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Precipitation nowcasting: from Lagrangian models to advanced ML approaches

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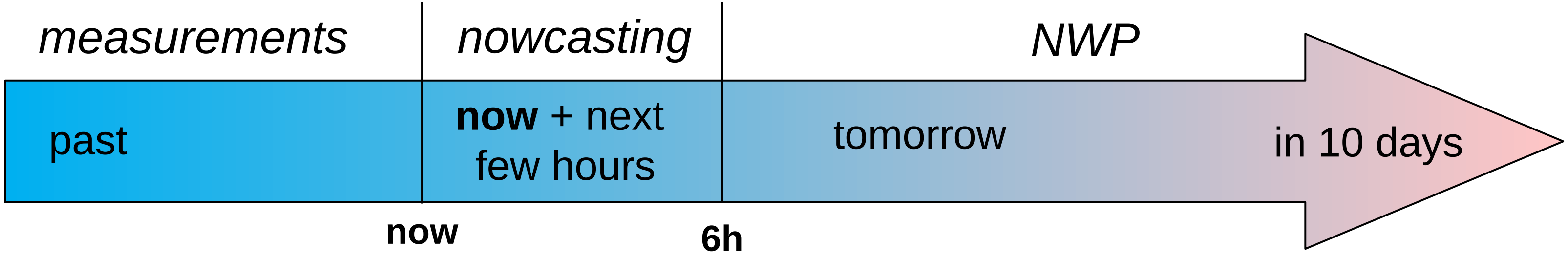
What is nowcasting ?

Definition by Paul Joe, following K Browning (1981) and Conway (1998):
Nowcasting is forecasting with **local** detail, by any method, over a period **from the present to a few hours ahead**; this includes a detailed description of the **present weather**.



Step 1: Optical flow methods

- **Spectral** method (DARTS)
- **Local** Lucas Kanade (LK)
- **Global** variational echo tracking approach (VET)
- **Anisotropic diffusion** method (Proesmans)

pysteps.motion.lucaskanade.dense_lucaskanade

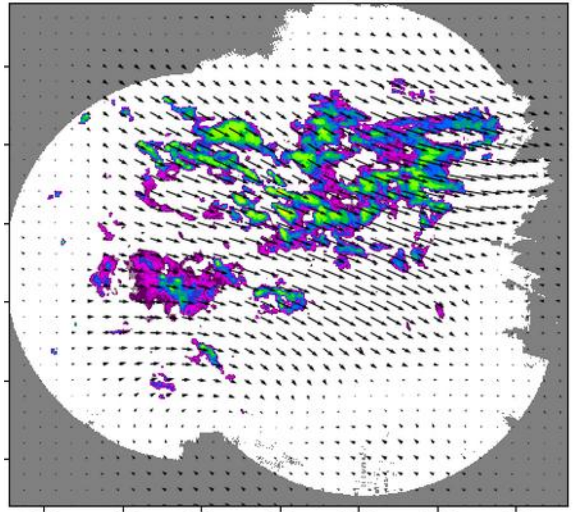
`pysteps.motion.lucaskanade.dense_lucaskanade`*(input_images, lk_kwargs=None, fd_method='ShiTomasi', fd_kwargs=None, interp_method='rbfinterp2d', interp_kwargs=None, dense=True, nr_std_outlier=3, k_outlier=30, size_opening=3, decl_scale=10, verbose=False)*

Run the Lucas-Kanade optical flow routine and interpolate the motion vectors.

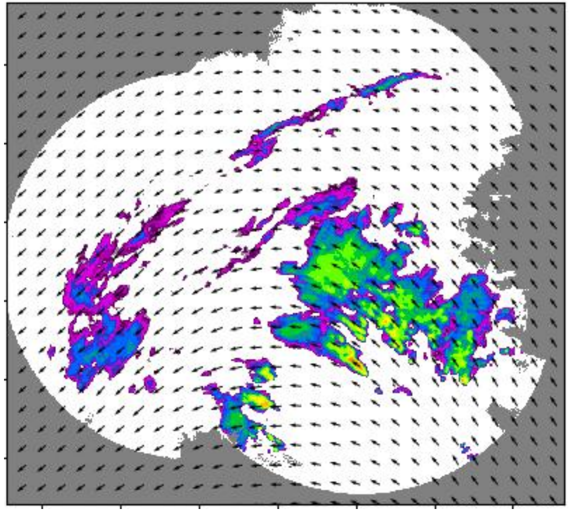
Interface to the OpenCV implementation of the local Lucas-Kanade optical flow method applied in combination to a feature detection routine.

The sparse motion vectors are finally interpolated to return the whole motion field.

Spectral method DARTS



Local Lucas-Kanade

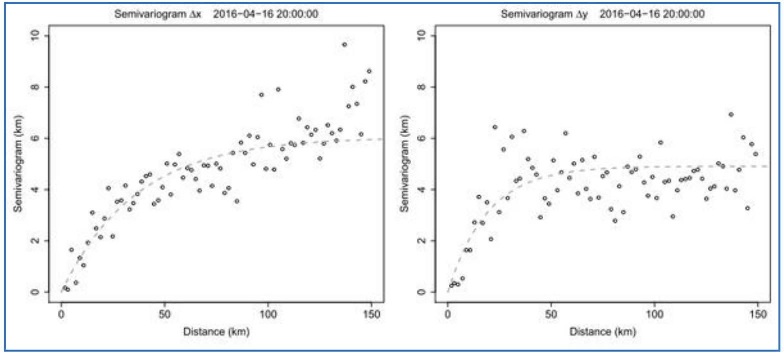


Pulkkinen, Seppo, et al. "Pysteps: An open-source Python library for probabilistic precipitation nowcasting (v1. 0)." *Geoscientific Model Development* 12.10 (2019): 4185-4219.

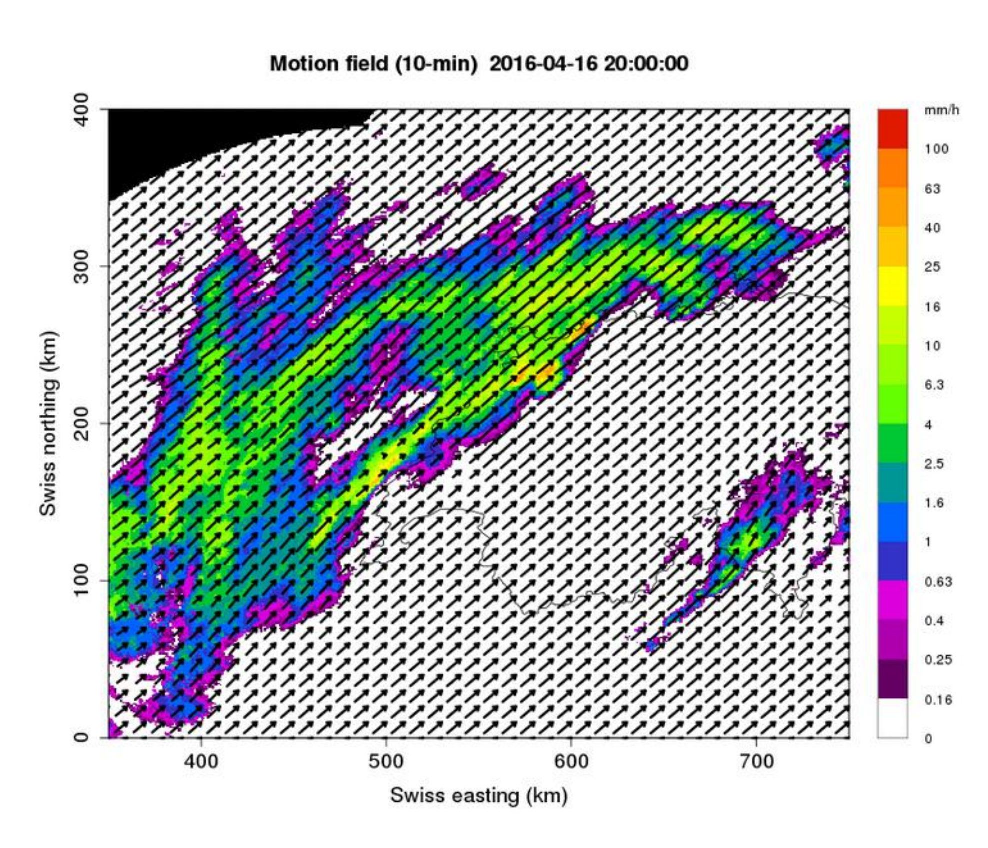
```
from pysteps import motion, nowcasts

oflow_method = motion.get_method("lucaskanade")
V = oflow_method(R)
```

