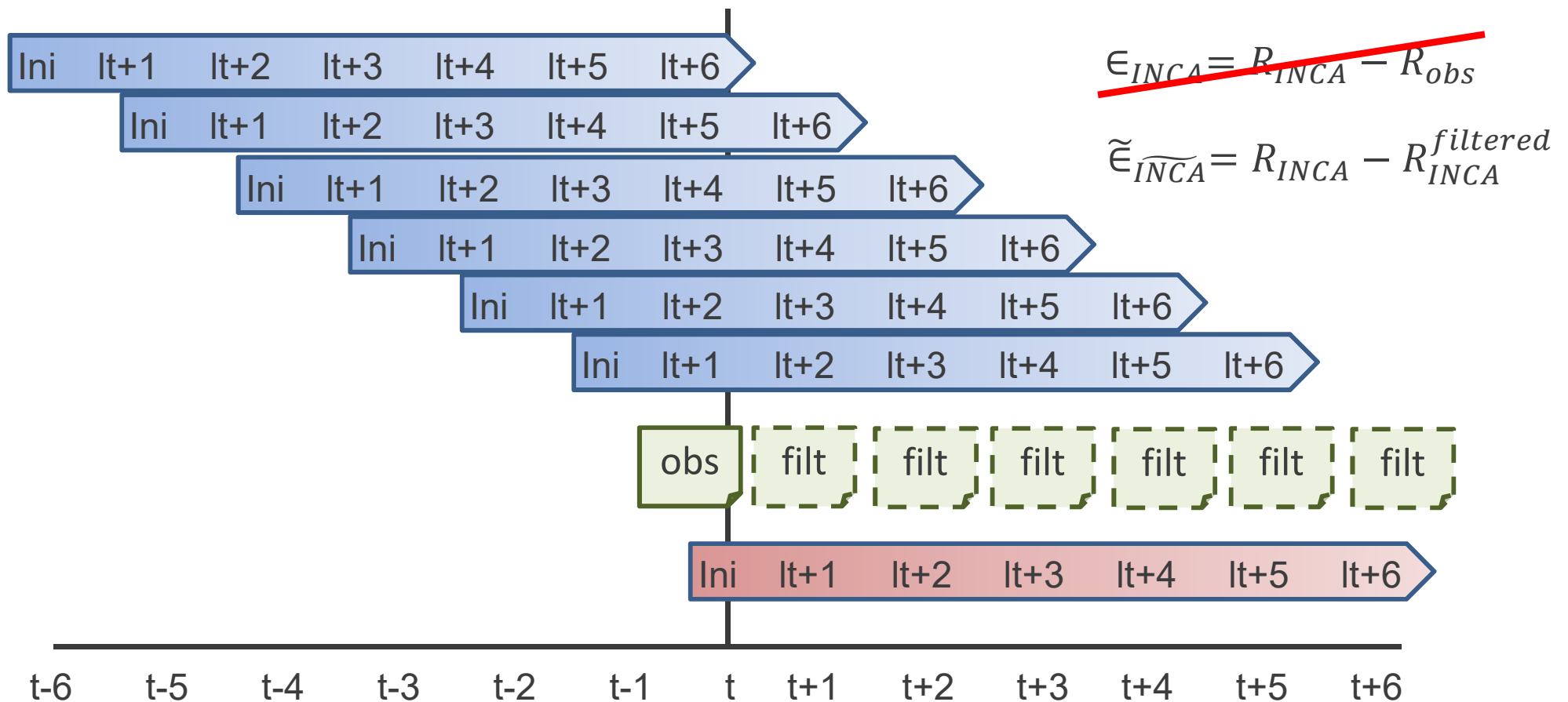
$w(lt, t)$ where t is the time of the month

Location dependency



Flow and location dependence on the weights

The main goal is to have local information but in a flow dependent way so it account for the different quality depending on the weather performance.

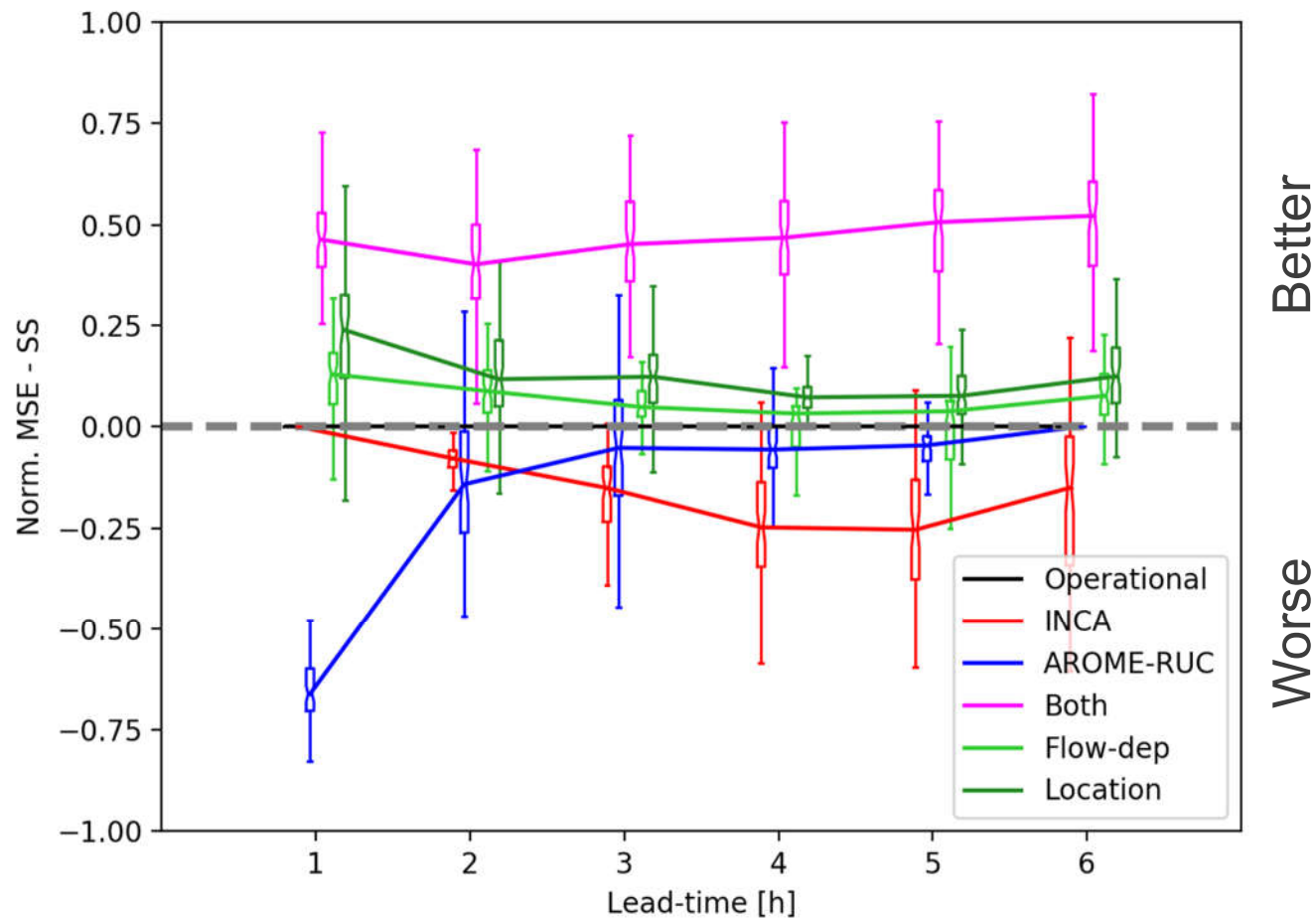


Deterministic blending: new strategy 2D-VAR



$$J = [x - x_b]^T B^{-1} [x - x_b] + [x - y]^T R^{-1} [x - y]$$

B & R: no bias, no cov. globally constant!



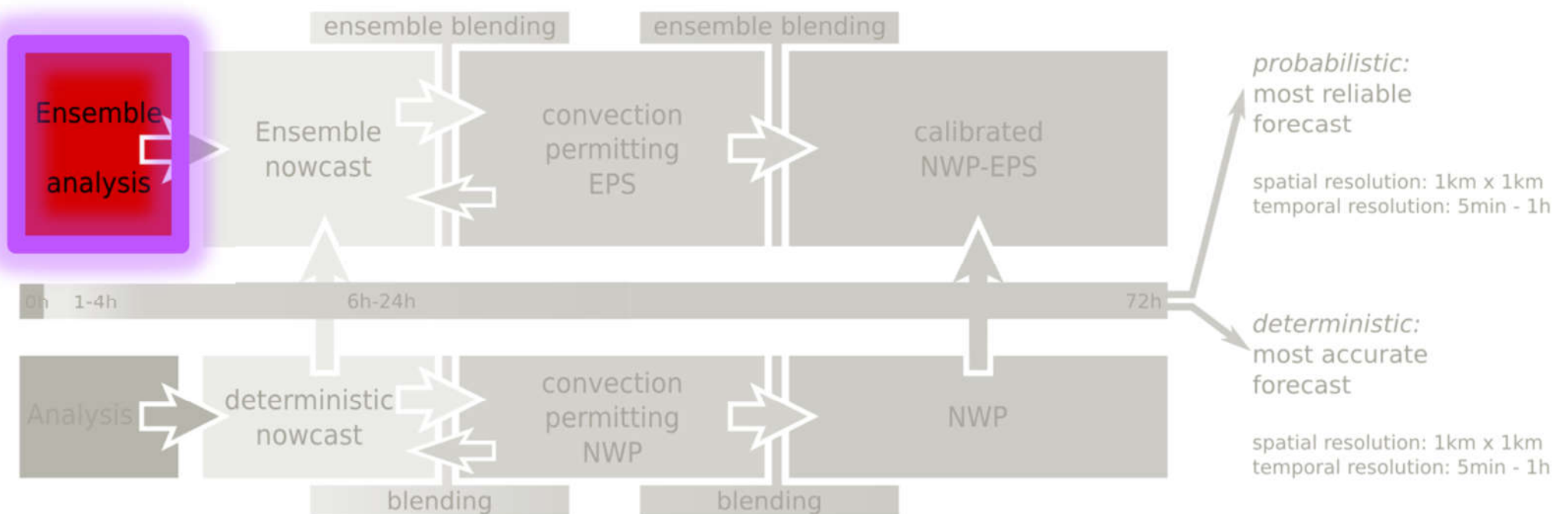
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Seamless probabilistic Analysis and Prediction in very High Resolution



Creation of an ensemble of analysis

Lukas Tüchler
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uncertainties in radar precipitation estimation
→ ensemble precipitation estimation

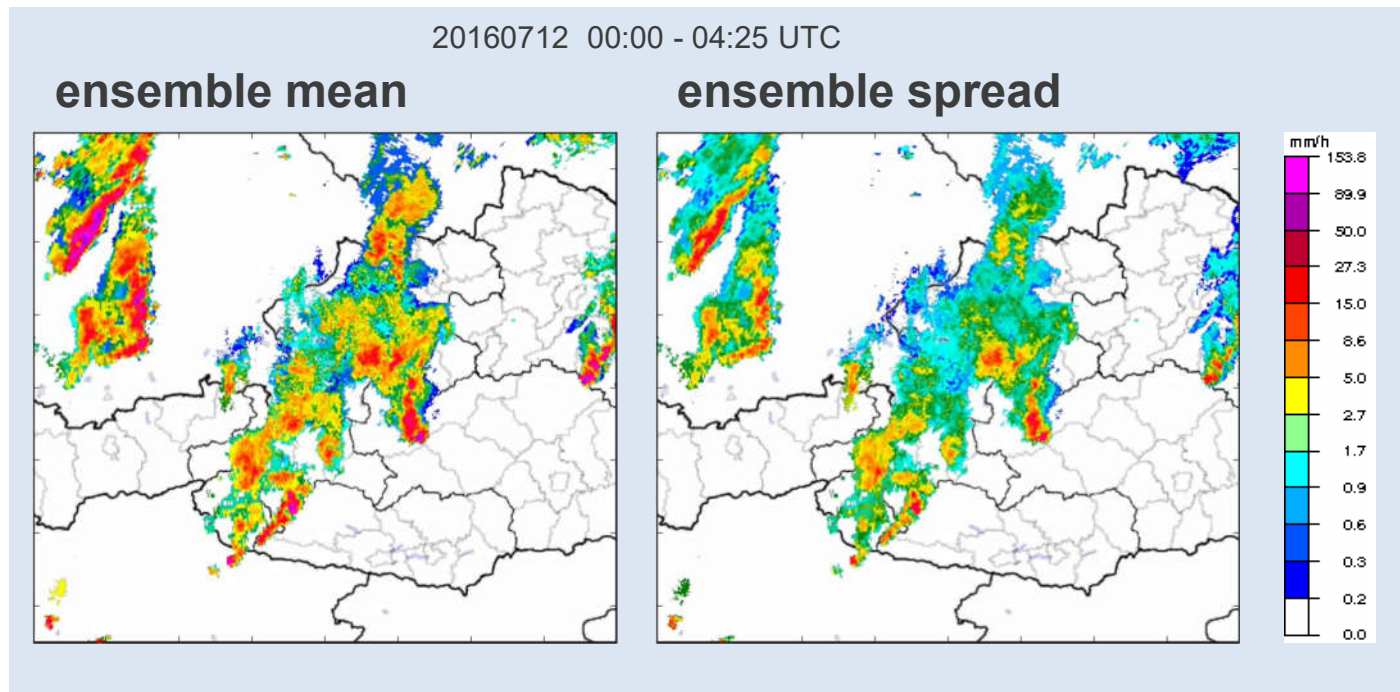
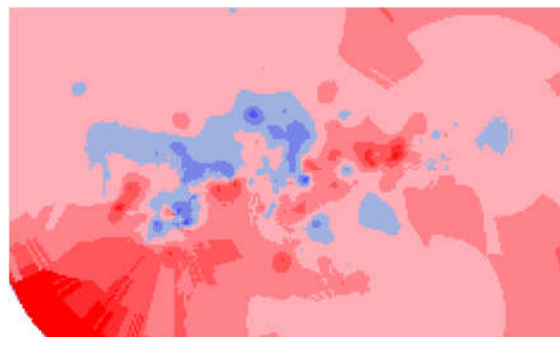
REAL algorithm (Germann et al., 2009):

$$\underbrace{\Phi_{t,i}}_{\text{probabilistic}} = \underbrace{\mathbf{R}_t}_{\text{deterministic}} + \underbrace{\delta_{t,i}}_{\text{stochastic}}$$

$$\delta_{t,i} = \boldsymbol{\mu} + \mathbf{L}y_{t,i}$$

1. Estimation of error covariance matrix (radar-gauge-agreement) \mathbf{C}

2. Generation of perturbations by Cholesky/SV decomposition

$$\mathbf{C} = \mathbf{L}\mathbf{L}^T$$


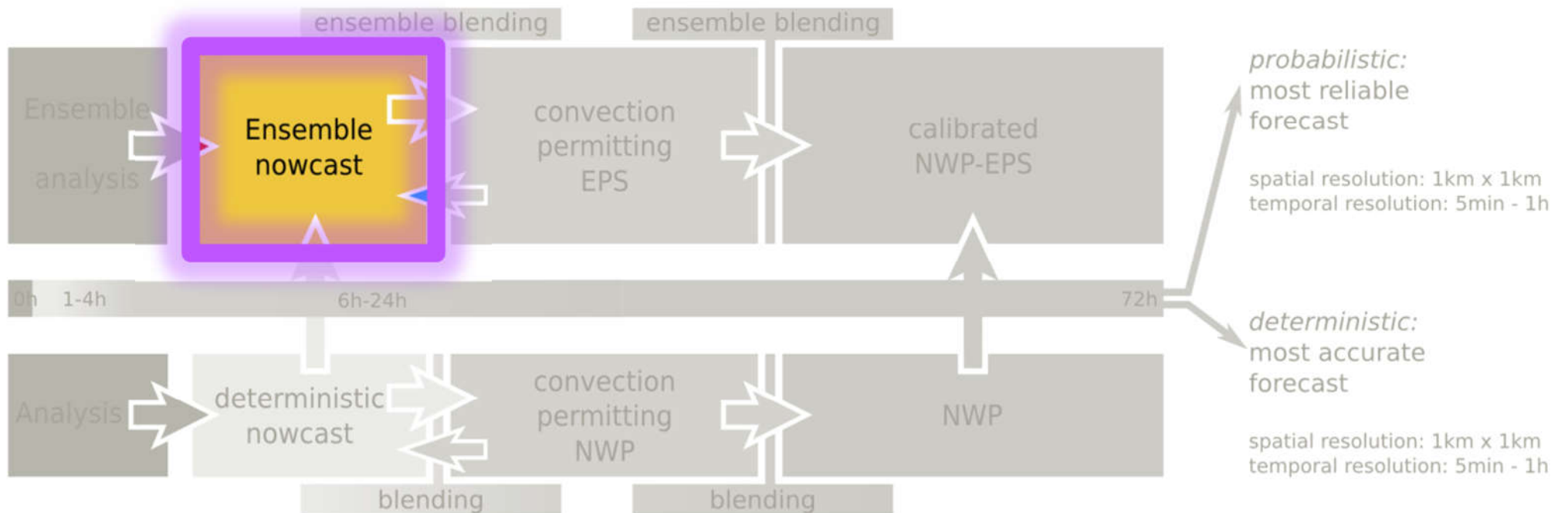
System design



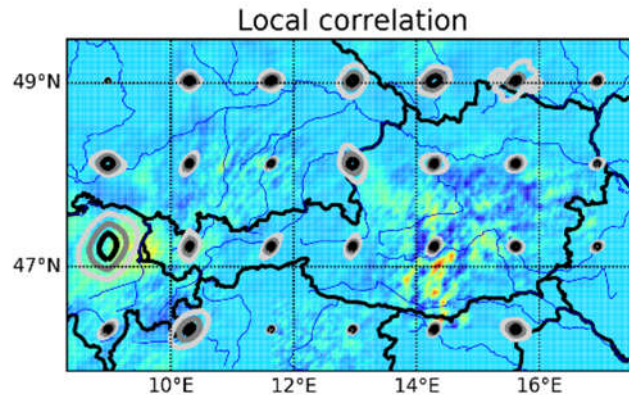
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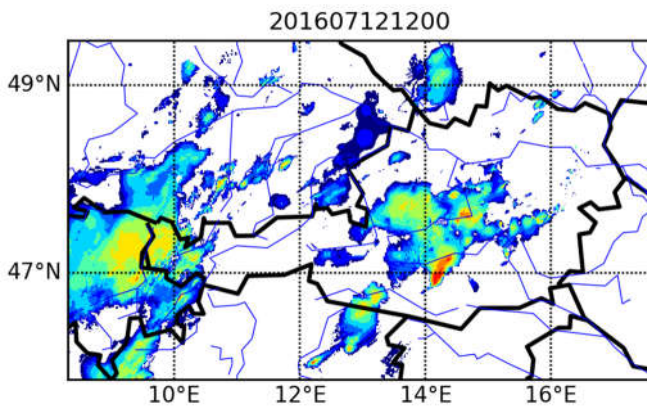
Seamless probabilistic Analysis and Prediction in very High Resolution



Ensemble nowcasting



A non-stationary stochastic ensemble generator for radar rainfall fields based on the short-space Fourier transform (Nerini et al, 2017).