Step 1: Optical flow methods (nowtrack)

- The motion field of NowPrecip is based on **block optical flow and kriging.**
- The name of this method is **NowTrack**
- Chooses randomly a small number of points and determines their velocity
- Then interpolates this information to each pixel of the raster using kriging.
- The current motion field is dynamic radar-NWP-based

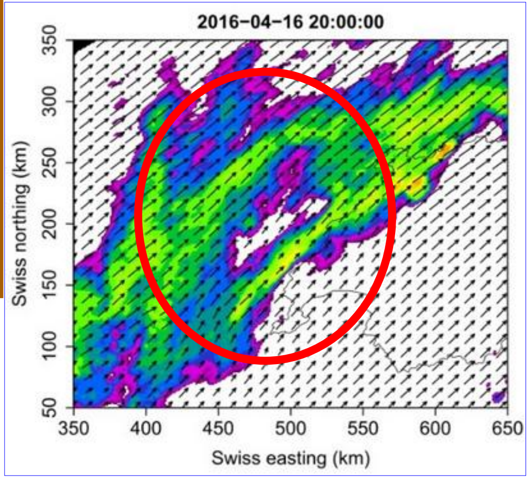


Two variograms Δx and Δy are fit automatically to determine the correlation between the velocities of the few random points. Then estimation at each pixel follows.

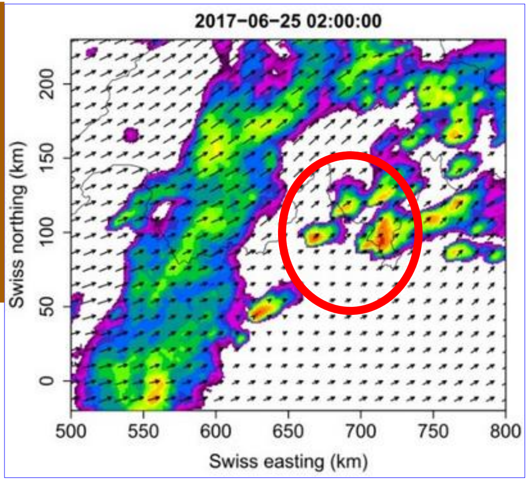


Optical flow methods (nowtrack)