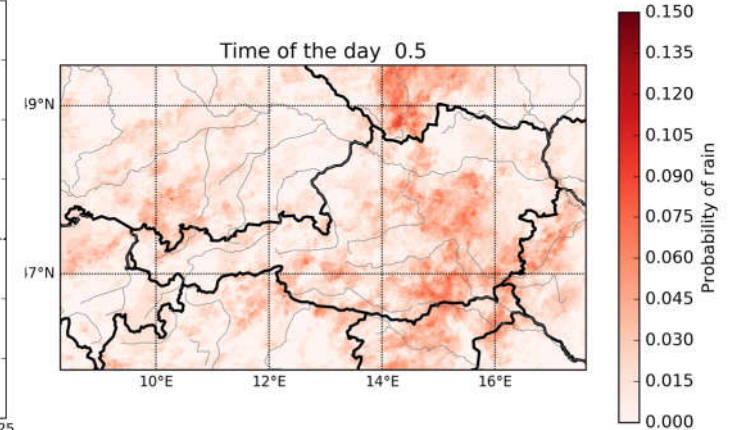
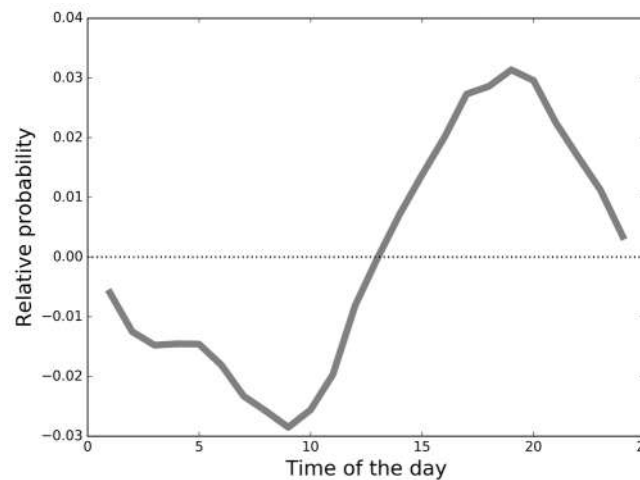


Stochastic noise is added to the INCA field using the local correlation information.

Physical processes such as the diurnal cycle of precipitation is introduced as an external forcing to the ensemble generator.



Storms organized into several large front-like systems that persisted over many hours; it was the worst severe weather day of the year.

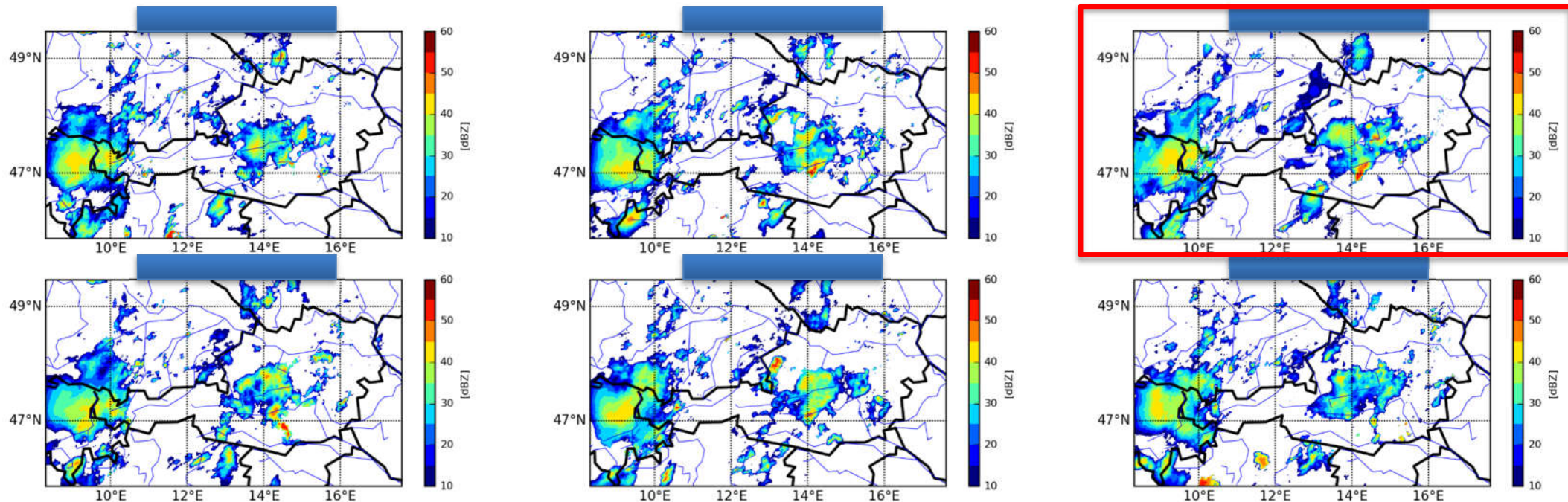


Ensemble nowcasting (eyeball verification)



An ensemble of realistic rainfall fields.

2016/07/12 12:00 (10:00 initialization + 2 h lead-time)



- Can you recognize the real observation?

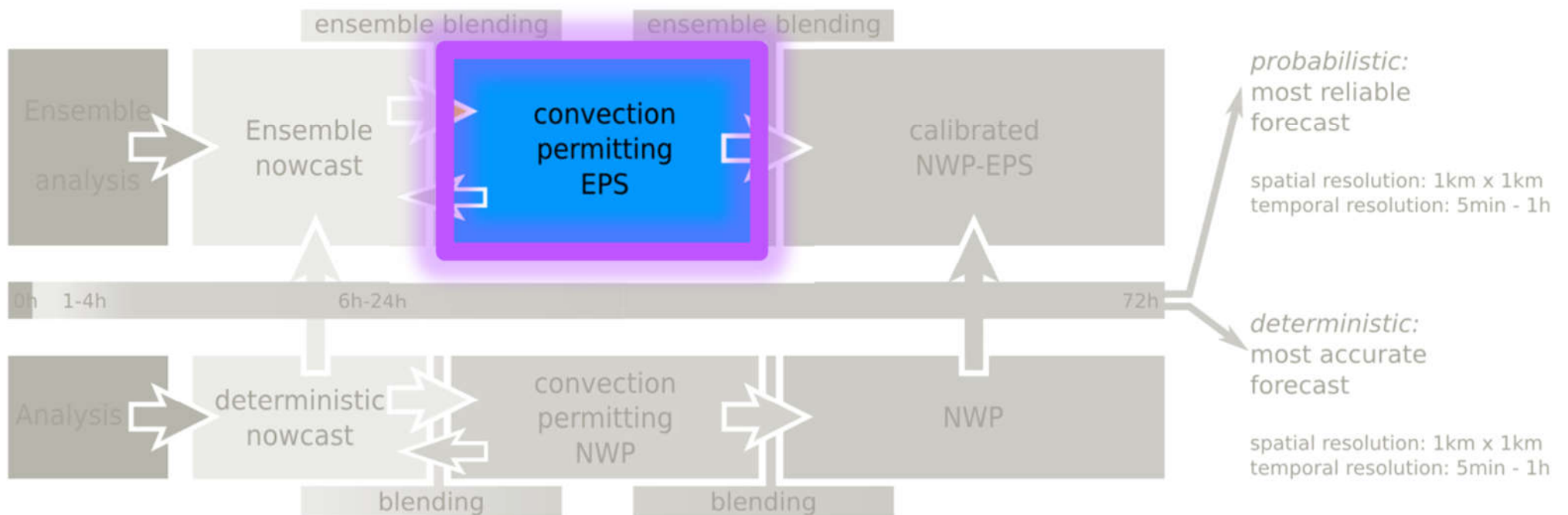
System design



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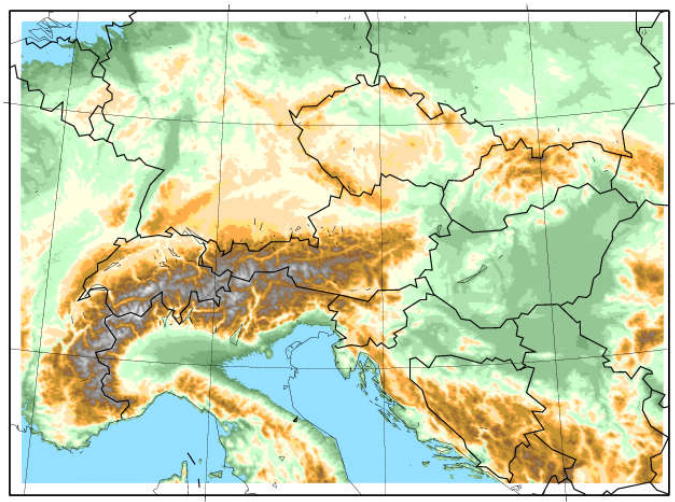


C-LAEF: Convection permitting – Limited Area Ens. Forecasting

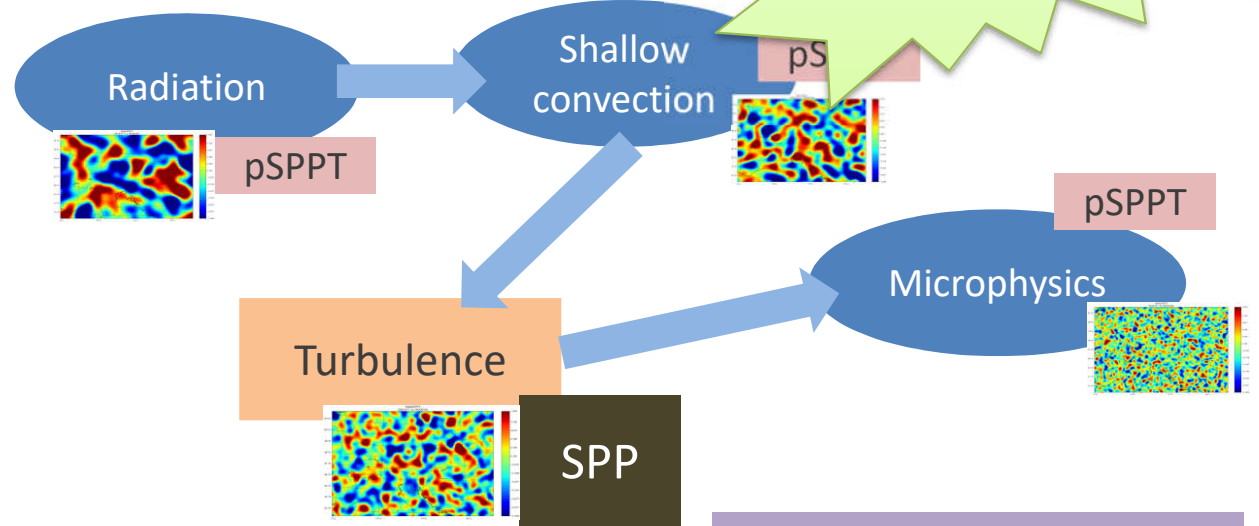
Clemens Wastl
clemens.wastl@zamg.ac.at

**Presentation
 Wednesday
 11:55**

2.5km / 90 levels; 16 members



A Hybrid-stochastic physics package



IC perturbation EDA + ensemble Jk

$$J(x) = J_b + J_o + \underbrace{\frac{1}{2} (x - x_{ls})^T V^{-1} (x - x_{ls})}_{J_k} = J_b + J_o + J_k$$

Energy conservation;
 physically consistent;
 processes based uncertainty;
 no tapering function.

Introduction of ECMWF large scale perturbation

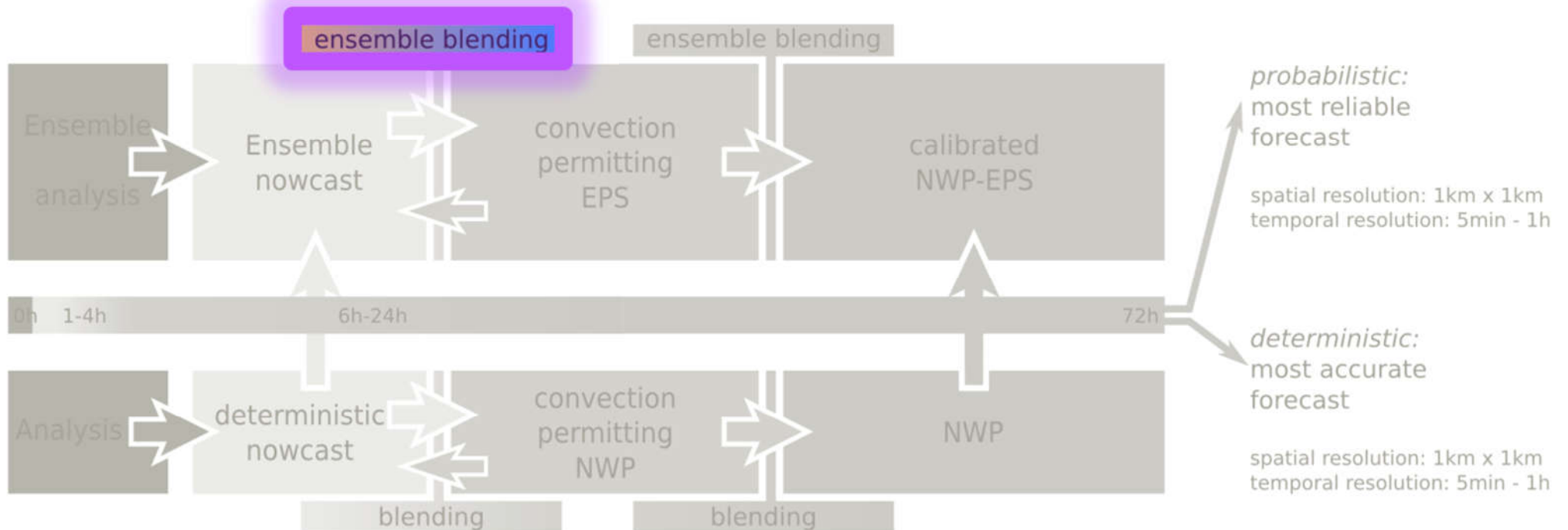
System design



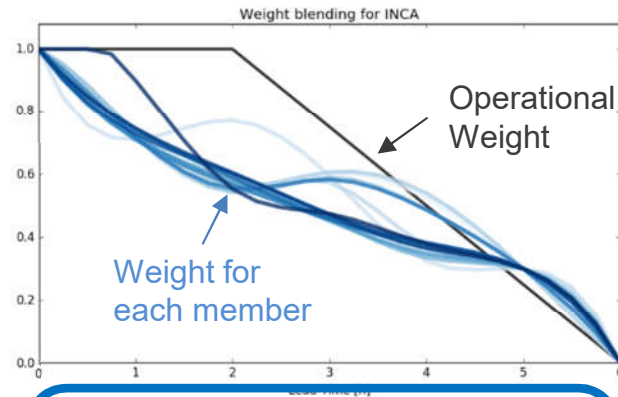
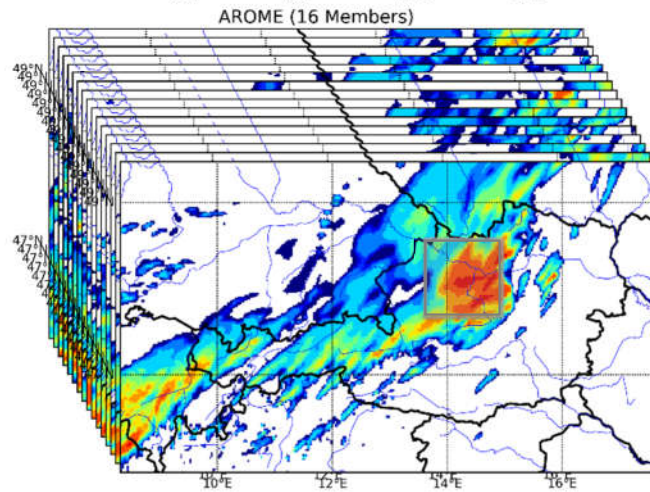
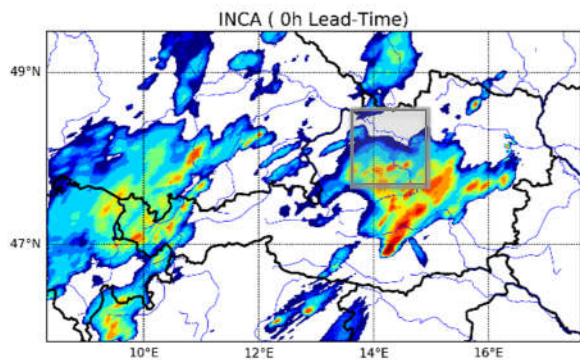
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Seamless probabilistic Analysis and Prediction in very High Resolution



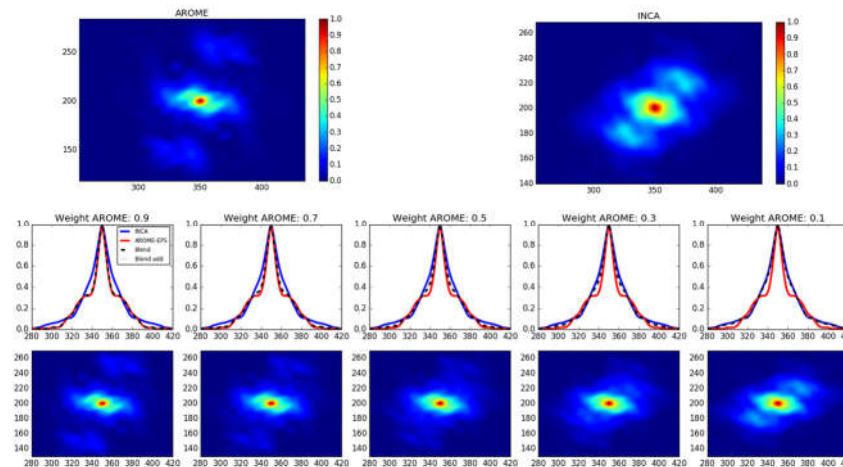
Probabilistic blending (INCA + AROME – EPS)



Member-dependent weight as function of lead-time, variance and distance to observations.

The weights are used to blend the local correlations in order to reconstruct a rainfall field with self-similarity information from both fields.

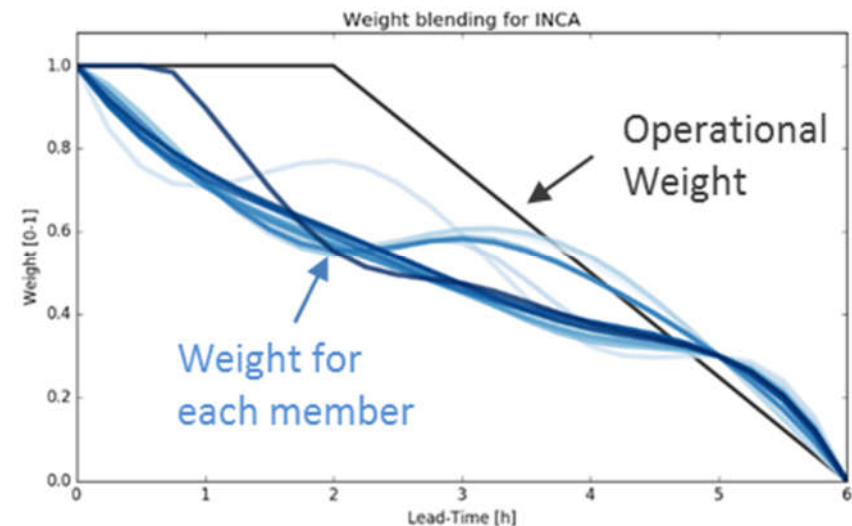
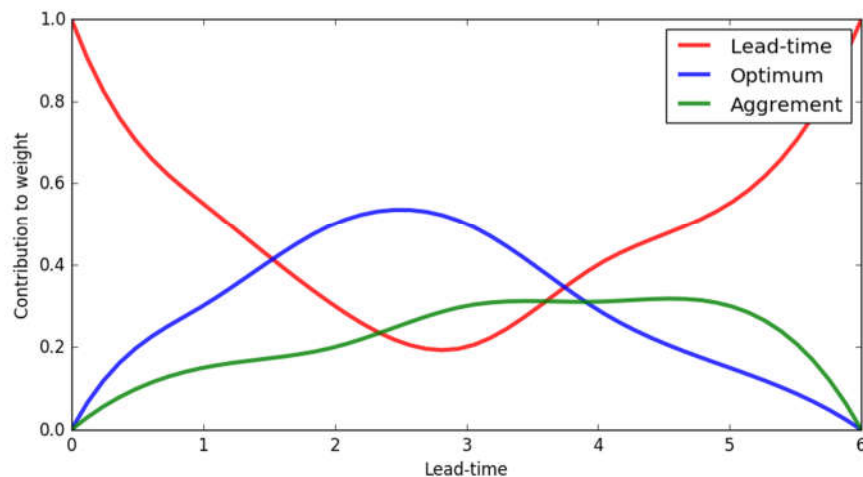
INCA and 16 members of the AROME-EPS are probabilistically blended in sub-domains of 100x100 such as the grey box overlotted in the image.