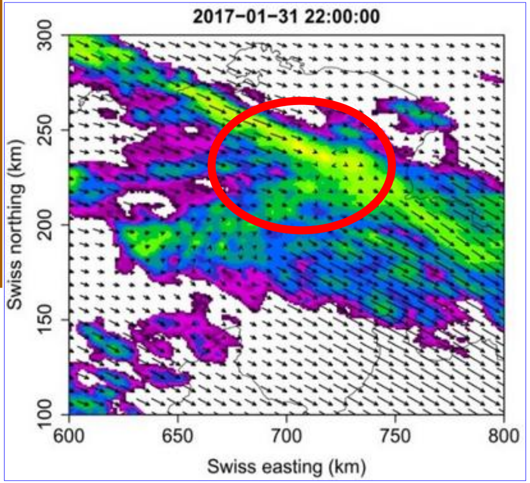
Stratiform



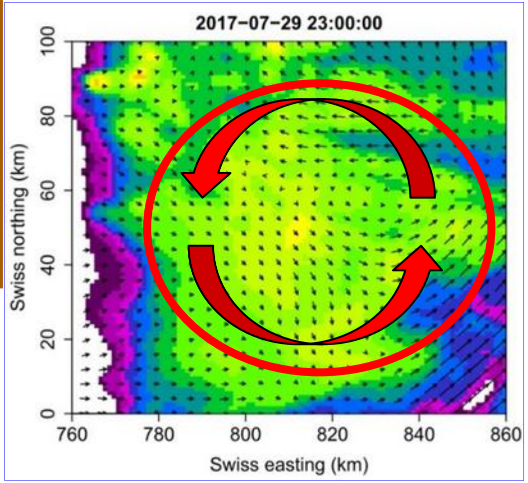
Convection



Orographic



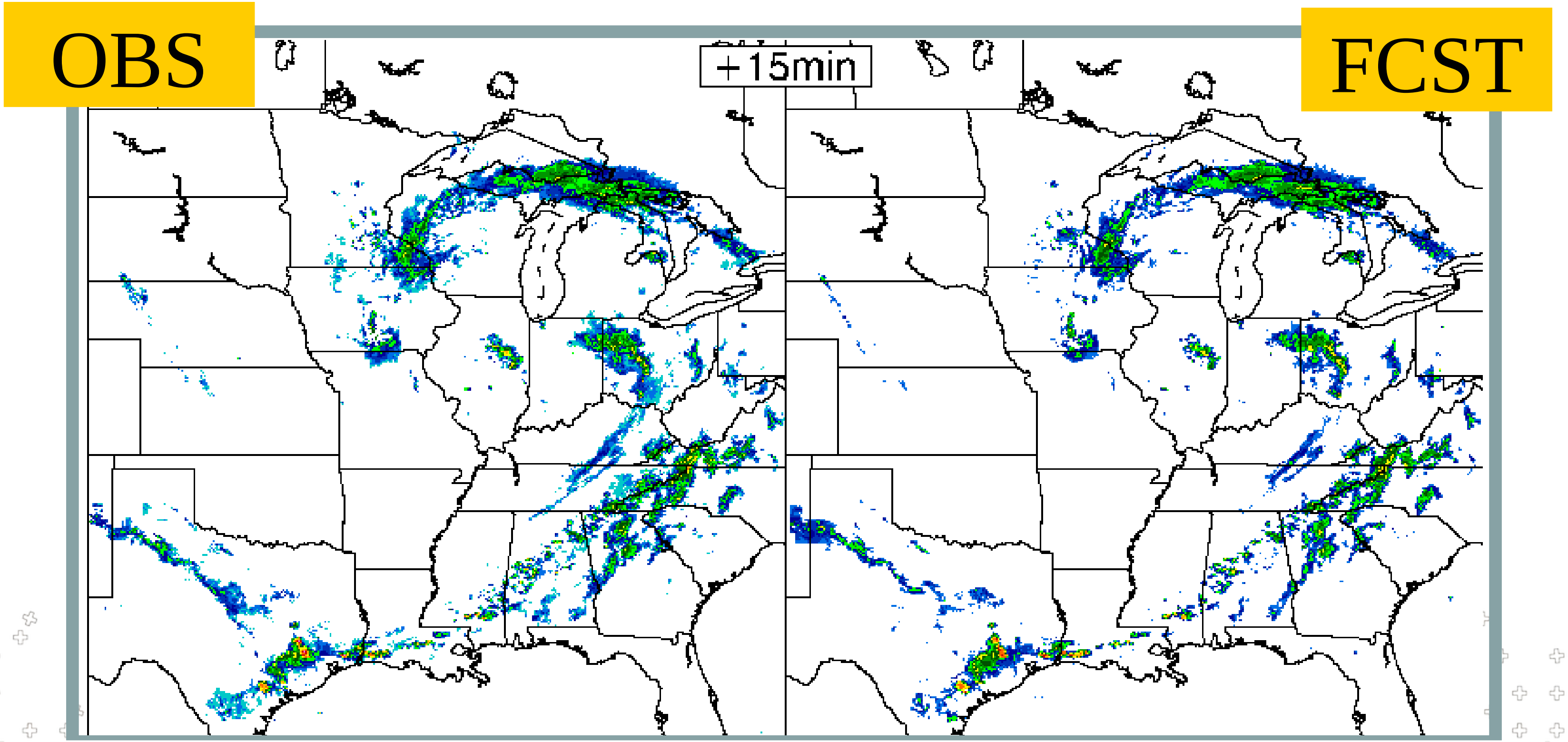
Rotation



- Nowtrack is very flexible in functioniong in all sorts of motion
- It seems to excel even on very challenging motions like localized rotations which take place within a few tens of kilometers.

Step 1: Lagrangian models

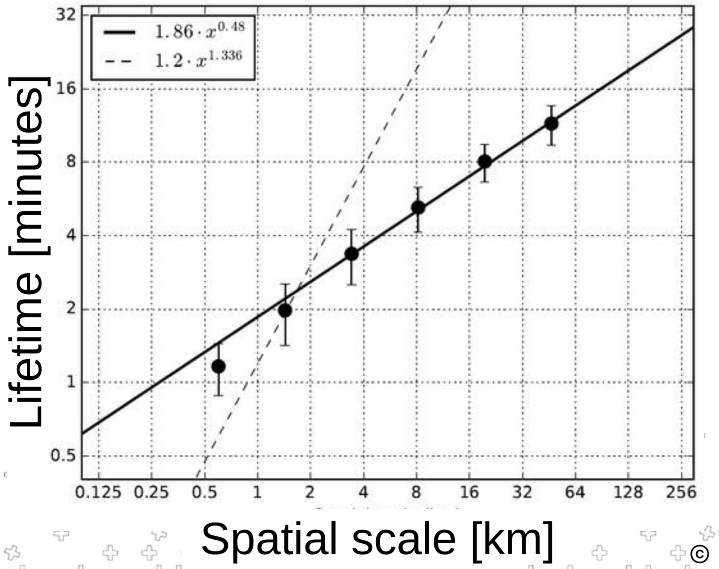
Method: Move the patterns according to latest motion.

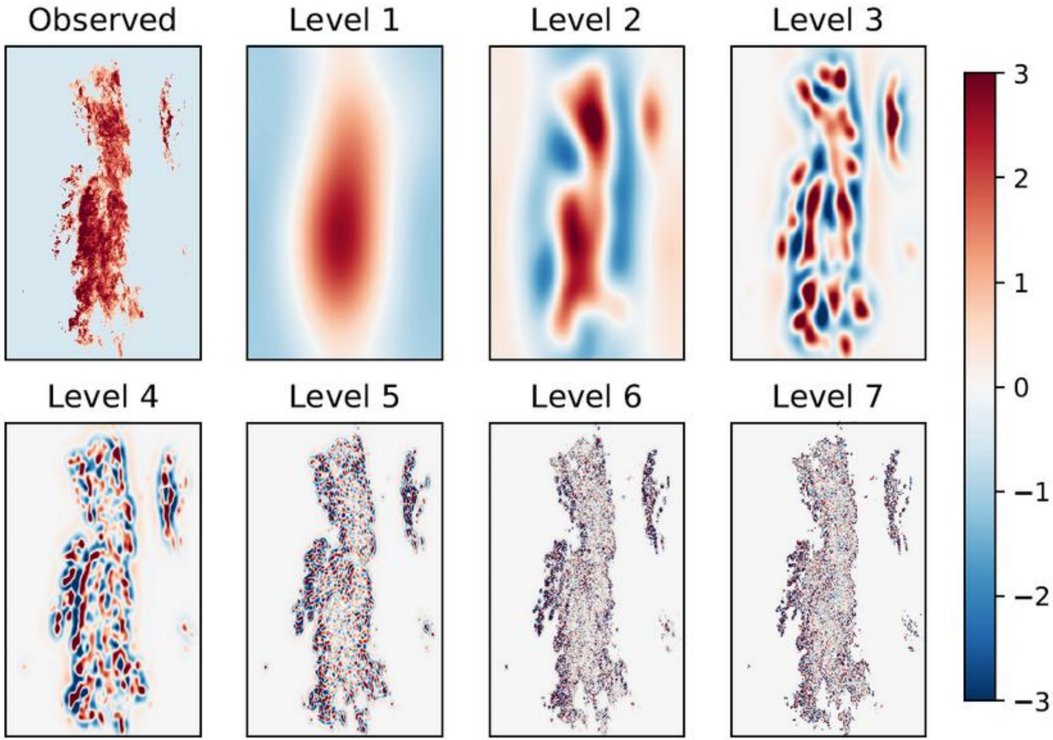


25 May 2001, 08:00 UTC, 0 - 6h nowcast

Step 2: Cascade decomposition

Predictability of precipitation
depends on spatial scale!
log(lifetime) ~ k*log(scale)





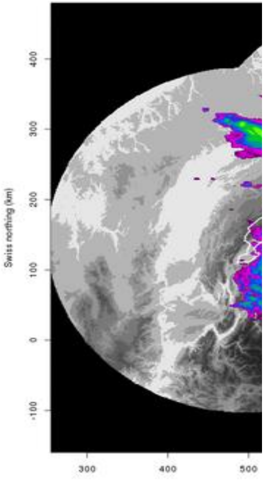

```
decomp = decomposition_fft(R, filter)
```

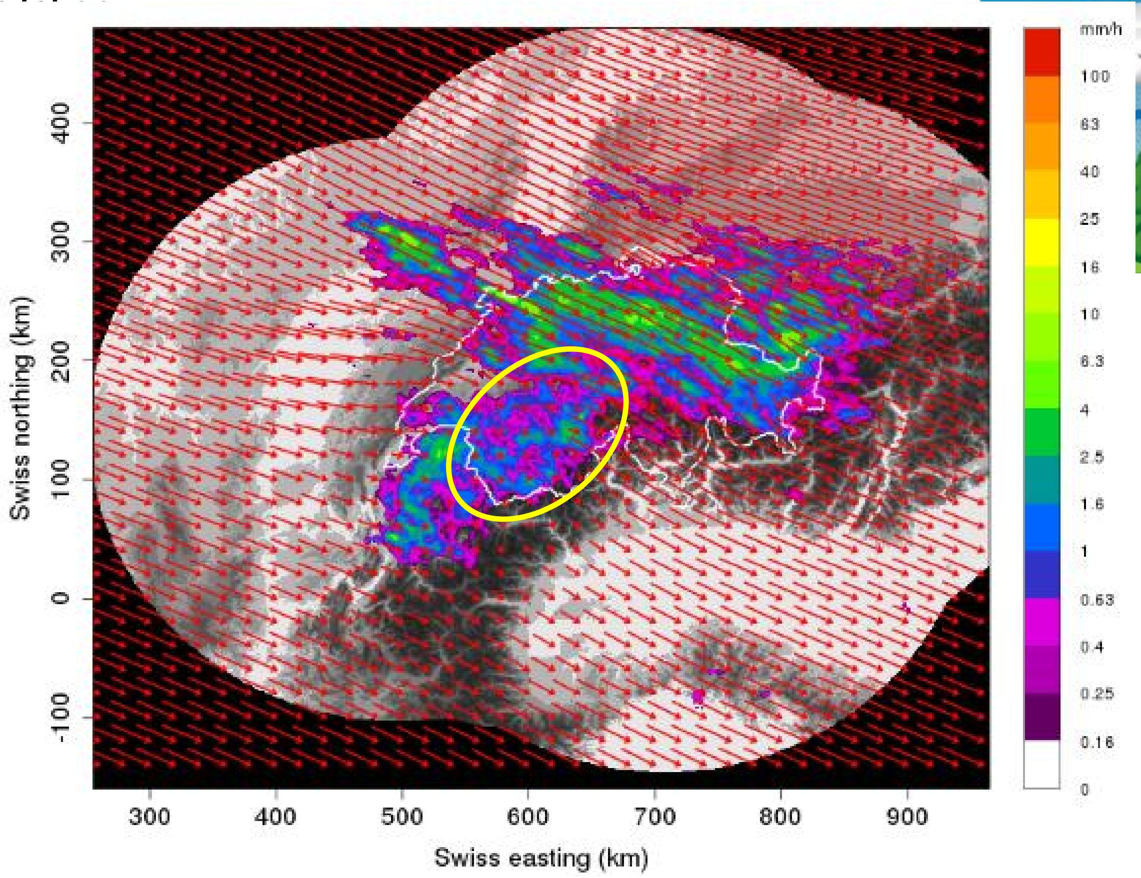
Step 3: Growth and decay

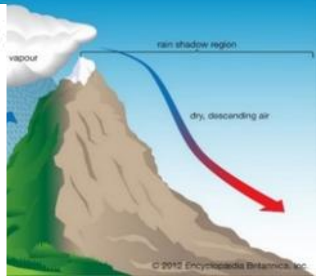
1 **Orographic preci**

- Moist air is li **cools**, orogra **upwind** of th
- On the **lee si** shadow).

Radar 2







2 Optical flow slow-down accompanied by decay on the entire rainfall front.

Total change

$$\frac{dR}{dt} = \frac{\partial R}{\partial t} + \nabla \cdot \mathbf{V}R.$$

Growth/ decay

Advection

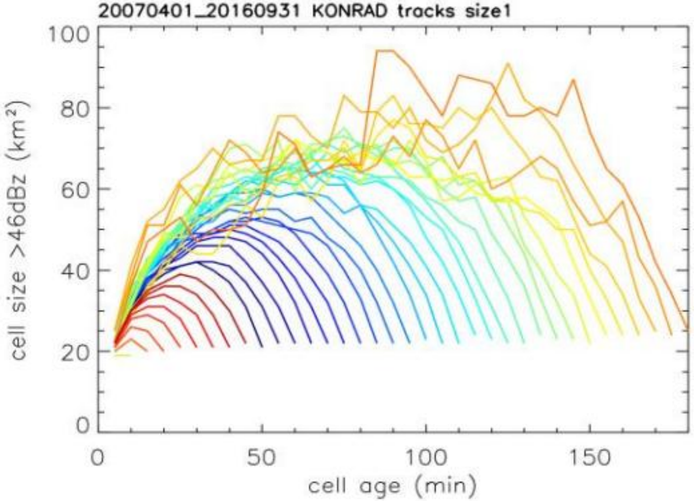
Prototype object-based SINFONY Nowcasting ensemble:

Deutscher Wetterdienst
Wetter und Klima aus einer Hand

Ansatz to generate object ensemble:

➔ **For now:** For newly detected cells, „first-guess“ parabola ensemble with wide-spread shape- and width parameters as initial forecast. Successive correction by **Ensemble Kalman Filter**

➔ **Later:** replace first-guess“ parabolas by refined / more advanced mathematical models, potentially depending also on evironmental conditions from NWP (project @ KIT)



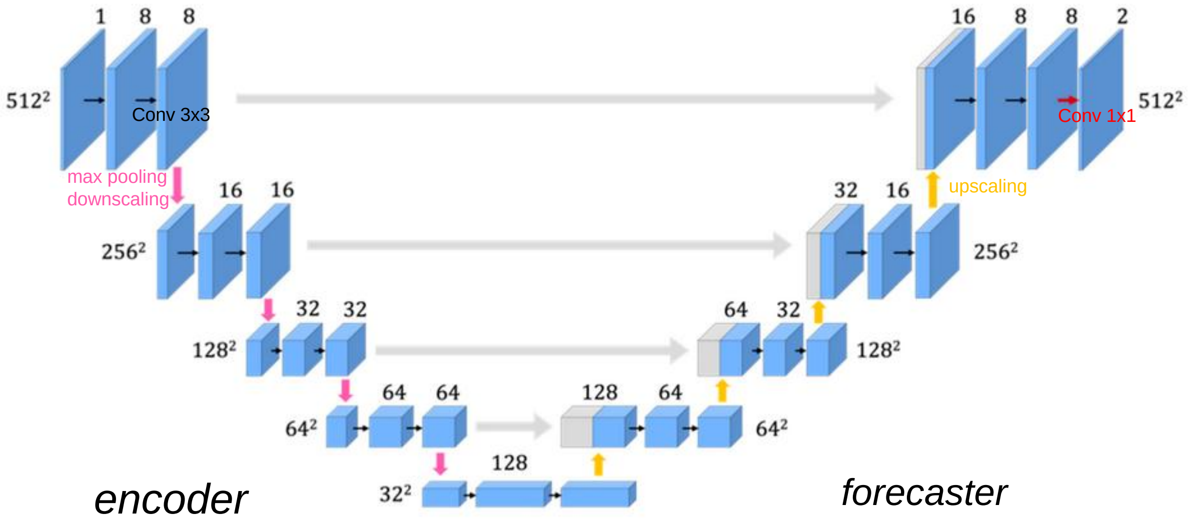
Climatology (Wapler et al. 2017): Median cell size as function of cell age for different life-time classes (colors), Germany, 2007 – 2016.
However: huge deviations for individual cases!

From: Ulrich Blahak, SINFONY - the Combination of Nowcasting and NWP on the Convective Scale at DWD

Step 1+2+3: Nowcast with CNNs

- Input are 2D images (satellite image, radar image, topography…)
- Deep learning applies filters on several spatial scales
- Adapted for nowcasting by Leinonen et al. 2022 for the weather4cast competition
- Extended with recurrent layers to exploit temporal trends and to predict several lead time steps

Illustration of a U-net architecture



Hirose, Ikumi, et al. "U-Net-Based Segmentation of Microscopic Images of Colorants and Simplification of Labeling in the Learning Process." *Journal of Imaging* 8.7 (2022): 177.