Weight computation

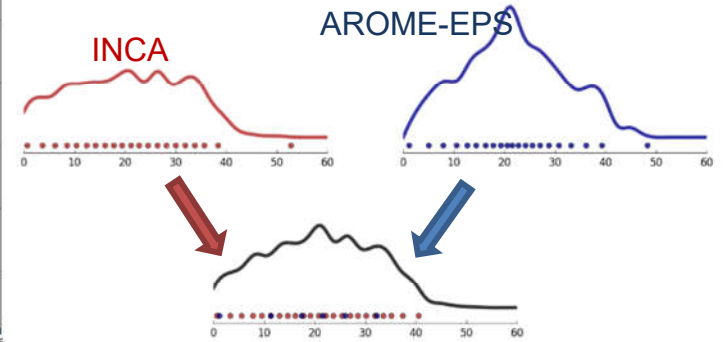
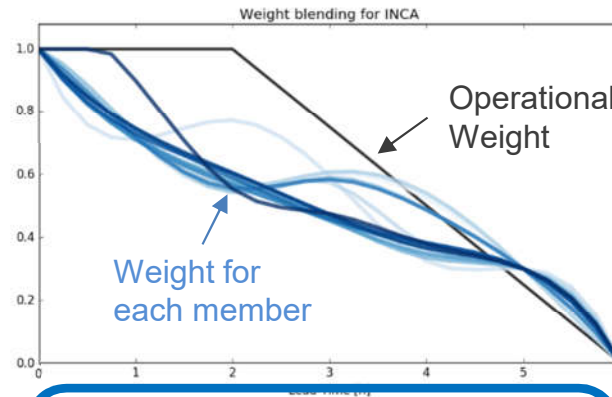
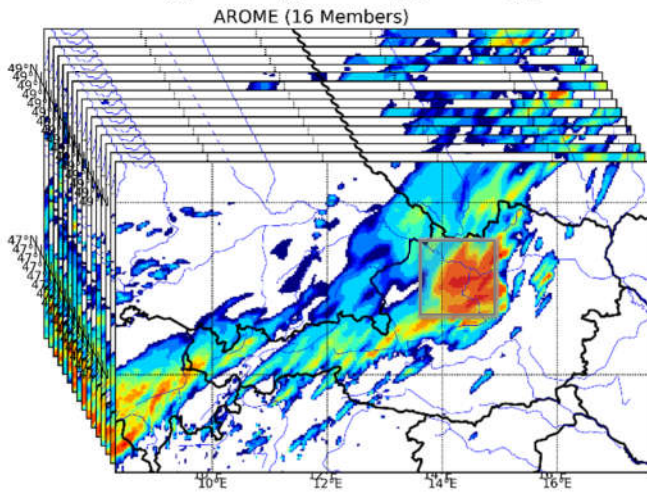
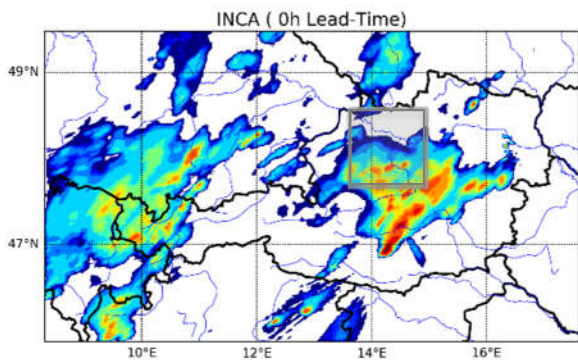
The rainfall field is divided in boxes of 100 x 100 pixels for introducing the spatial dependence on the location. At each of these boxes a different weight is used which depends on three factors:

- **A** lead-time function based on the operational weight in the INCA nowcasting system.
- **A** nudging term of the weight towards/against the ensemble prediction system when there is agreement among the ensemble members (small uncertainty).
- **A** portion based on the quality of the ensemble member in comparison with the **latest observations** and the evolution of the variances of both sources (and covariances)



Shown for one box here

Probabilistic blending (INCA + AROME – EPS)

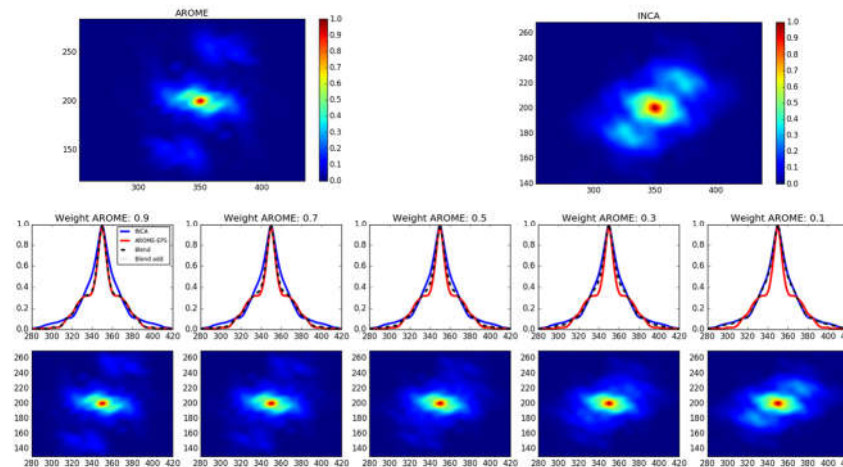


Member-dependent weight as function of lead-time, variance and distance to observations.

The rainfall empirical distribution function (edf) is resampled from INCA and AROME-EPS edf's.

The weights are used to blend the local correlations in order to reconstruct a rainfall field with self-similarity information from both fields.

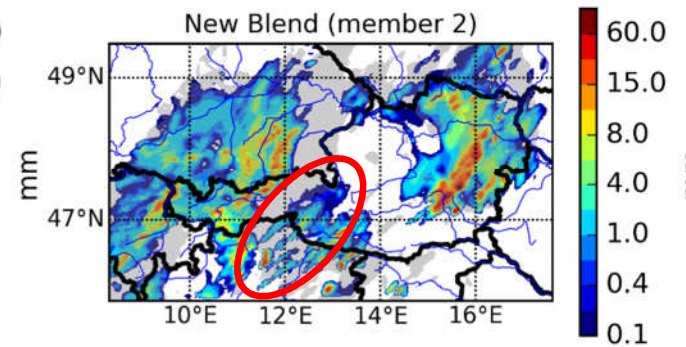
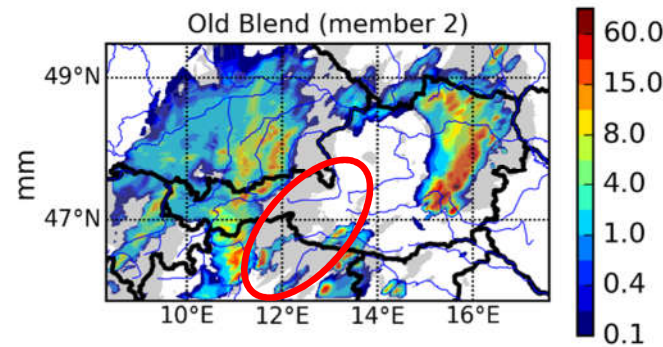
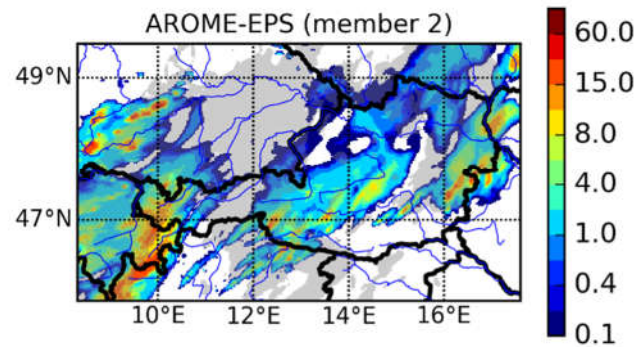
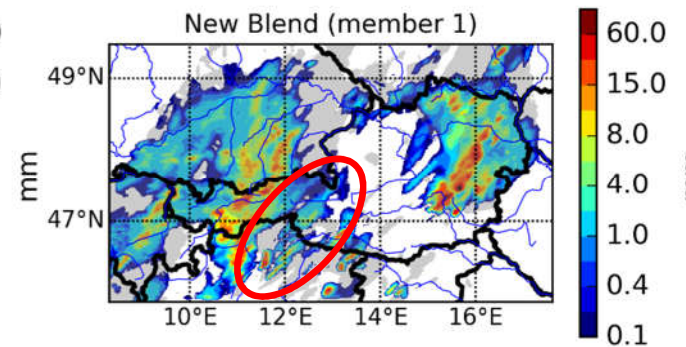
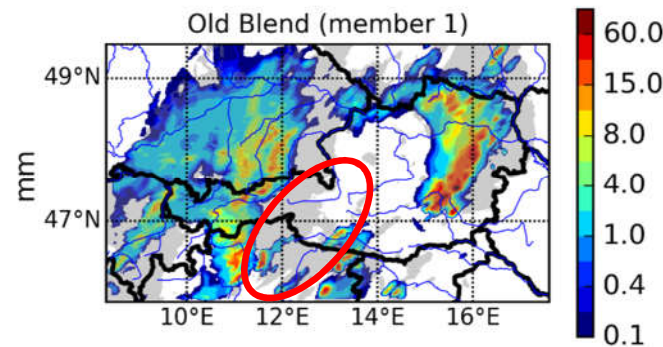
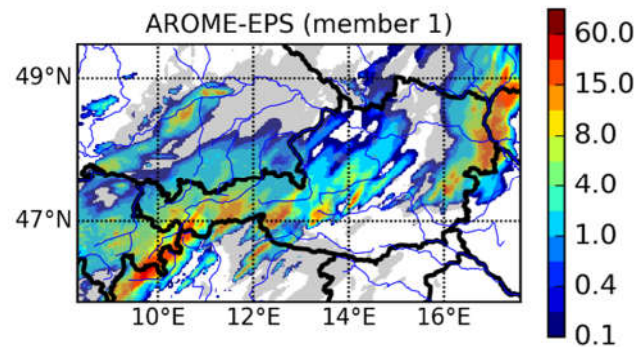
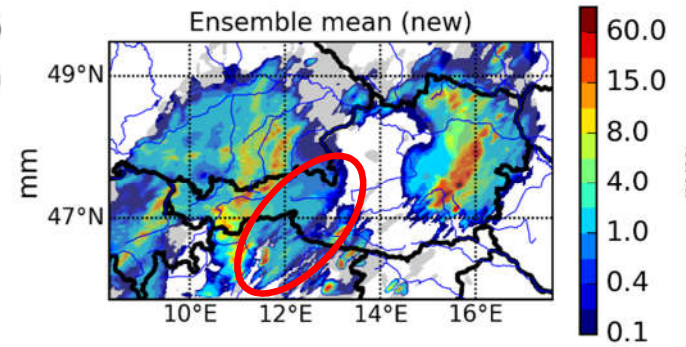
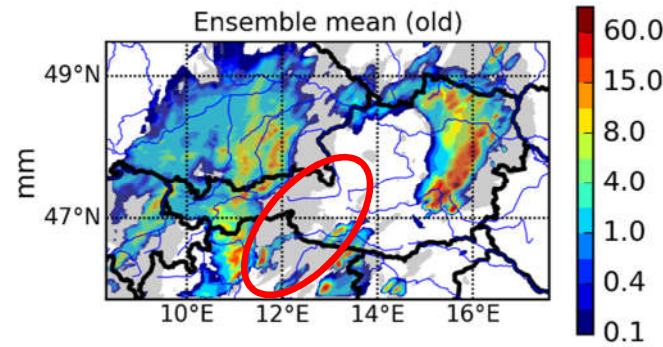
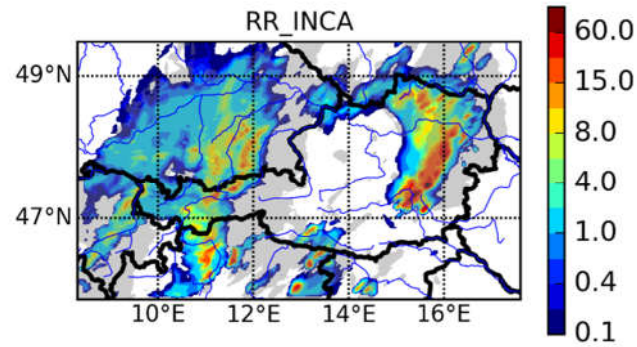
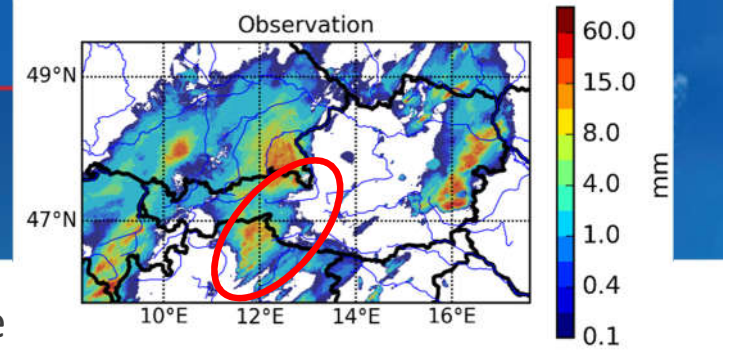
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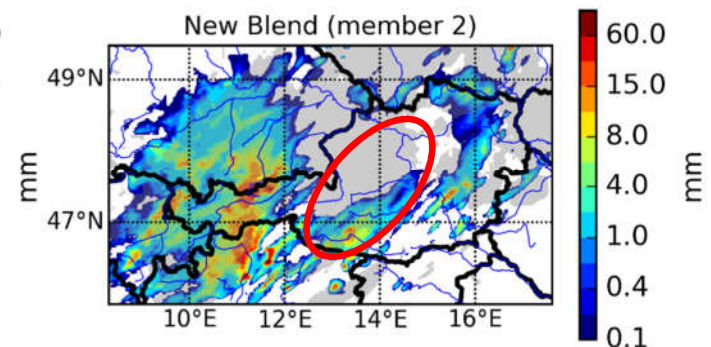
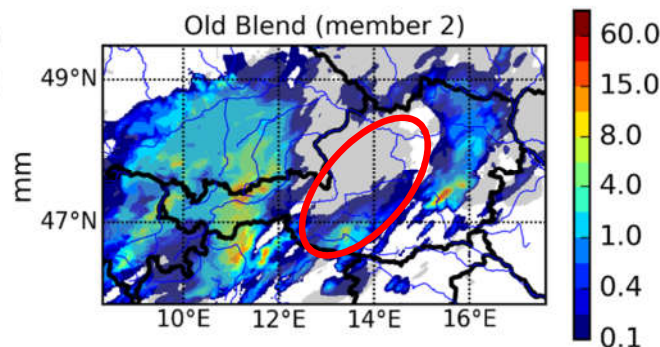
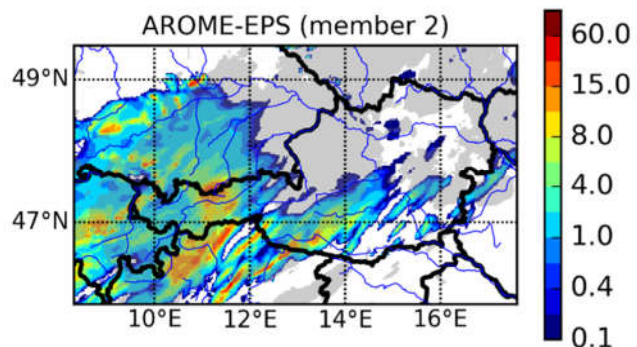
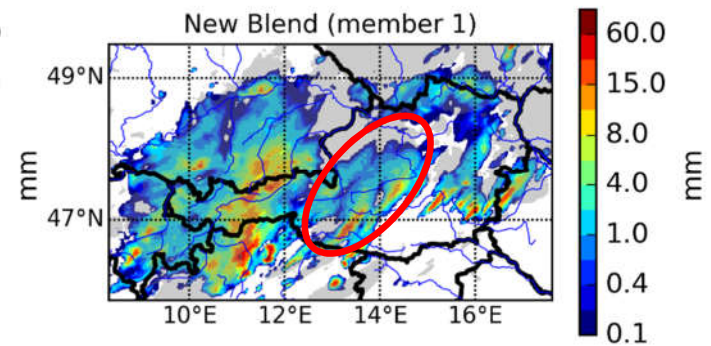
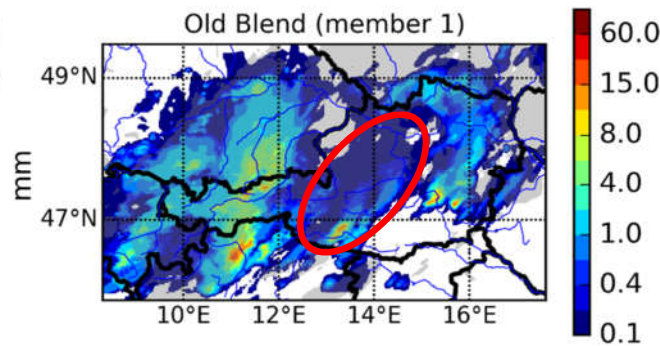
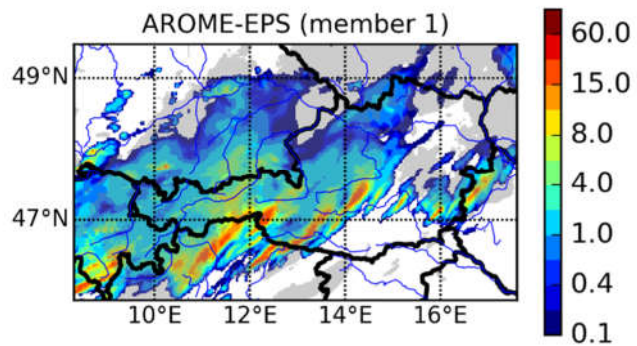
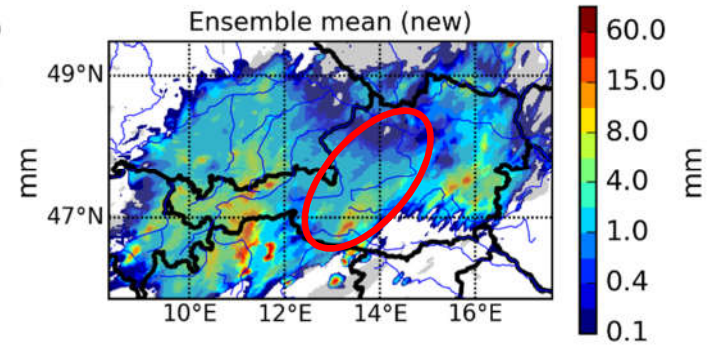
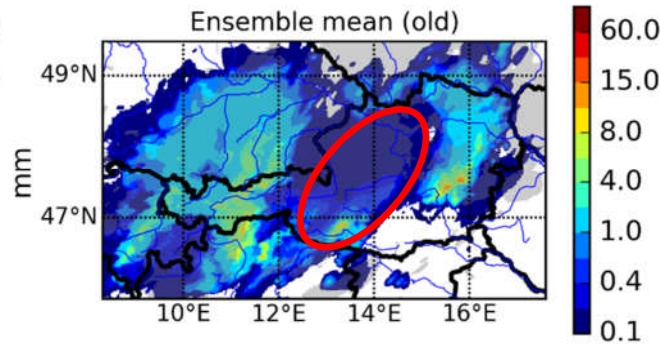
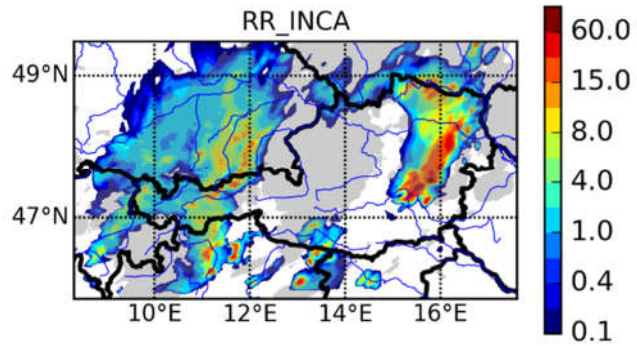
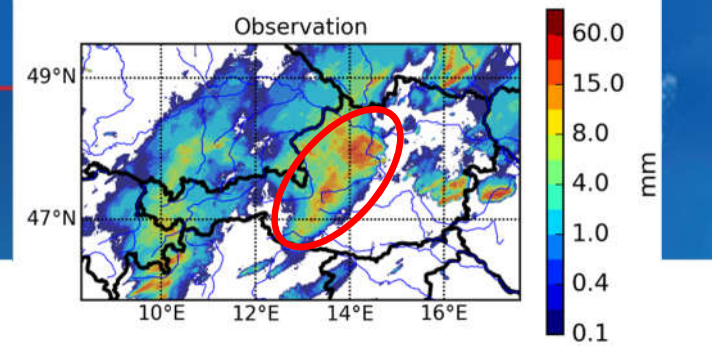
An ensemble of realistic rainfall fields.

Effect of the localization of the weights observed in the 1st h lead-time



An ensemble of realistic rainfall fields.

Effect of the resampling of the distributions in the 4th h lead-time.



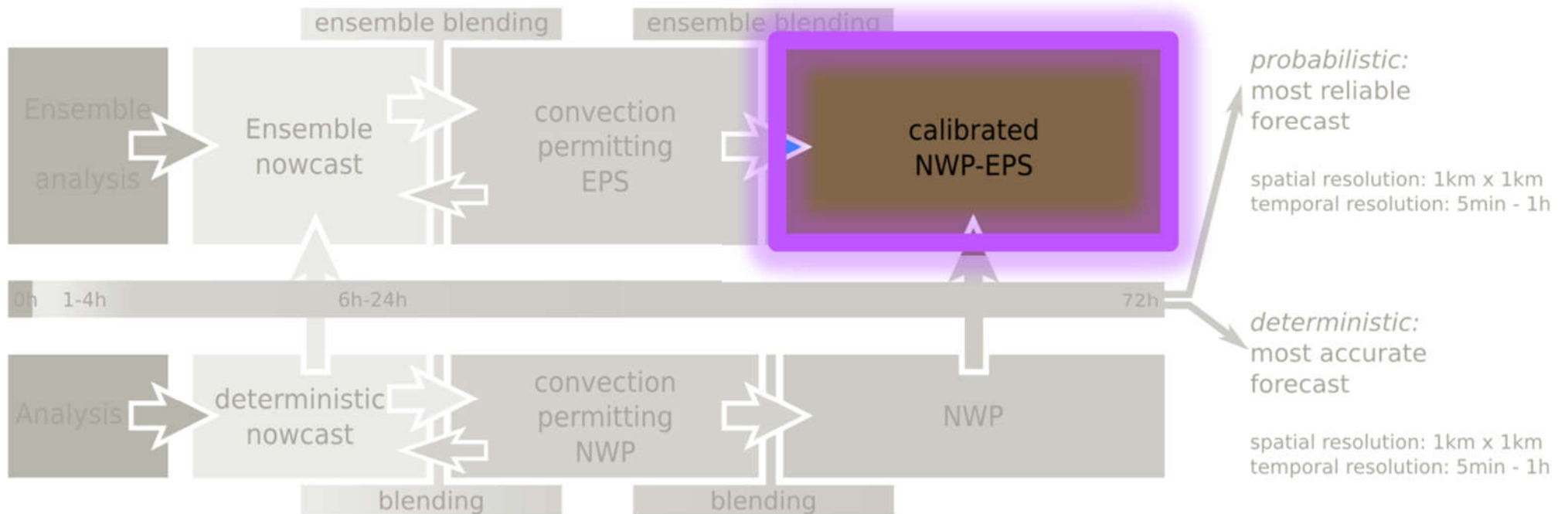
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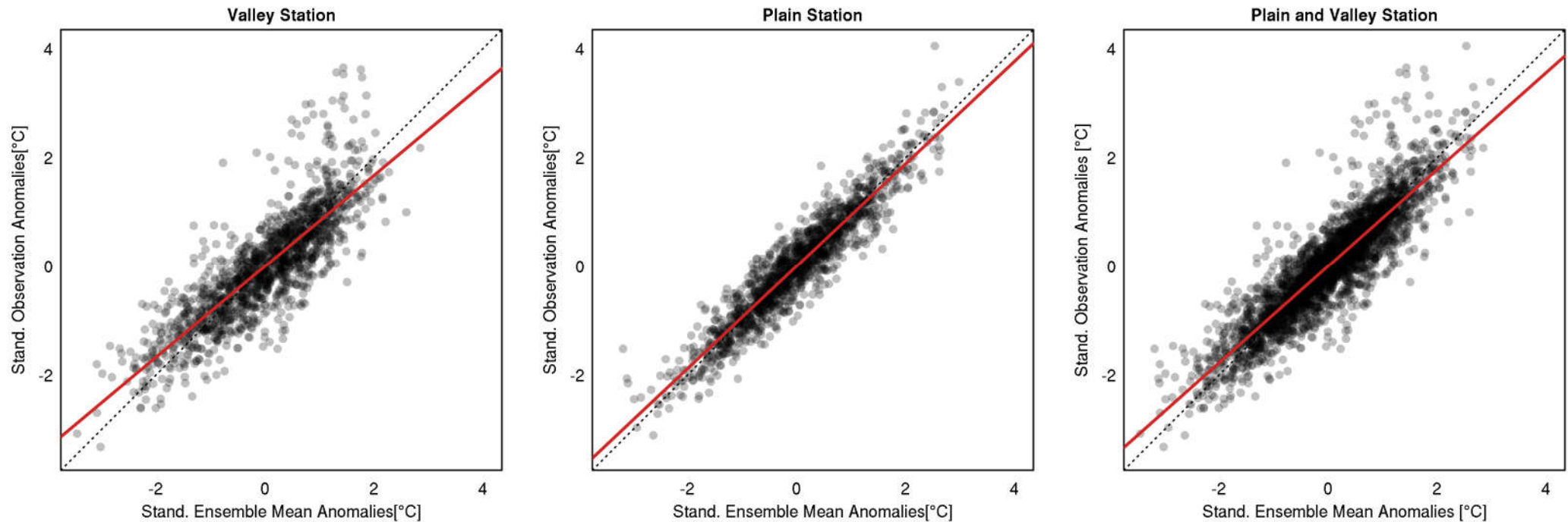
Seamless probabilistic Analysis and Prediction in very High Resolution



Standardized Anomaly Model Output Statistics (SAMOS)

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Markus.Dabernig@zamg.ac.at

11.10.2018
Folie 31



$$\frac{y - \mu_y}{\sigma_y} \sim N(\mu, \sigma)$$

$$\mu = b_0 + b_1 \text{mean} \left(\frac{\text{ens} - \mu_{\text{ens}}}{\sigma_{\text{ens}}} \right)$$

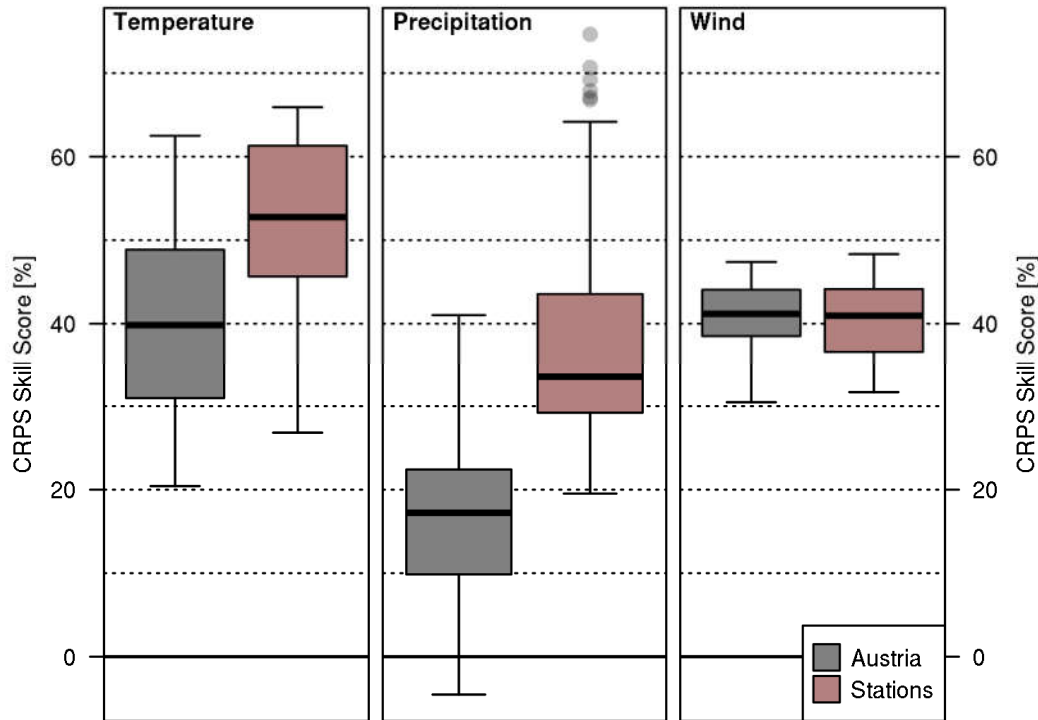
$$\sigma = c_0 + c_1 \text{sd} \left(\frac{\text{ens} - \mu_{\text{ens}}}{\sigma_{\text{ens}}} \right)$$



All 305 stations and
all ~ 80 000 grid points
can be fitted and
forecasted simultaneously

Standardized Anomaly Model Output Statistics (SAMOS)

Markus Dabernig
Markus.Dabernig@zamg.ac.at



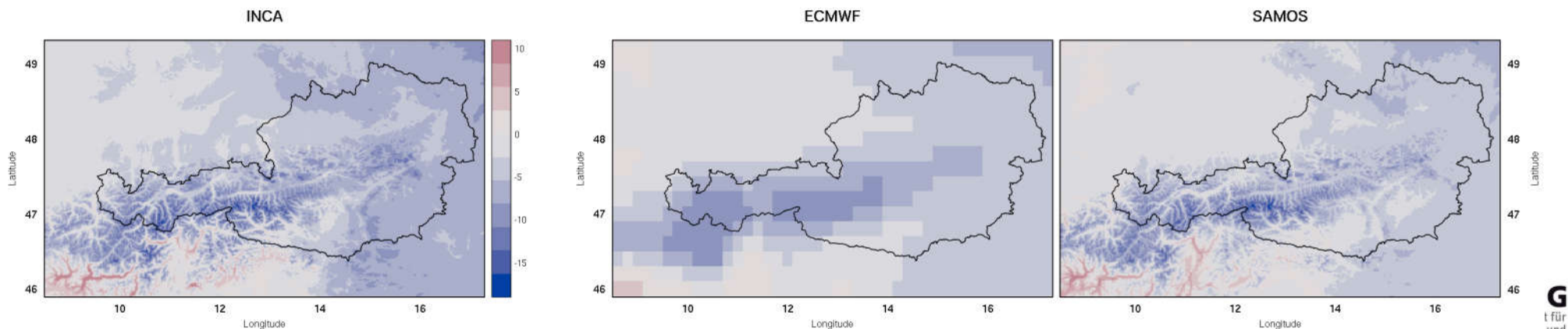
Averaged over all stations:

+ Improvements at all variables between 20 and 70 %

Averaged over all grid points:

+ Only precipitation could not be improved at all lead times

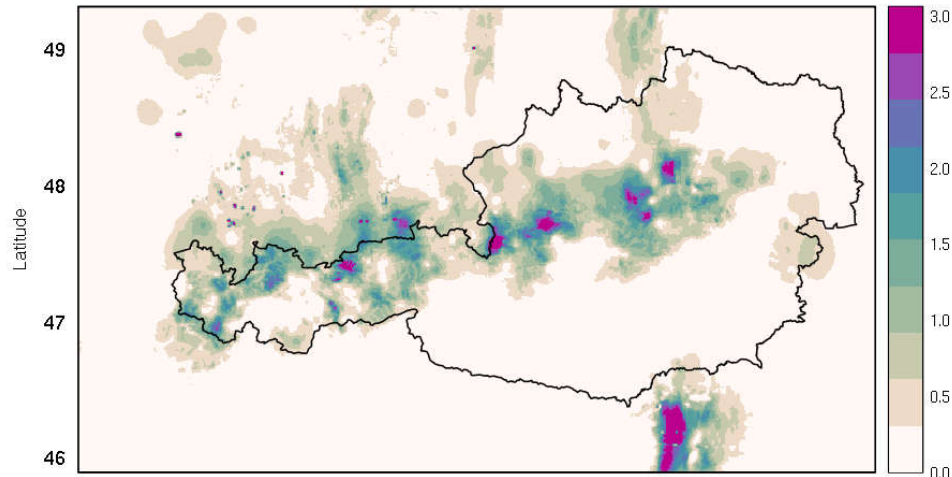
→ Difference between all grid points and stations due to different height distribution



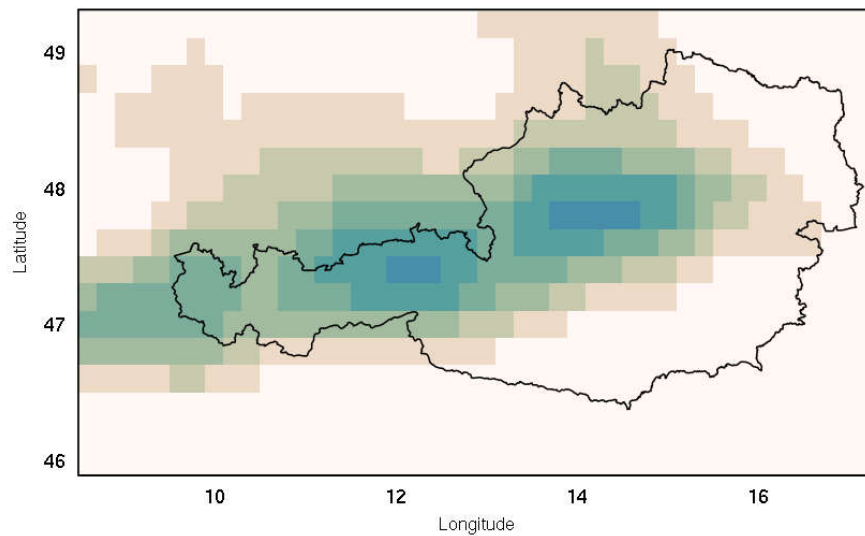
Examples: precipitation

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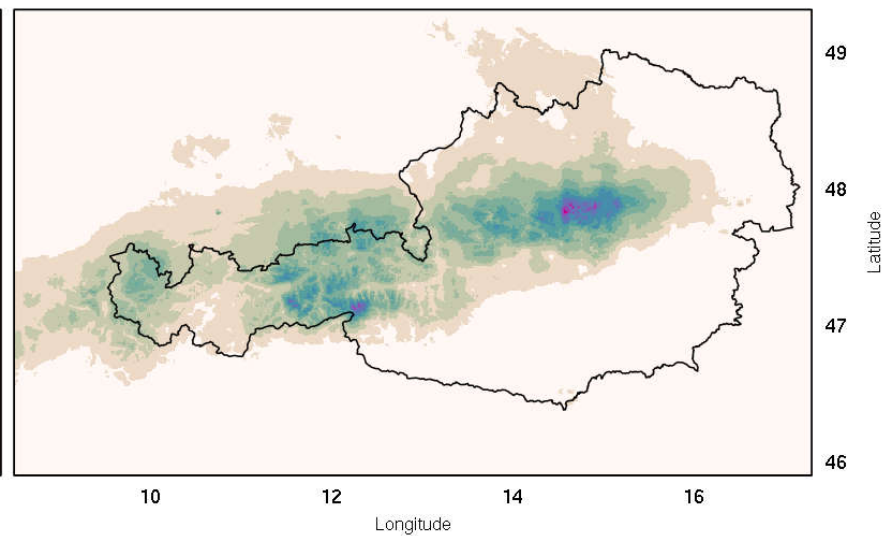
INCA