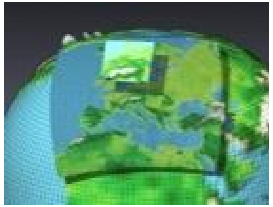
Step 1+2+3: Multi-data fusion with RCNNs

COALITION-4
Hazard specific thunderstorm nowcast based on deep learning
Existing products: Heavy precipitation, hail, hail size, and lightning

1. Extensive database

Radar

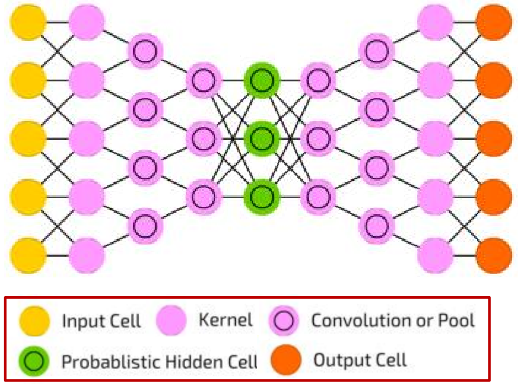
COSMO/ICON-1E



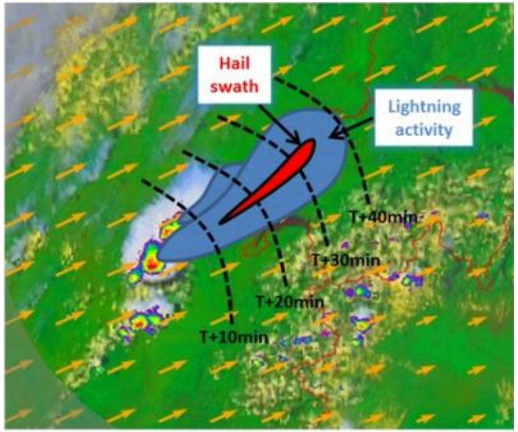
Satellite

Lightning

2. Deep Learning Neural Network



3. Thunderstorm Nowcast



Rain **Hail** **Lightning** **Wind**



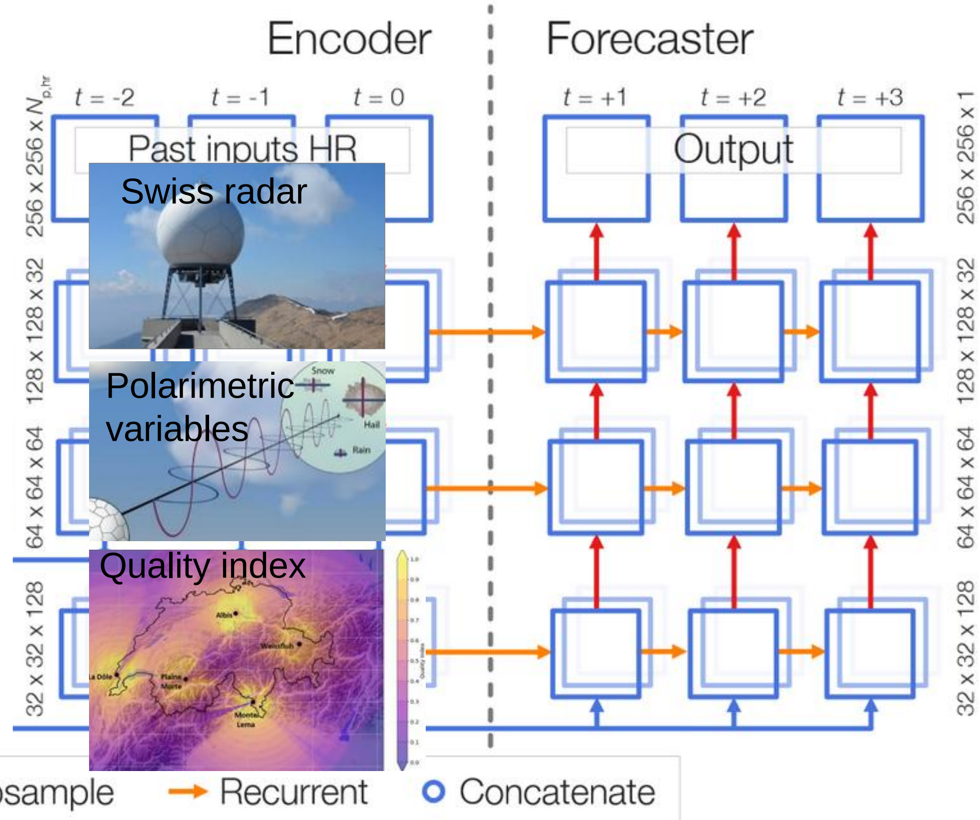

Step 1+2+3: Exploit polarimetric radar obs.

Dataset: Convective season of 2020

Swiss radar data (R)[1,2,3]**:**
Rain-rate and vertical structure of radar reflectivity such as echo top height

Polarimetric variables (P):
co-polar cross correlation (ρ_{hv}), differential reflectivity (Z_{DR}), vertical reflectivity (Z_v) and specific differential phase (K_{dp})→ aggregated to the ground[4].

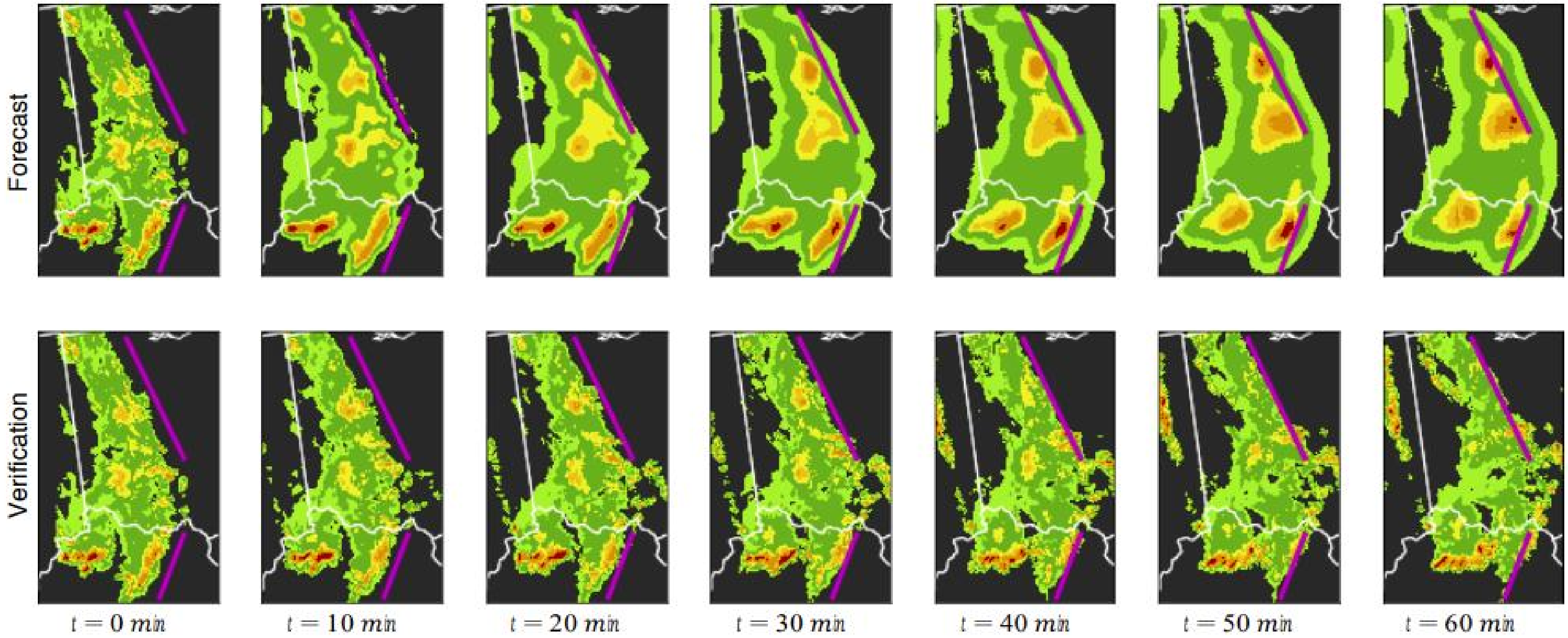
Quality index (Q)[5]