ECMWF



SAMOS



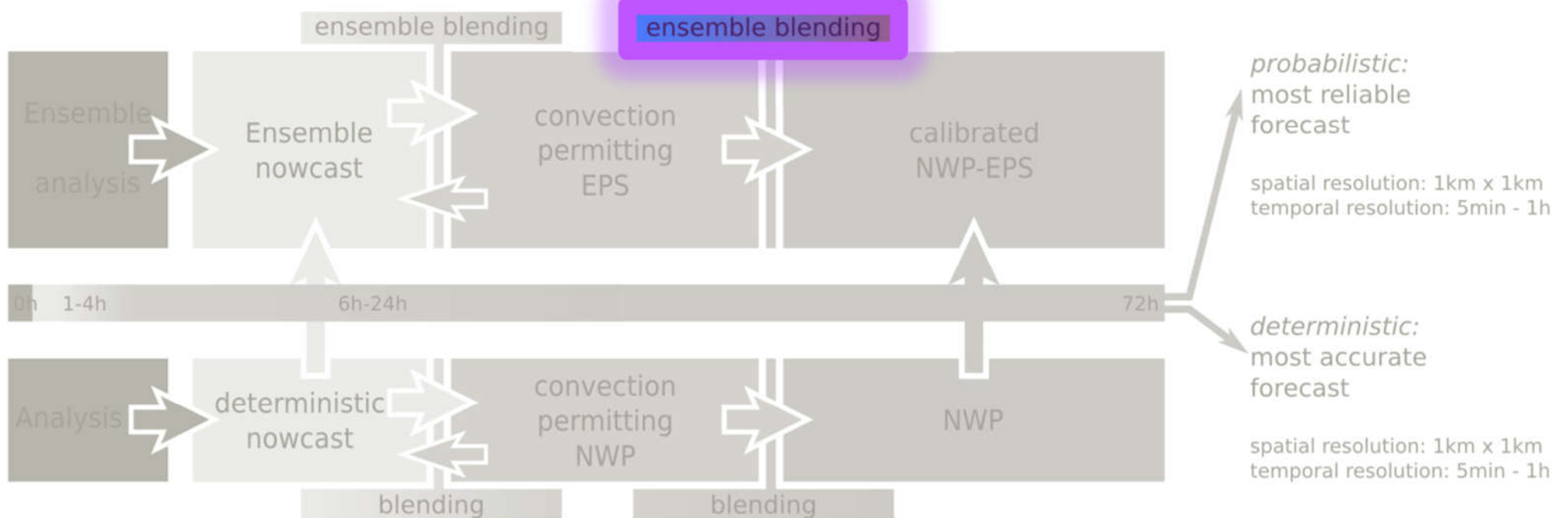
System design



SAPHIR



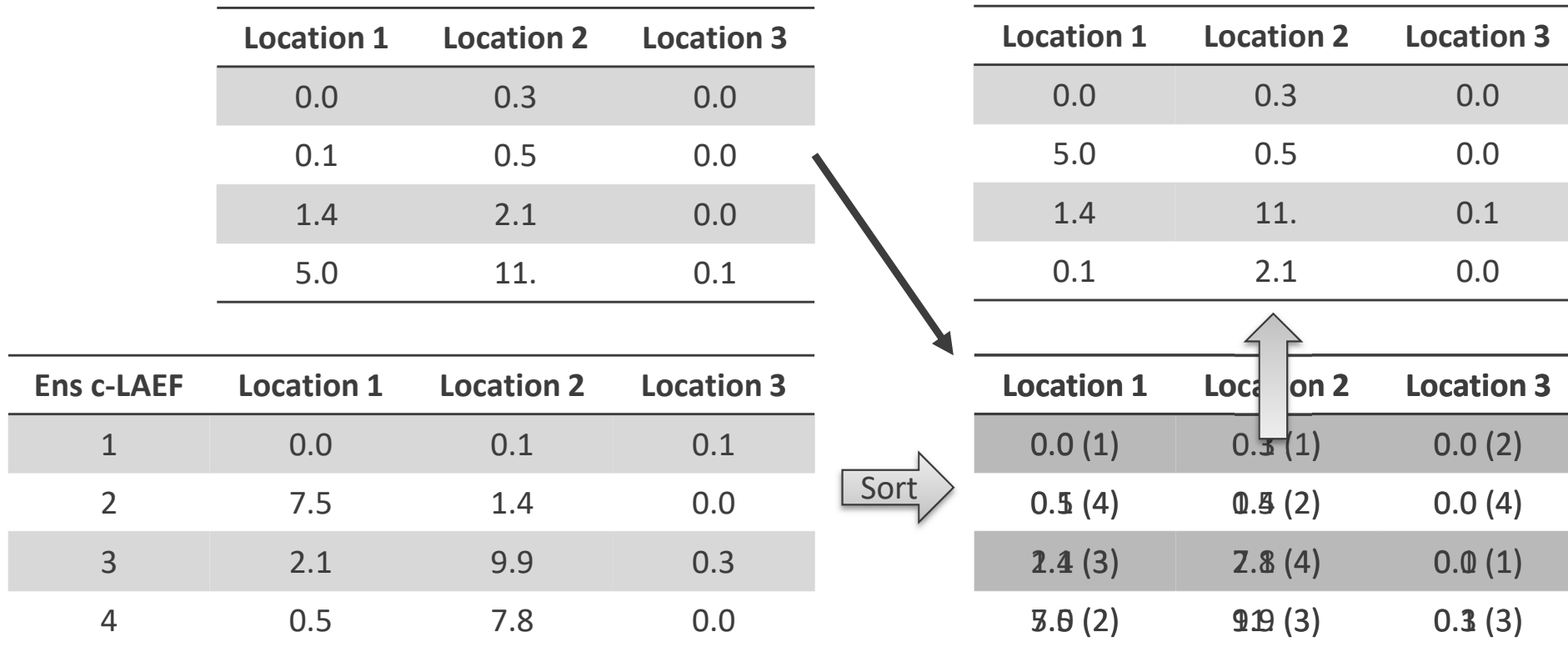
Seamless probabilistic Analysis and Prediction in very High Resolution



The schaake Shuffle for introducing calibrated statistics



1. The mean and standard deviation obtained at each pixel by SAMOS (calibration) it is introduced in the empirical distribution from C-LAEF by a weight as a function of the lead-time.
2. From these modified distribution, 16 new rainfall values are obtained at each pixel.
3. The spatial correlation is reproduced by the Schaake Shuffle technique:

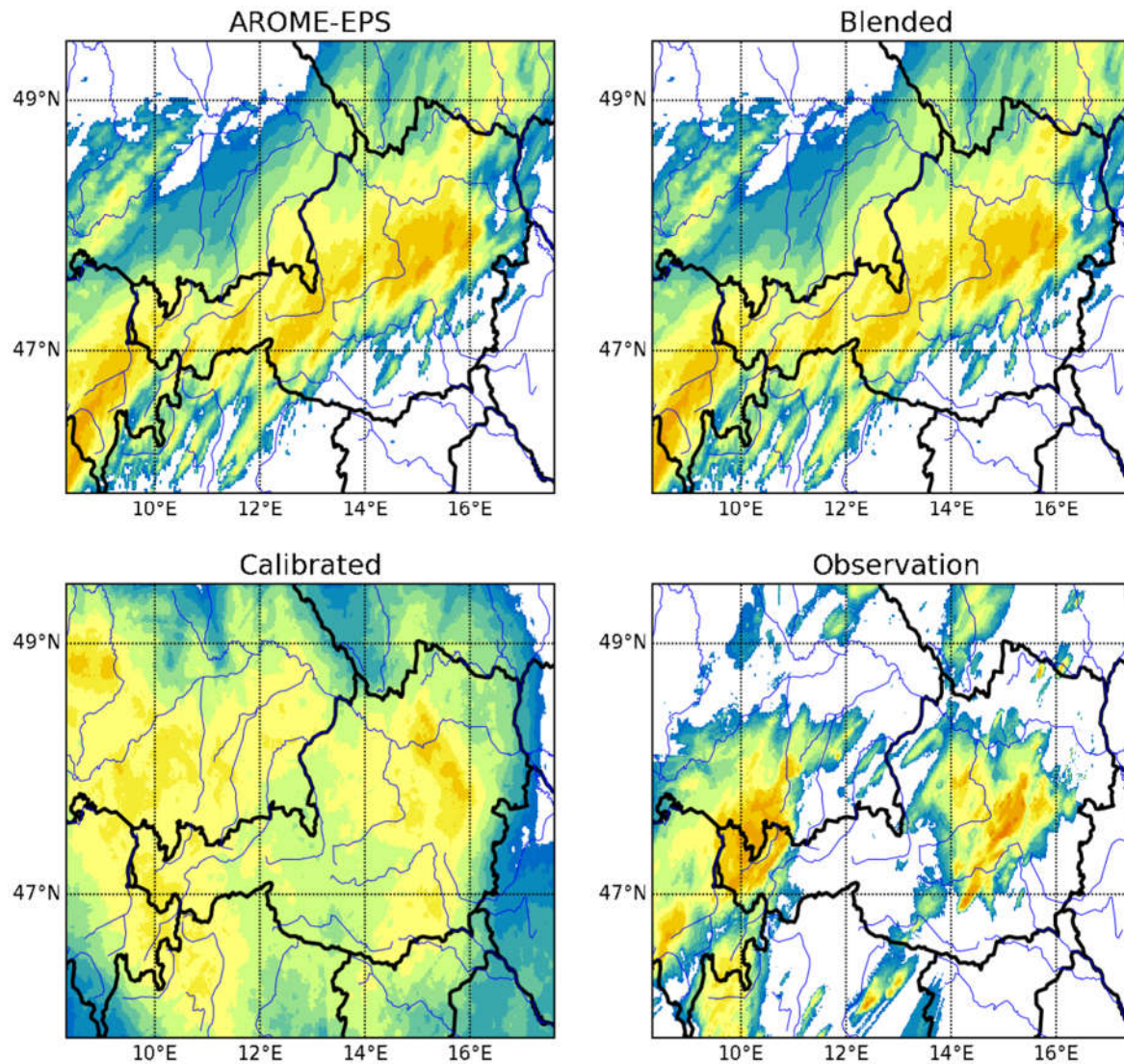


Spatial structure from C-LAEF

The schaake Shuffle for introducing calibrated statistics

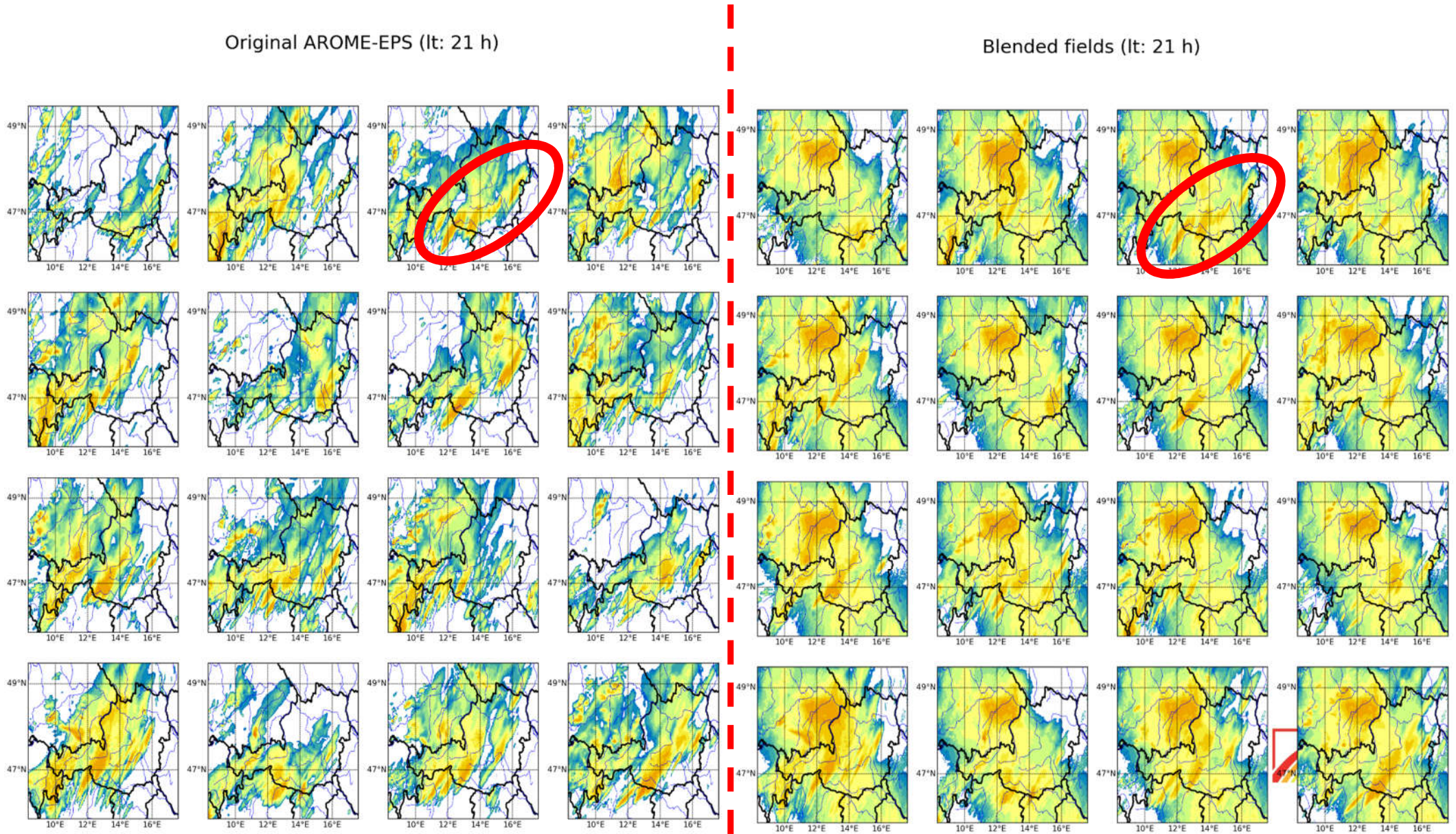
- The animation shows a smooth transition from C-LAEF to the calibrated mean

Ensemble mean (lt: 12 h)



The schaake Shuffle for introducing calibrated statistics

- And the spatial structure can be observed in the different ensemble members:



Conclusions & next plan

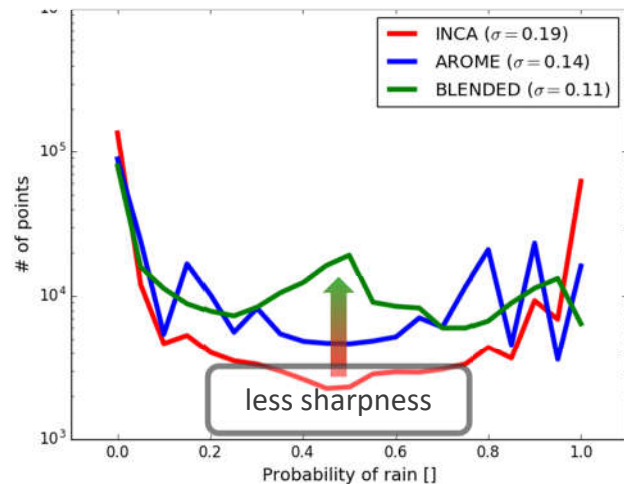
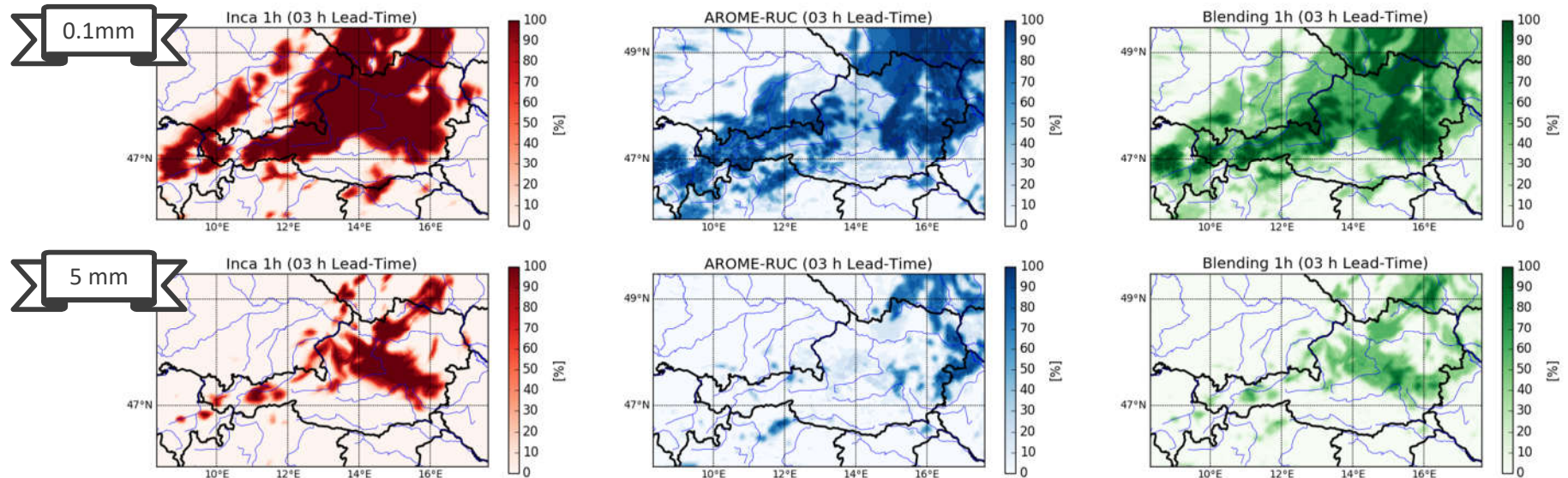


- ✓ Seamless system SAPHIR has been designed, and its basic components are available.
- ✓ There are still a lot of challenges in all aspect of related science and technology.
- ✓ Other R&D activities have been started or in plan, e.g. SAPHIR at 100m resolution; extension to medium range, etc.

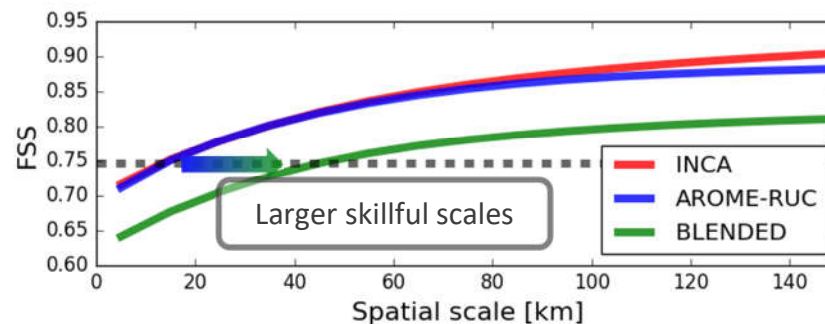


Challenges of the current methodologies

The **probability-based blending (2)** avoids the losing of intense precipitation values in the blended forecast but shows also the reduction of variance, larger skillful scales and, furthermore, the obtained field is not a realistic precipitation field.



The probability of rain fields are constructed for different thresholds. This approach only allows to differentiate among rainfall regimes (light rain, moderate, heavy rainfall).



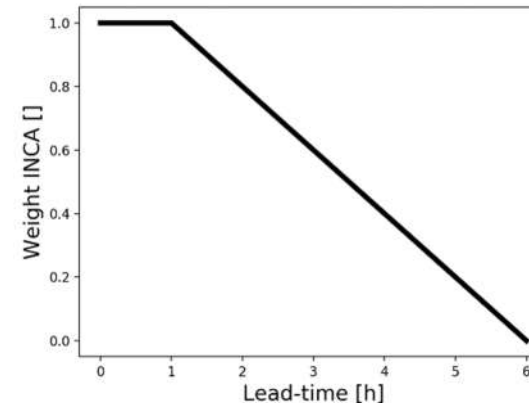
Blending: State of the art

The current state of the art for creating a seamless prediction for high impact weather, storm prediction and so on for very short-term is still adding:

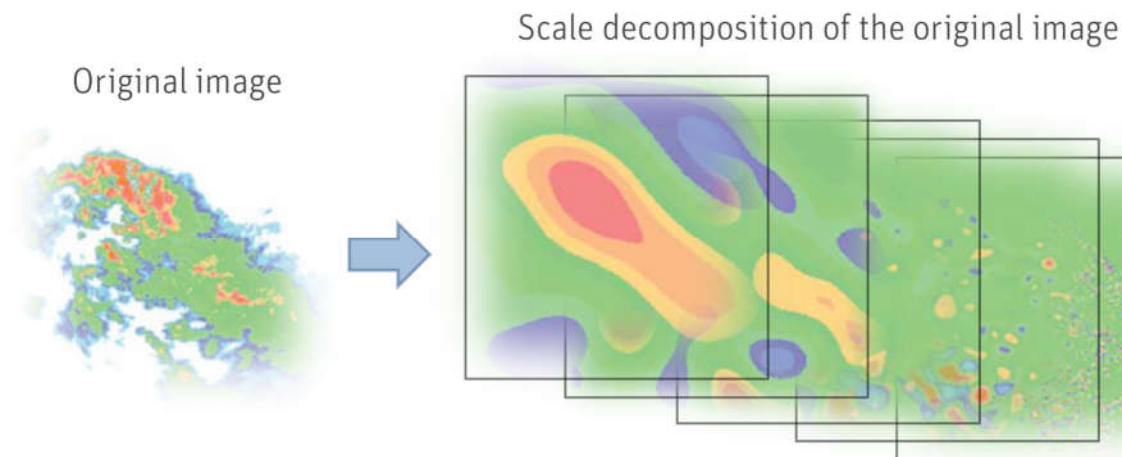
1. Linearly both fields (Golding, 1998),

$$w_{inca} = \begin{cases} 0 & \text{Lead-time} > 6 \text{ h} \\ \frac{(6 - \text{leadtime})}{6 - 1} & \text{Lead-time} \leq 6 \text{ h} \end{cases}$$

$$w_{AROME} = 1 - w_{inca}$$

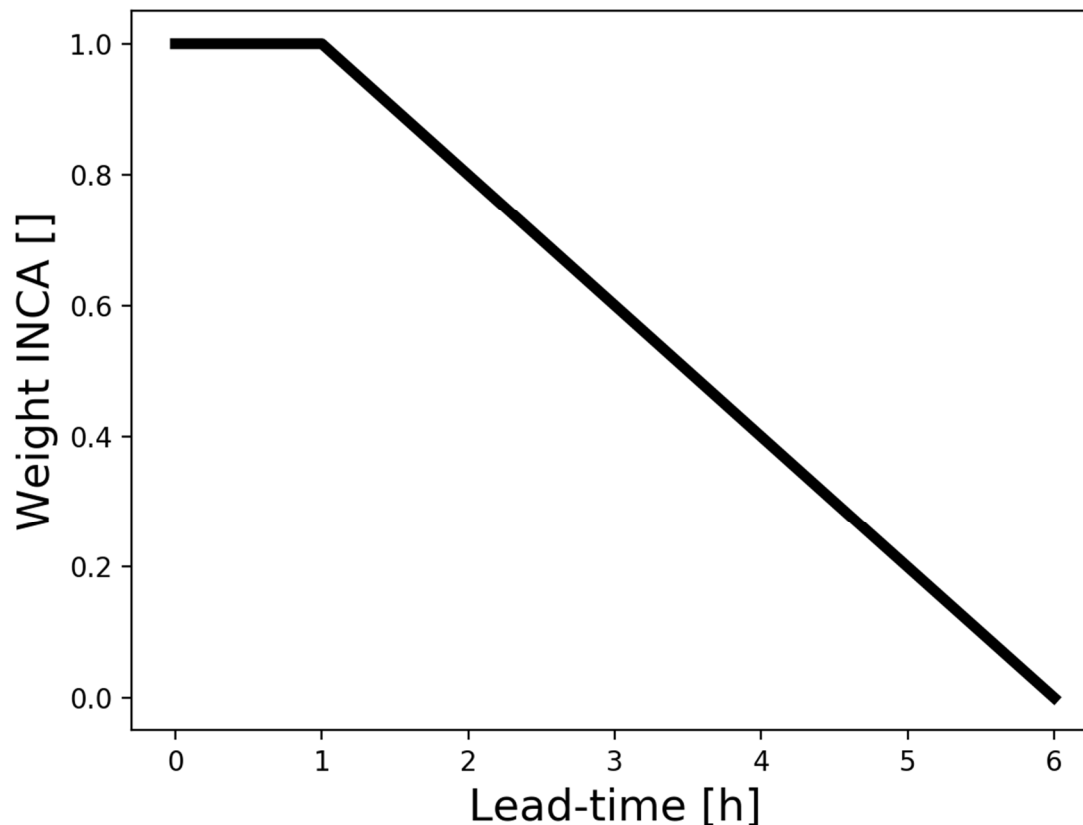


2. Linearly the probabilities of occurrence (Kober et al., 2012).
3. Cascades from a scale decomposition of the reflectivity fields (Bowler et al., 2006) from both sources the Lagrangian extrapolation and the NWP output (e.g. STEPS, Alan Seeds).



Current operational setting

- The INCA (Integrated Nowcasting through Comprehensive Analysis) system provides analysis and nowcasting fields of temperature, humidity, wind, precipitation amount, precipitation type, cloudiness, and global radiation. The nowcasting part employs classical correlation-based motion vectors derived from previous consecutive analyses. In the case of precipitation the nowcast includes an intensity-dependent elevation effect. After 2–6 h of forecast time the nowcast is merged into an NWP forecast provided by a limited-area model, using a predefined temporal weighting function:



$$w_{inca} = \begin{cases} 0 & \text{Lead-time} > 6 \text{ h} \\ \frac{(6 - \text{leadtime})}{6 - 1} & \text{Lead-time} \leq 6 \text{ h} \end{cases}$$

$$w_{AROME} = 1 - w_{inca}$$

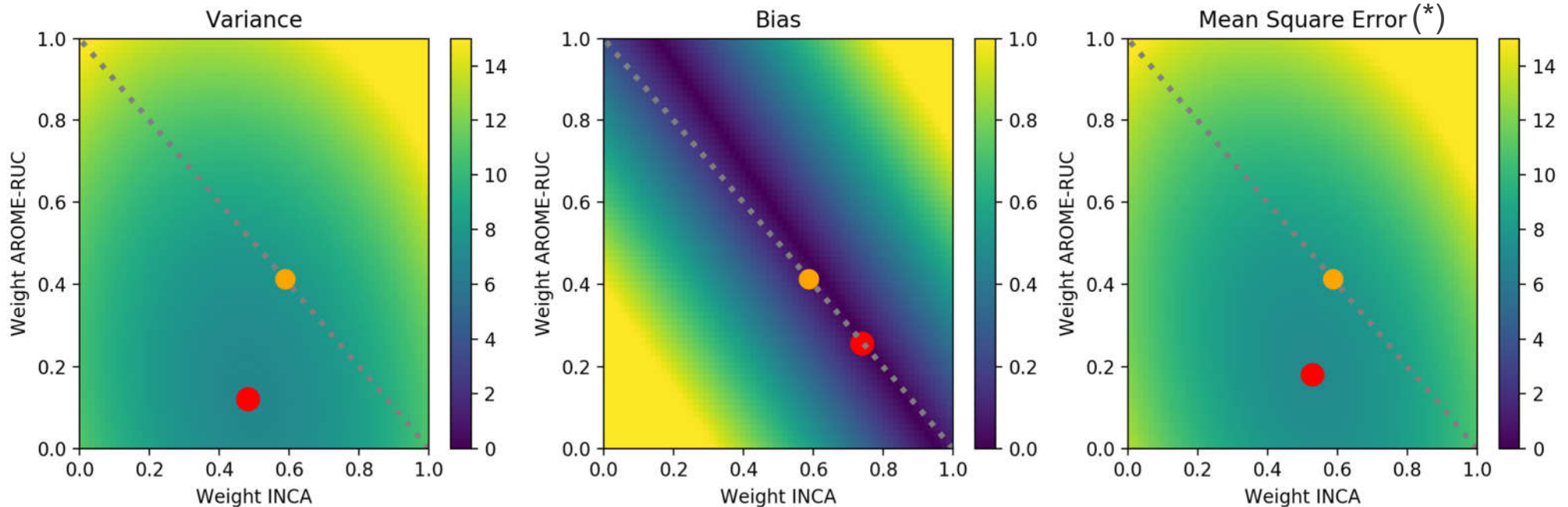
Methodology to compute the „optimal“ weights

- In the literature (for example; Kalnay 2003), it can be found the weights for the optimal interpolation (merging) of two different sources. The simple example for a given measurement, assuming no bias and no correlation between the sources of information, is:

$$w_{INCA} = \frac{\sigma_{AROME}^2}{\sigma_{AROME}^2 + \sigma_{INCA}^2}$$

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- However, we can plot the errors as a function of the weights for the two different forecasts:



(*) $Var(\epsilon) + Bias^2 = MSE$

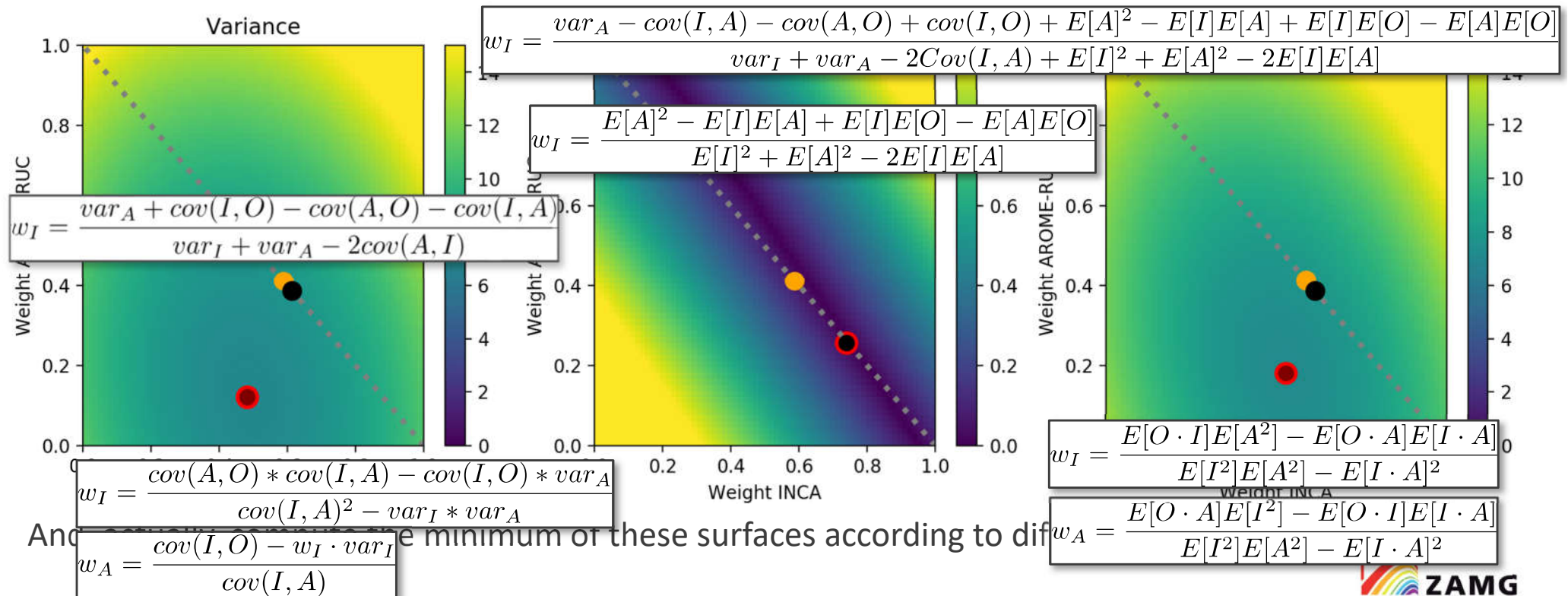
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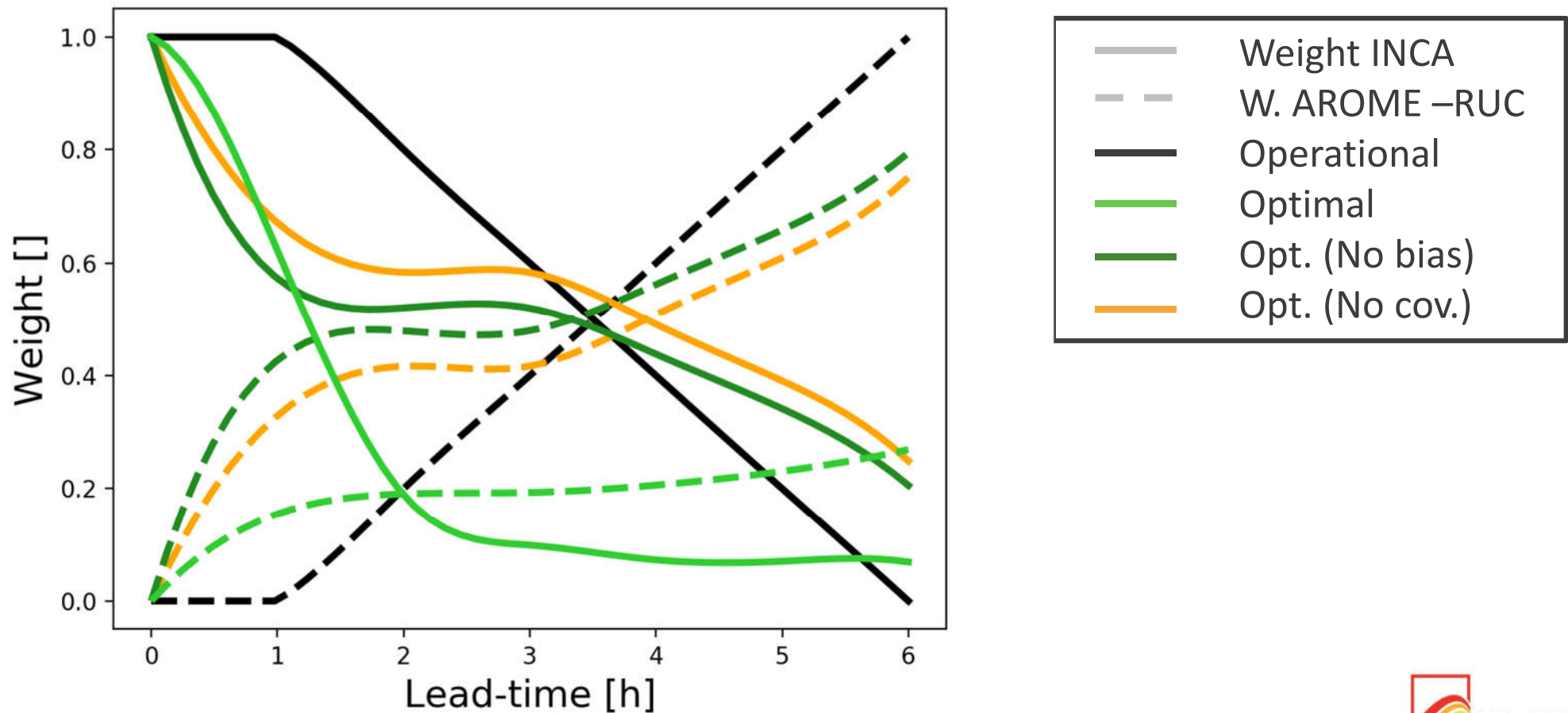


- And find the minimum of these surfaces according to different criteria:

(* $Var(\epsilon) + Bias^2 = MSE$)

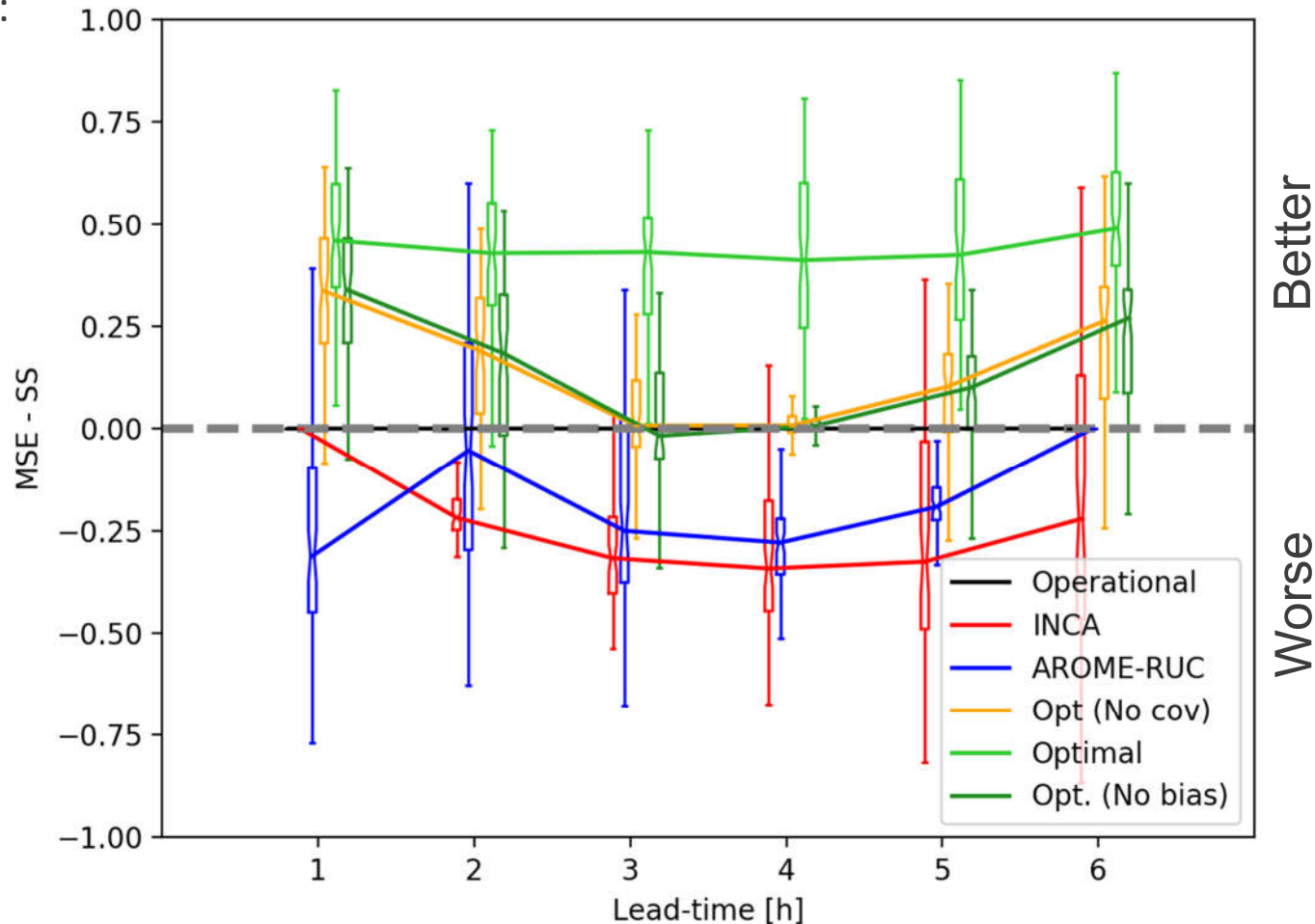
Some information from the „optimal“ weights

- The whole month data from AROME-RUC, INCA and observations (obtained from INCA Analysis) is used to compute the weights as a function of the lead-time. Only the weights that optimizes the MSE are shown (taking into account correlation between sources, possible bias and so on):



Results from the „optimal“ weights

- The results are obtained for every hour of the whole month of July 2016 (a total of 744 hours) for each lead-time (6 hours of maximum lead-time). The **MSE Skill Score(*)** is computed as the verification index:

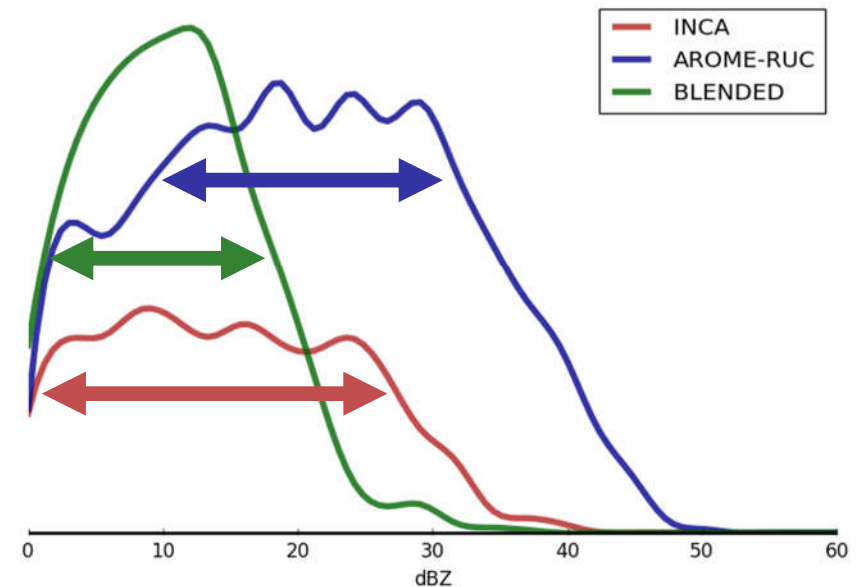
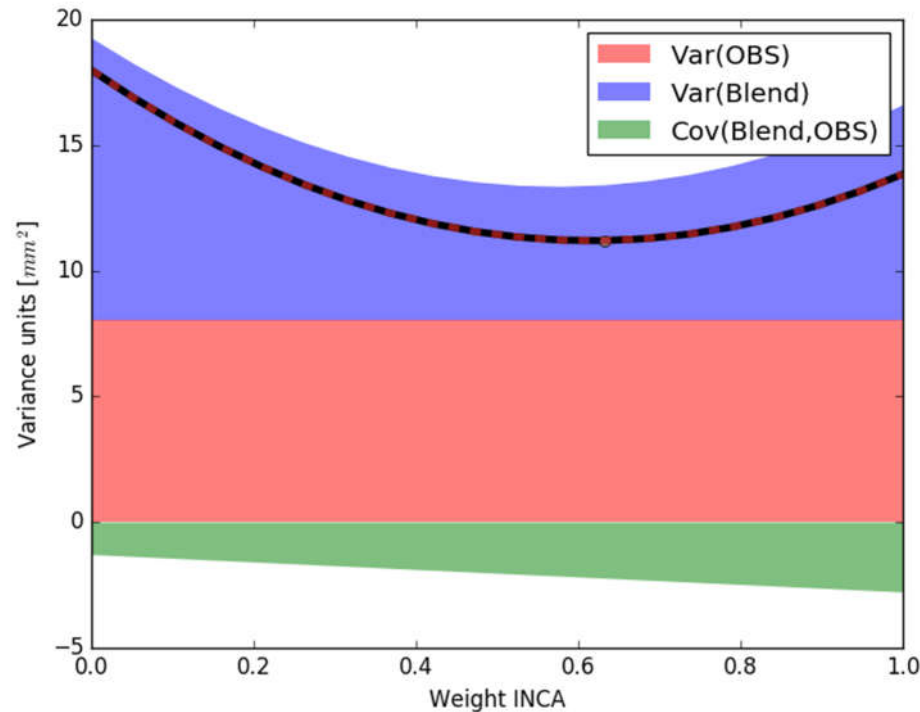


$$(*) MSE - SS' = \begin{cases} 1 - \frac{MSE_{fcst}}{MSE_{ref}} & : MSE_{fcst} < MSE_{ref} \\ \frac{MSE_{ref}}{MSE_{fcst}} - 1 & : MSE_{fcst} \geq MSE_{ref} \end{cases}$$

Is this improvement “real”?

- The MSE has a dependence with the variance of the resulting blended field. Consequently, a reduction of the variance would result in an improvement of the scores.

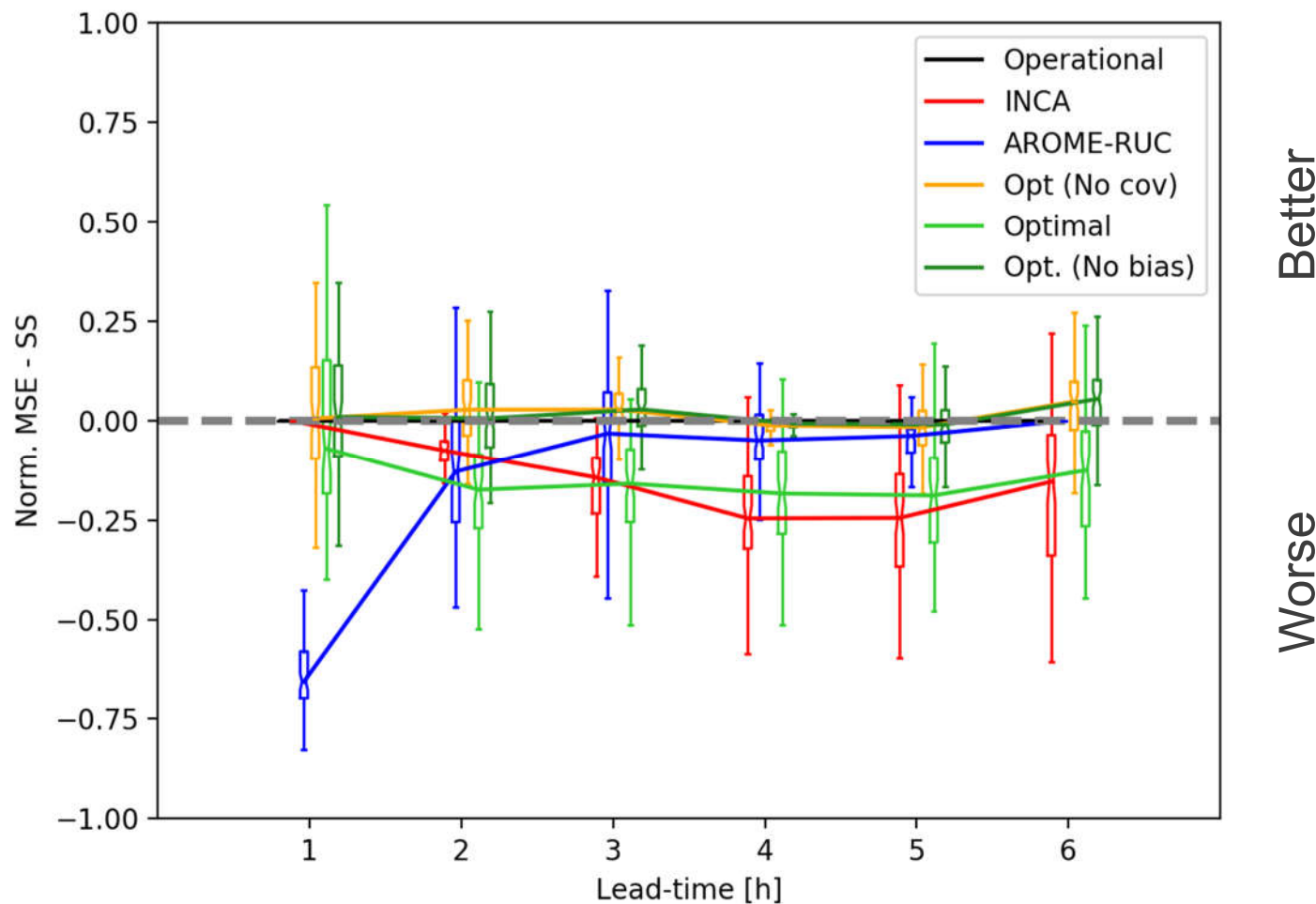
- $MSE(f_B) = Var(f_B - O) = \boxed{Var(f_B)} + \boxed{Var(O)} - \boxed{2Cov(f_B, O)}$



The empirical probability distribution of rainfall values of both INCA (radar extrapolation) and AROME-RUC (NWP) is compared to the epdf of the blended forecast showing the lessening of the intense rainfall and the reduction of variance.

Results from the „optimal“ weights

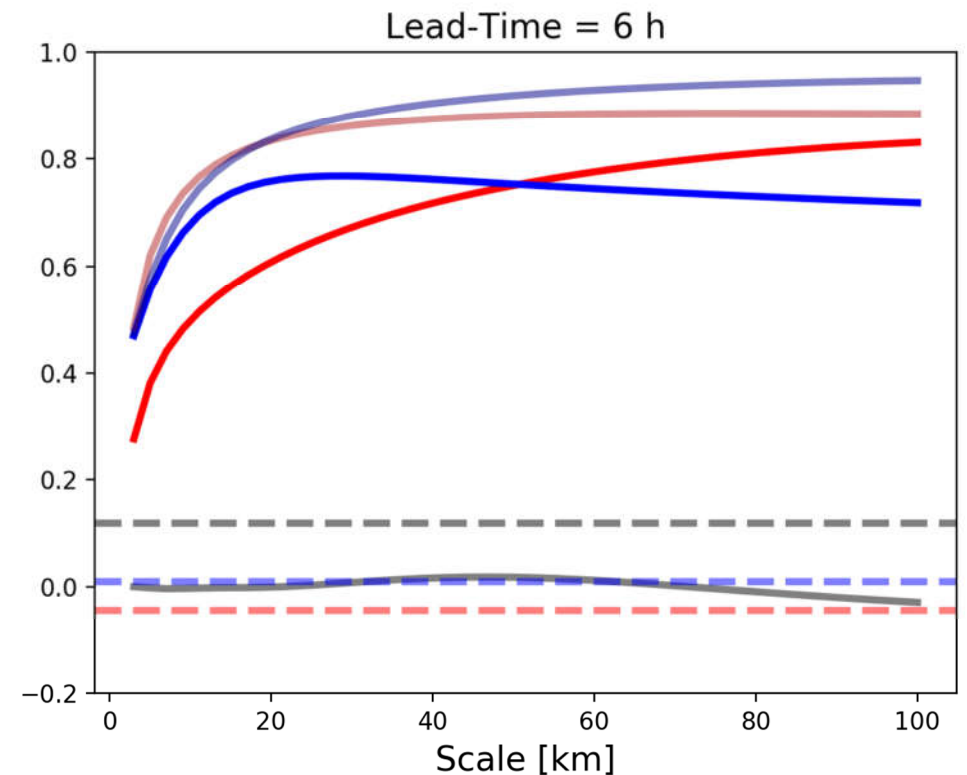
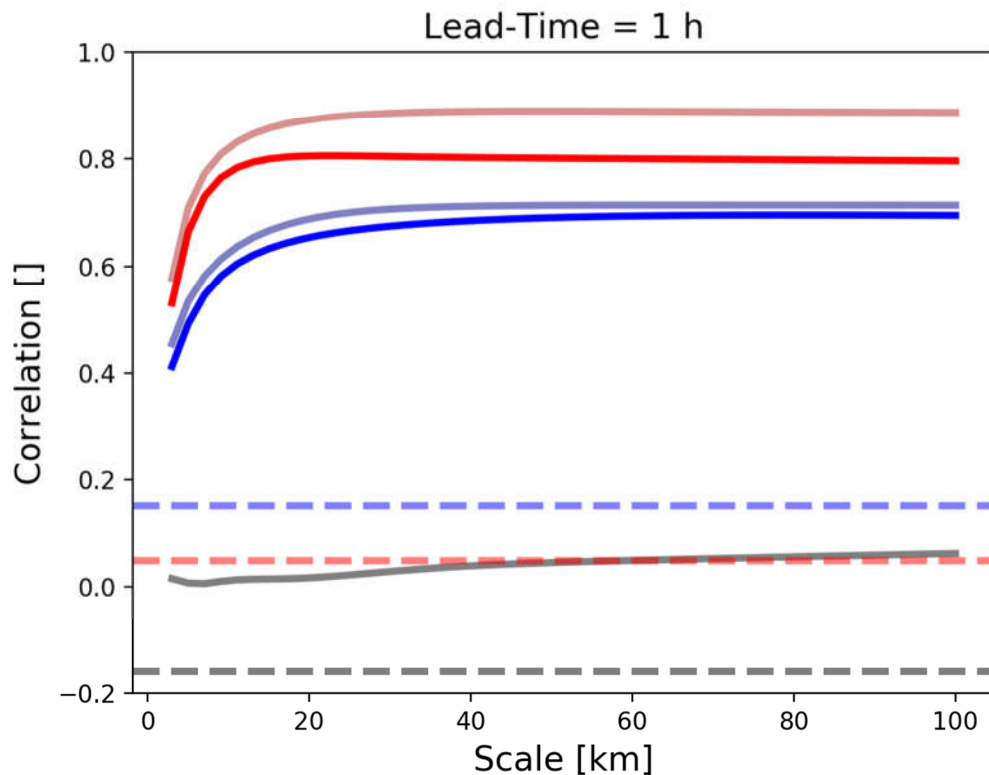
- The results are obtained for every hour of the whole month of July 2016 (a total of 744 hours) for each lead-time (6 hours of maximum lead-time). The **Normalized MSE Skill Score** is computed as the verification index:



Flow and location dependence on the weights



The main goal is to have local information but in a flow dependent way so it account for the different quality depending on the weather performance.



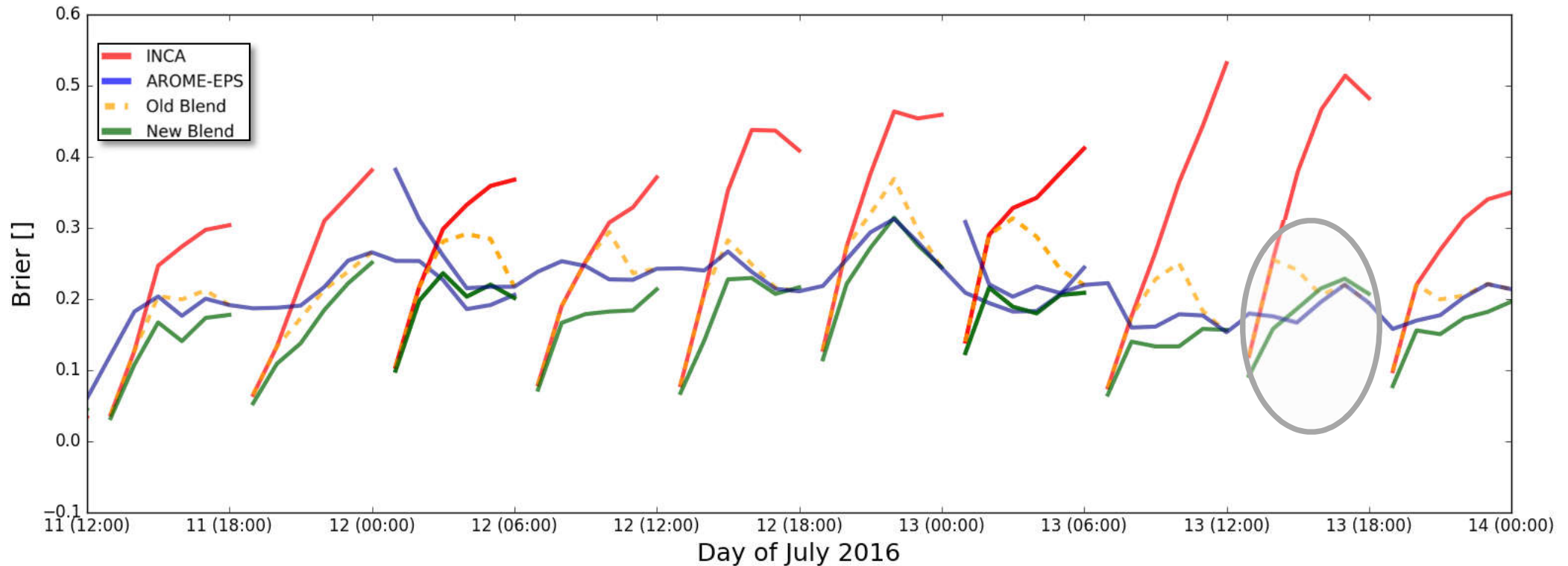
--- Correlation between ϵ of two consecutive times steps for INCA, AROME-RUC and common information

Correlation between ϵ and $\tilde{\epsilon}$ for INCA and AROME-RUC common information (past)

Correlation between ϵ and $\tilde{\epsilon}$ for INCA and AROME-RUC (future)

Verification and comparison with previous methodologies

The probabilistic verification is carried out for each hour ...



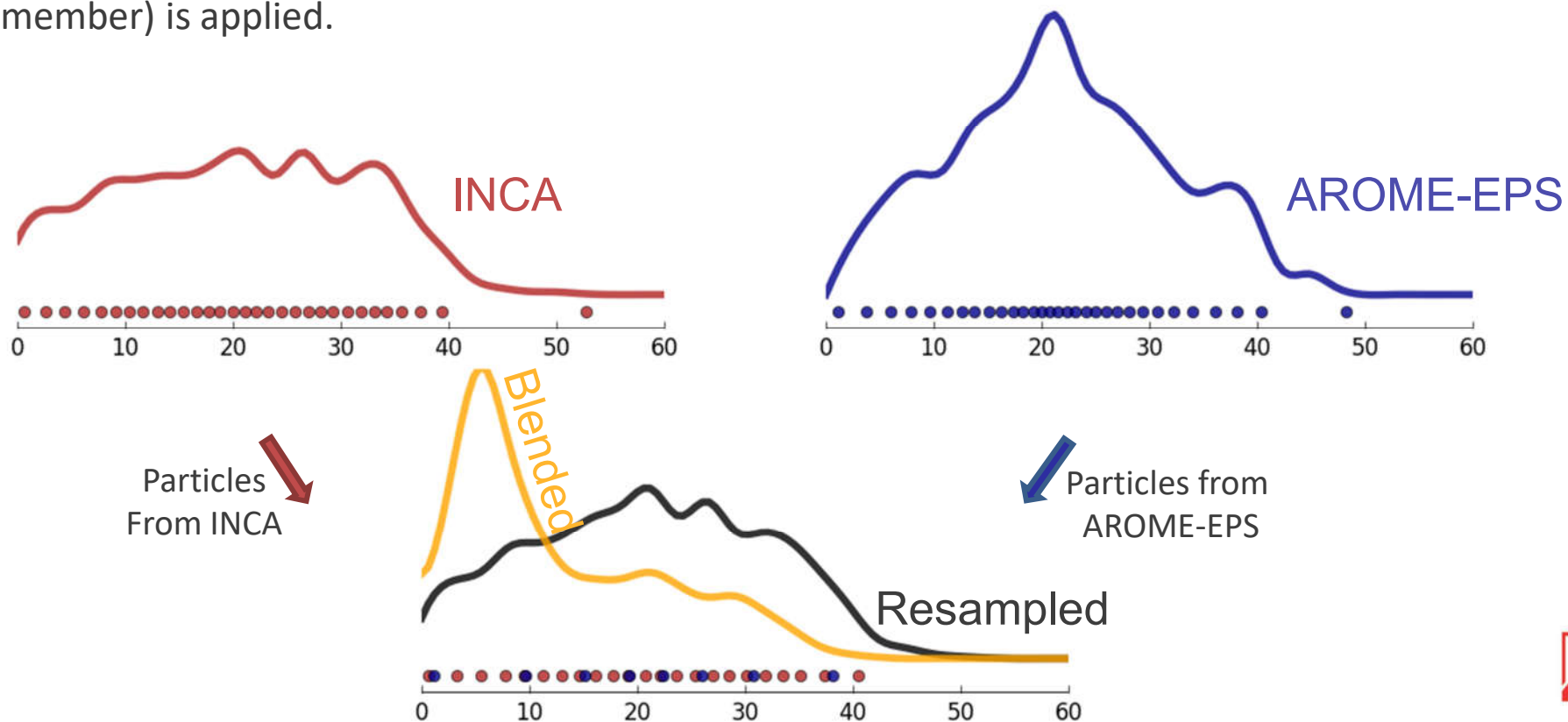
The threshold of 0.1 mm has been selected because the previous methodology for blending shows even worse results for larger rainfall amounts. The introduction of observation improves the performance of AROME-EPS during the different lead-times of the 30 hours forecast horizon. The blending methodology not always improve the forecast (grey circle highlight an example).