Rombeek, Nathalie, Jussi Leinonen, and Ulrich Hamann. "Exploiting radar polarimetry for nowcasting thunderstorm hazards using deep learning." *Natural Hazards and Earth System Sciences* 24.1 (2024): 133-144.

2. Leinonen et al. (2022) 3. Leinonen et al. (2022)
4. Wolfensberger et al. (2021) 5. Feldmann et al. (2021)

Step 1+2+3: Nowcast with CNNs



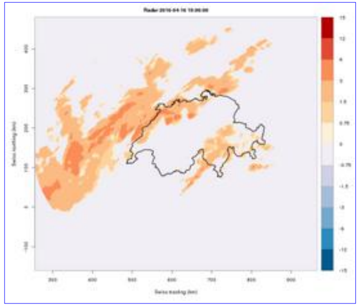
Samsi, Siddharth, Christopher J. Mattioli, and Mark S. Veillette. "Distributed deep learning for precipitation nowcasting." *2019 IEEE High Performance Extreme Computing Conference (HPEC)*. IEEE, 2019.

Step 4: Uncertainty and autocorrelation

- Autoregressive model plus spatially correlated noise
- Spatially correlated noise depends on the observations
- This takes place in **1km**^{2} scale

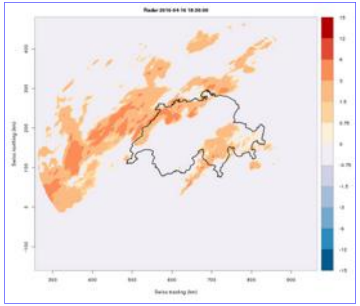
$$\varphi_1 \boldsymbol{R}_{i-1} \quad + \quad \varphi_2 \boldsymbol{R}_{i-2} \quad + \quad A s_i \quad = \quad \boldsymbol{R}_i$$

Observation$_1$



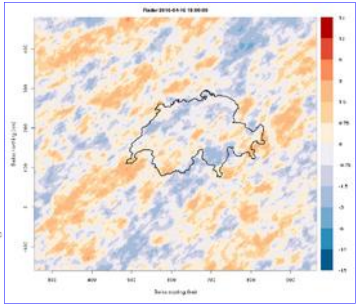
+

Observation$_2$



+

Colored Noise



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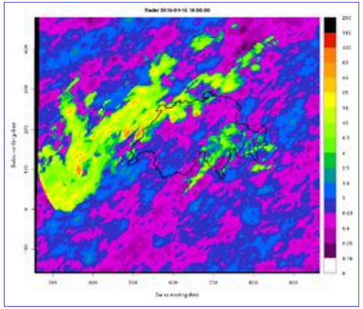
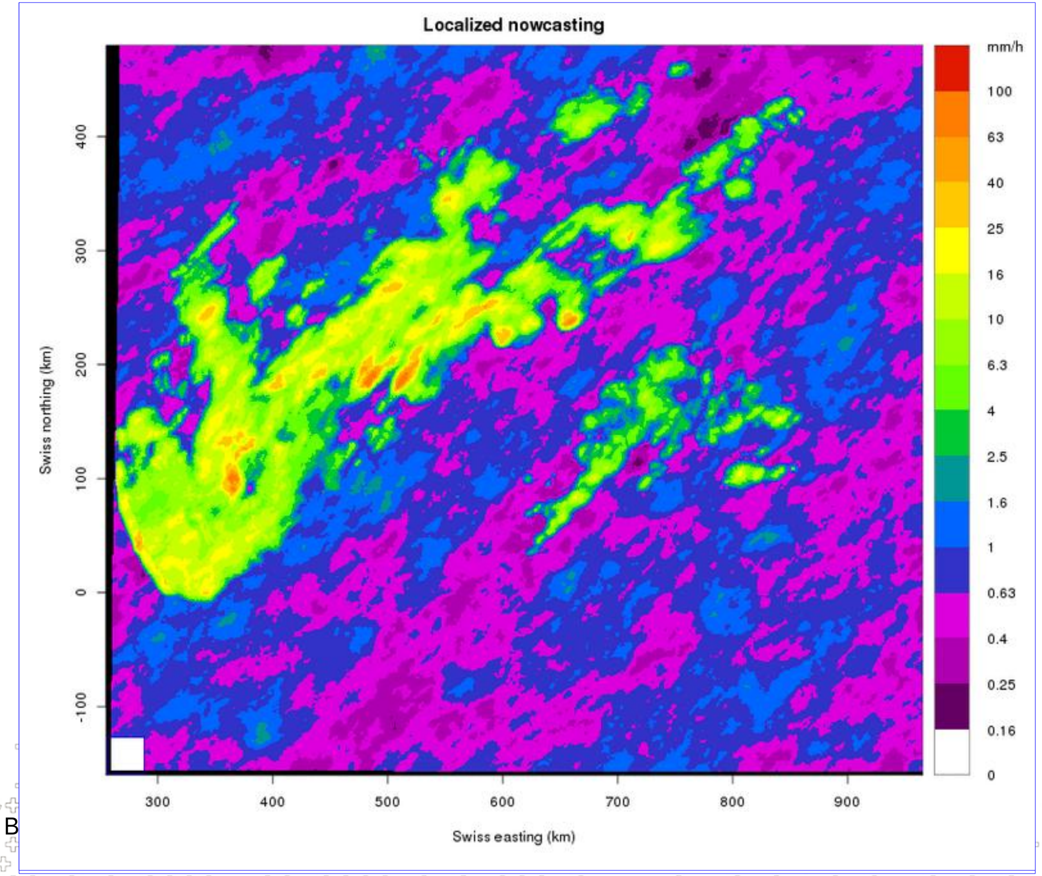
Next Frame



*This **1km²** operations takes place in a **transformed** space.*

Step 4: Uncertainty and autocorrelation

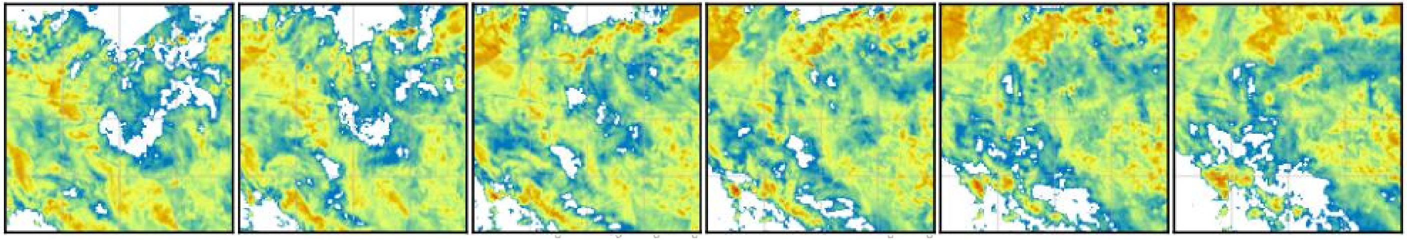
- **Localized adjustment on 64x64 km² boxes**:
- Shift and scale mechanism: two parameters control the appearance of each box:
    1. Mean value (IMF)
    2. Fraction of wet pixels (WAR)



Step 4: Generative model

LDCast Nowcasting Model, Jussi Leinonen

- Condition diffusion model on past frames
- Train to generate future frames
- Network based on Adaptive Fourier Neural Operator for conditioning
- Adapted Stable Diffusion U-Net for denoising
- Variational autoencoder (VAE) to reduce dimensions
  → Diffusion process in latent space reduces computational cost
  → *Latent* diffusion model (LDM)



Step 4: What are diffusion models?

1. **Forward process (in theory):** Image degraded gradually by noise until indistinguishable from random noise

2. Train a neural network as an inverse model to **denoise** the image step by step

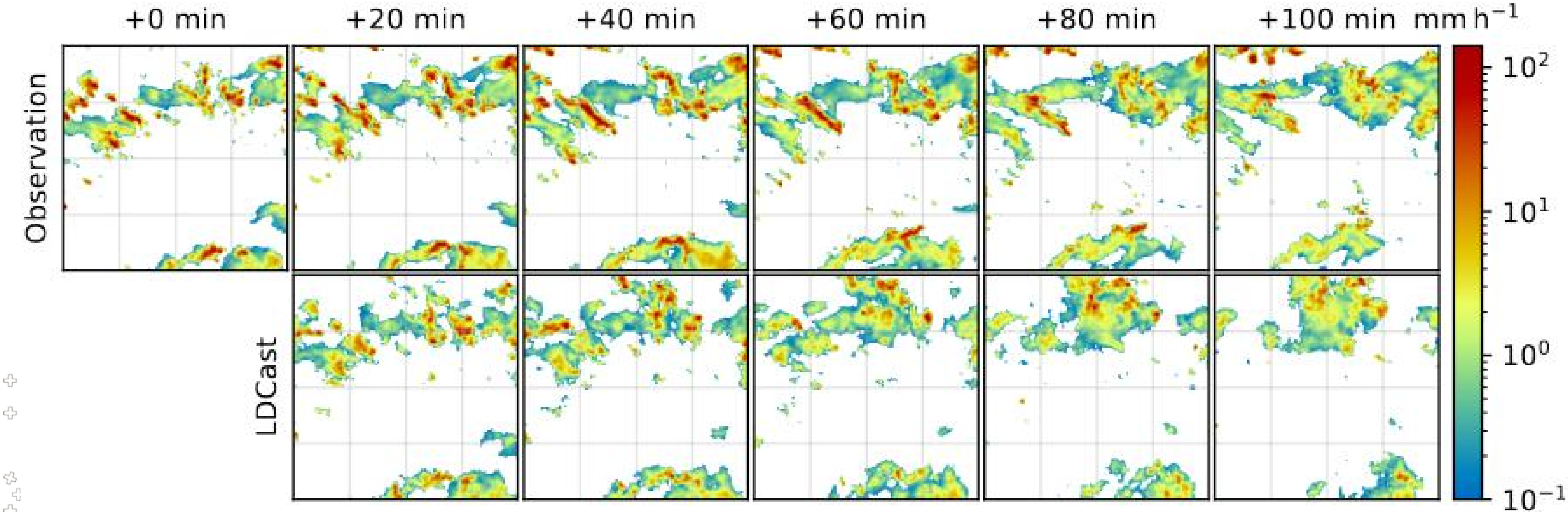
3. Apply this network to a completely noisy image step by step
   → Will converge to a random sample from the training distribution

Latent diffusion models use an autoencoder to transform data to a latent space before running diffusion

→ More stable models with lower computational requirements

Step 4: Nowcast example

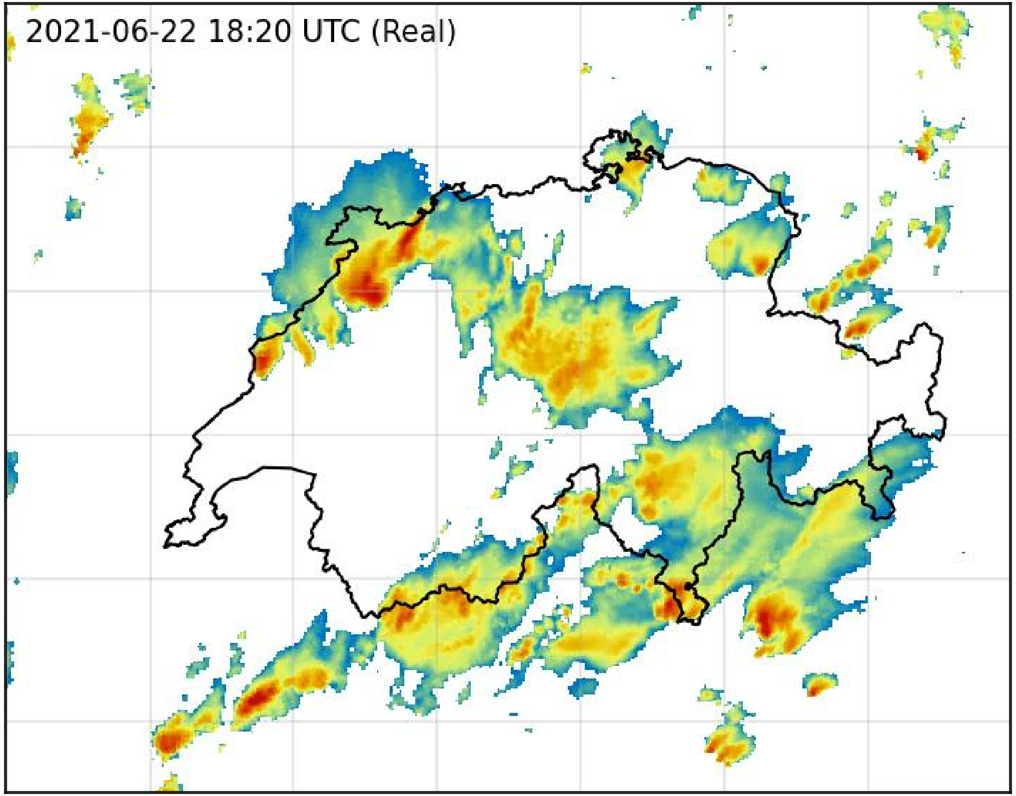
Realistic results that diverge gradually from the observed precipitation