Resampling and Matching Method



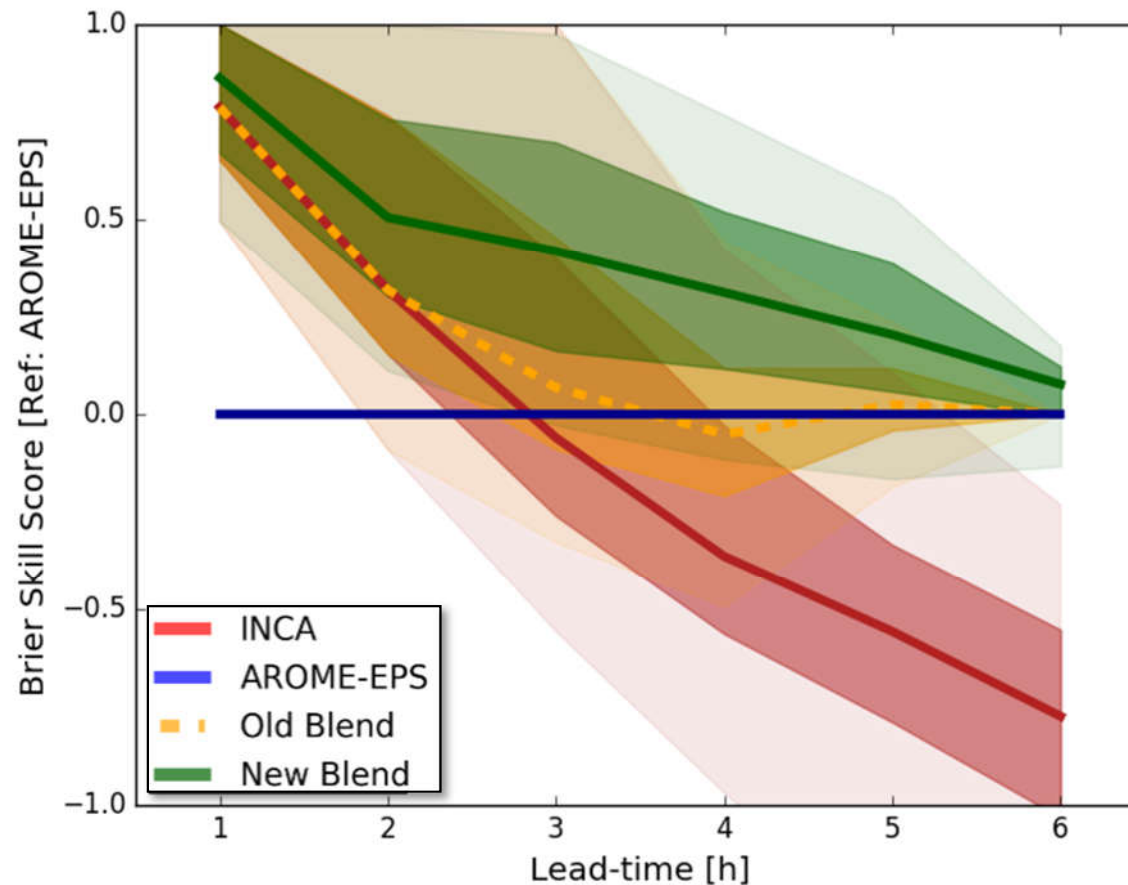
To avoid losing the heavy rainfall values and also the reduction of variance caused by the intensity-based blending methods, a matching method is applied to each of the subdomains. This method can keep the chosen empirical distribution of rainfall values.

However, a method to blend both empirical distribution has to be developed as well. Taking into account the non-Gaussian shape of the distribution, a resampling method from the sorted distribution of both sources of rainfall values (INCA and AROME-EPS member) is applied.



Verification and comparison with previous methodologies

... and then the results are pooled for the whole month of July



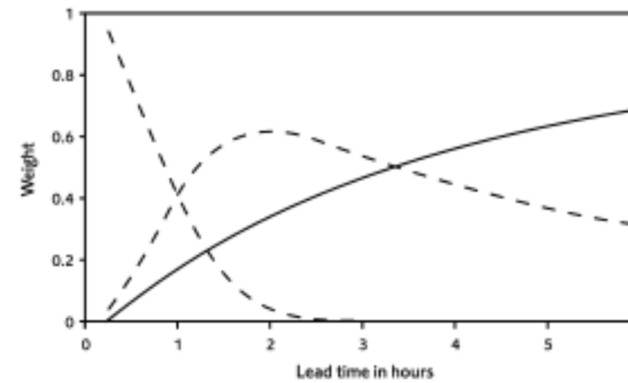
To remove the episode to episode variability, the Brier Skill Score using AROME-EPS as a reference has been computed and pooled for the whole month. The results shows the improvement of both blending methodologies and the benefits of the new one even for the first lead-times against INCA.

Blending: State of the art

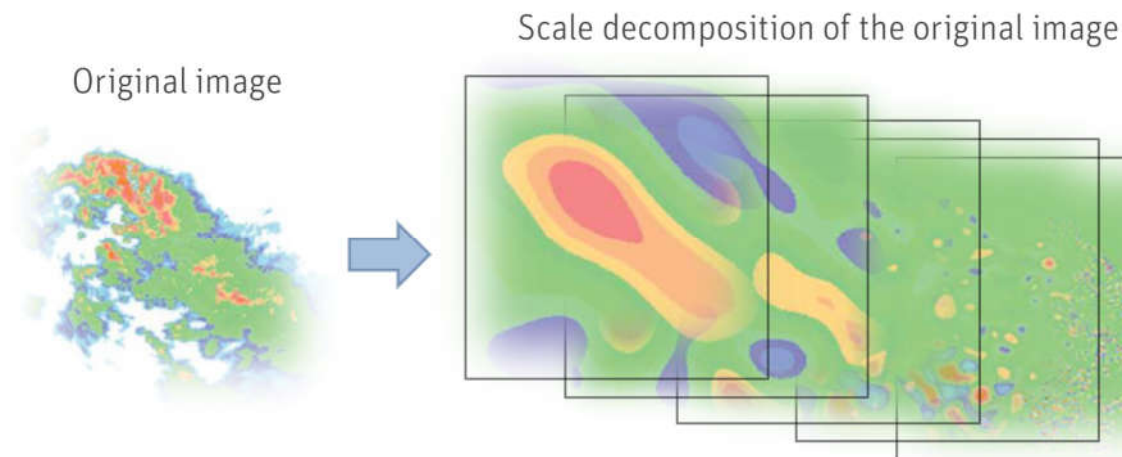
The current state of the art for creating a seamless prediction for high impact weather, storm prediction and so on for very short-term is still adding:

1. Linearly both fields (Golding, 1998),

$$W_A = \exp\left(\text{Ln}\left[\frac{C_0[(dt-1)/5]}{C_A}\right]\right)$$
$$W_M = C_0 + \frac{C_M(C_A - C_0)}{C_A}$$

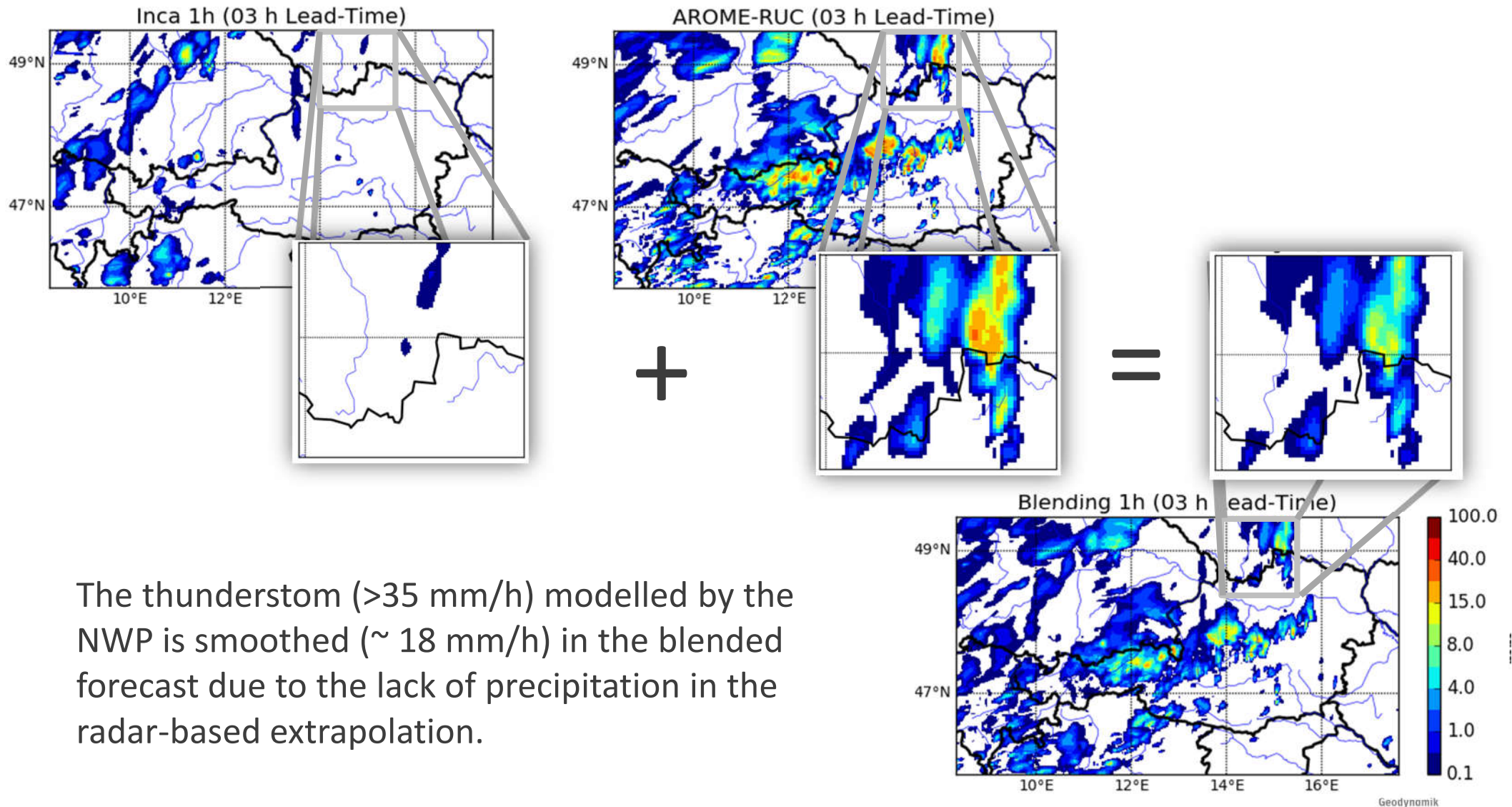


2. Probabilities of occurrence (Kober et al., 2012) depending on the synoptic forcing (Kober et al., 2014)
3. Cascades from a scale decomposition of the reflectivity fields (Bowler et al., 2006) from both sources the Lagrangian extrapolation and the NWP output (e.g. STEPS, Alan Seeds).



Challenges of the current methodologies

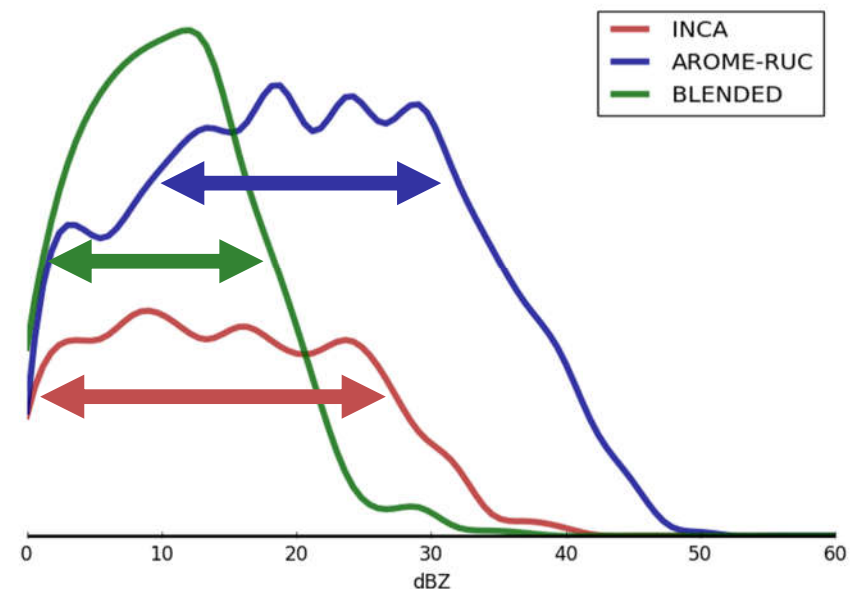
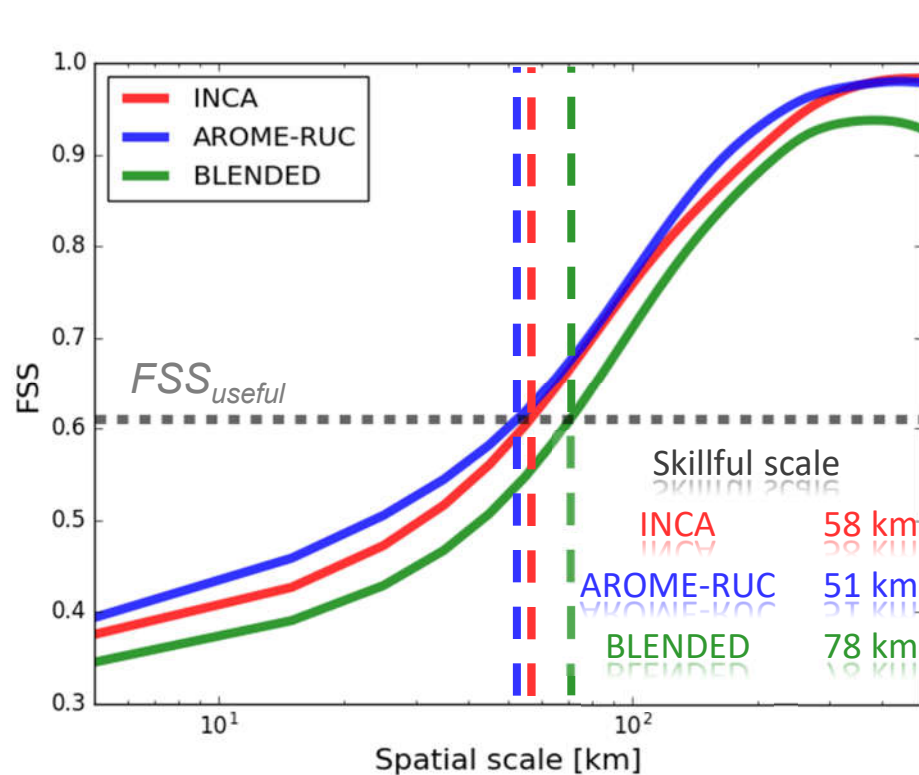
Methodologies **1** and **3** are **Blending in the intensity space**. They involve the following challenges which need to be tackled:



The thunderstorm (>35 mm/h) modelled by the NWP is smoothed (~18 mm/h) in the blended forecast due to the lack of precipitation in the radar-based extrapolation.

Challenges of the current methodologies

So, the **intensity-based blending (1 and 3)** reduces the heavy rainfall, the variance of the field and the spatial resolution:

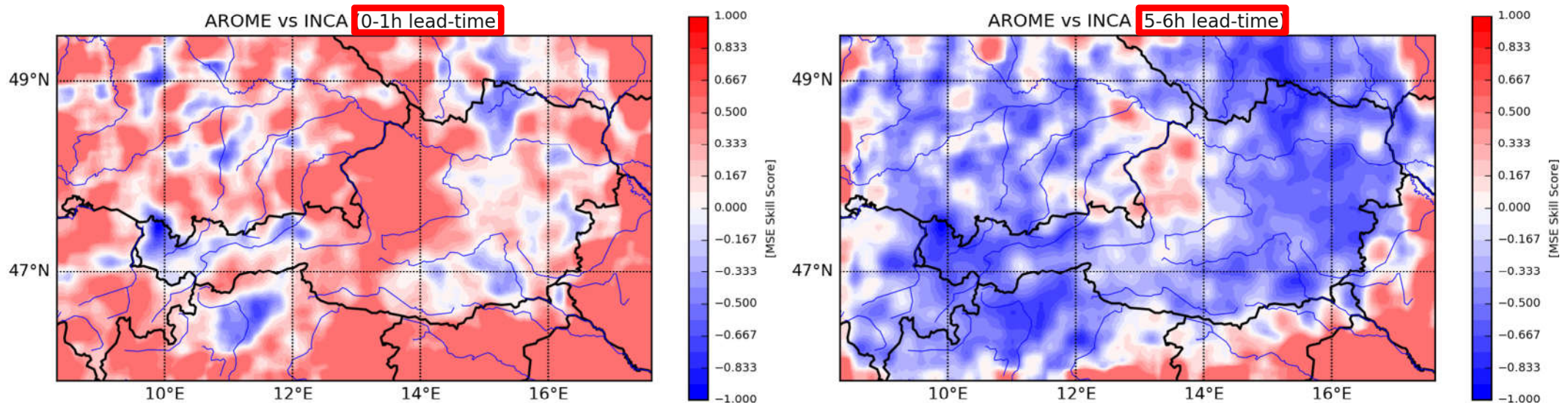


The Fractions Skill Score (FSS) measures at which spatial scales the forecast resembles the observations. The skillful scale represents the small window size for which the forecast is useful, giving information about the resolution of the forecast.

The empirical probability distribution of rainfall values of both INCA (radar extrapolation) and AROME-RUC (NWP) is compared to the epdf of the blended forecast showing the lessening of the intense rainfall and also the reduction of variance.

Challenges of the current methodologies

Besides, recent studies about the performance of NWP flood forecasts (Cloke et al. 2017) and Nowcasts (Berenguer et al, 2016) have shown that both forecast qualities vary locally. The MSE skill score* of AROME-RUC (NWP with data assimilation) versus the INCA (extrapolation radar-based nowcasting) for different lead-times is computed to demonstrate that local dependence of the forecasting systems.



$$(*) \quad MSE - SS' = \begin{cases} 1 - \frac{MSE_{INCA}}{MSE_{AROME}} & : MSE_{INCA} < MSE_{AROME} \\ \frac{MSE_{AROME}}{MSE_{INCA}} - 1 & : MSE_{INCA} \geq MSE_{AROME} \end{cases}$$

Creation of an ensemble of analysis

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uncertainties in radar precipitation estimation
→ ensemble precipitation estimation

REAL algorithm (Germann et al., 2009):

$$\underbrace{\Phi_{t,i}}_{\text{probabilistic}} = \underbrace{\mathbf{R}_t}_{\text{deterministic}} + \underbrace{\delta_{t,i}}_{\text{stochastic}}$$

1. Estimation of error covariance matrix (radar-gauge-agreement) \mathbf{C}

2. Generation of perturbations by Cholesky/SV decomposition

$$\mathbf{C} = \mathbf{L}\mathbf{L}^T$$
$$\delta_{t,i} = \mu + \mathbf{L}\mathbf{y}_{t,i}$$