Step 4: Predictions for Switzerland

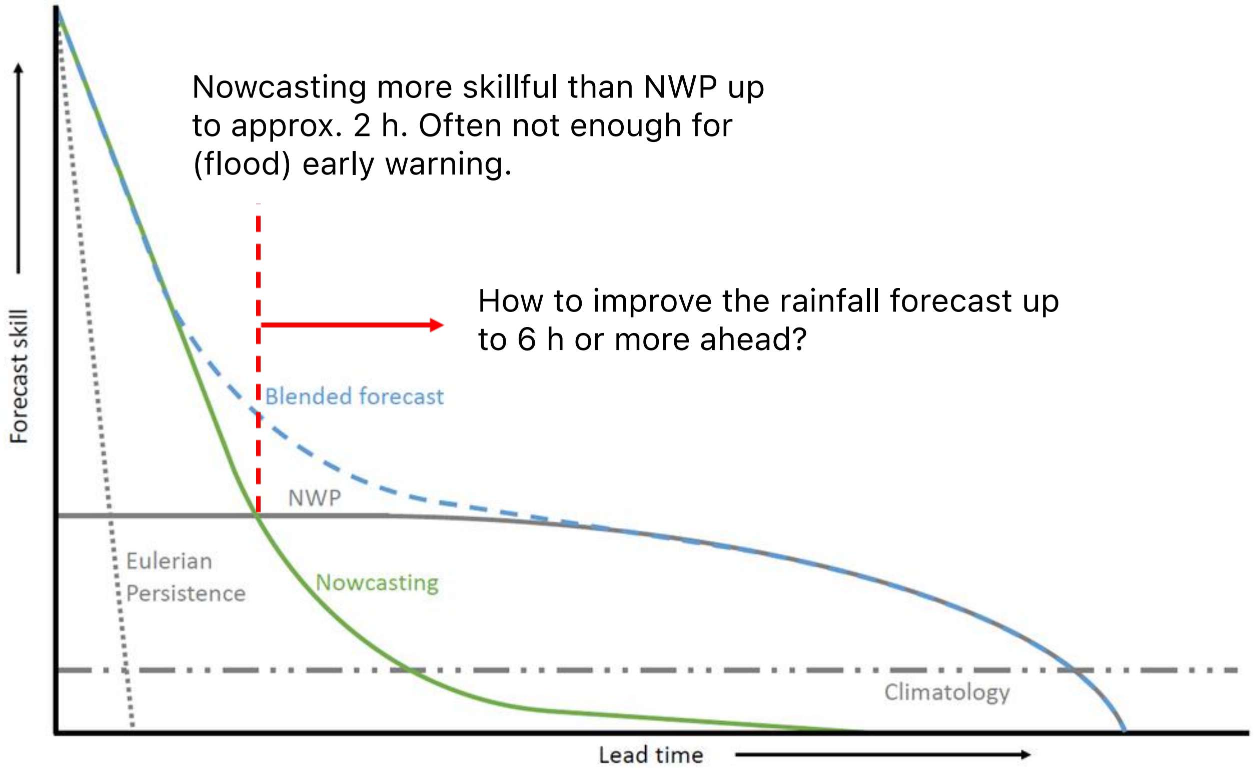
Works as a fully convolutional network:

- Possible to train on one size and apply to another

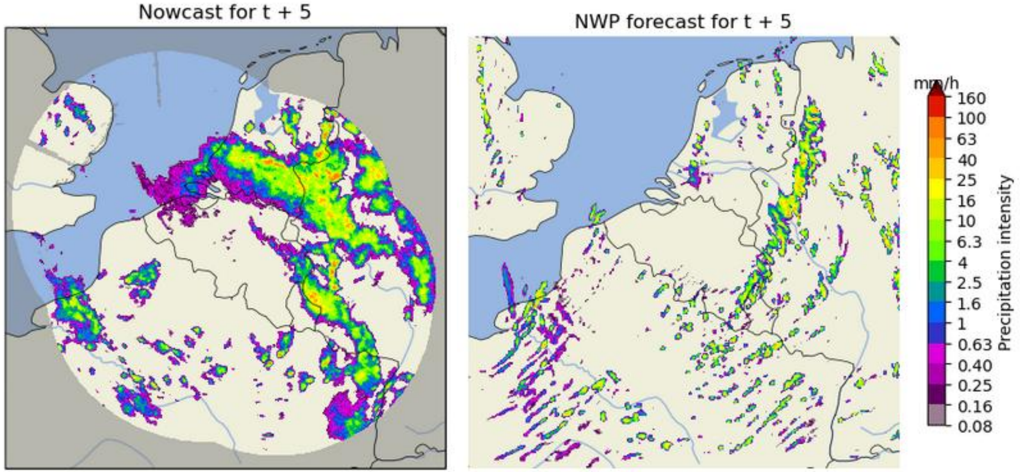


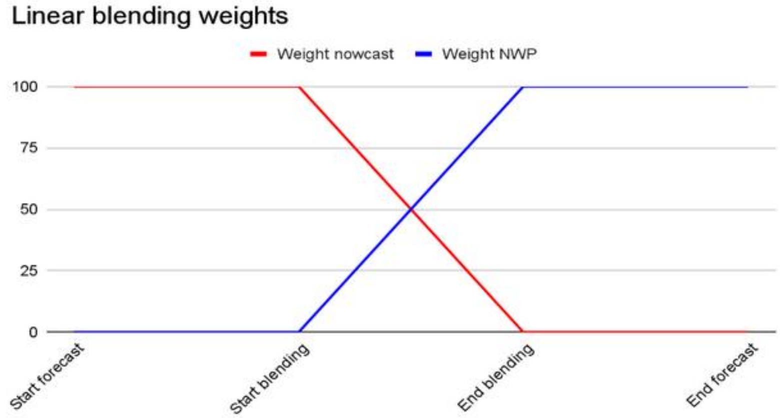
Step 5: Blending with NWP

Can we extend the skillful forecast horizon of nowcasting?



Step 5a: Simple linear blending, but





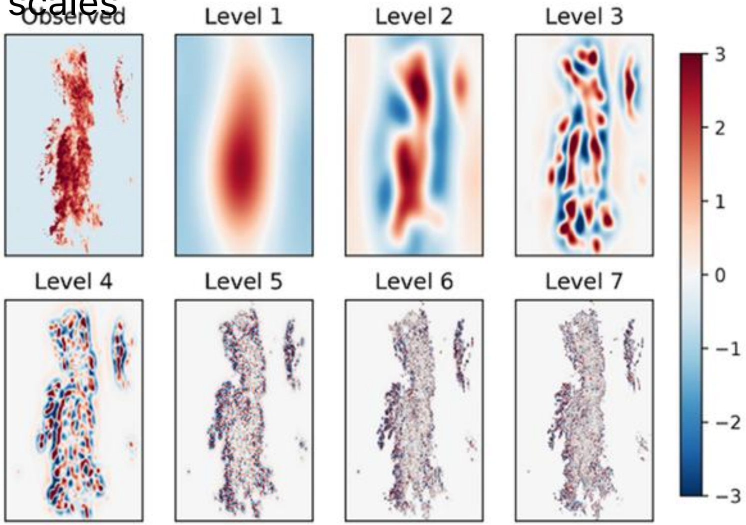
How to merge a case like this?

Implementation of STEPS blending scheme (Bowler et al., 2006; Seed et al., 2013) in pysteps:

- Scale-dependent blending
- Blending weights depend on skill of forecast components
- Ensemble forecasts with stochastic perturbations

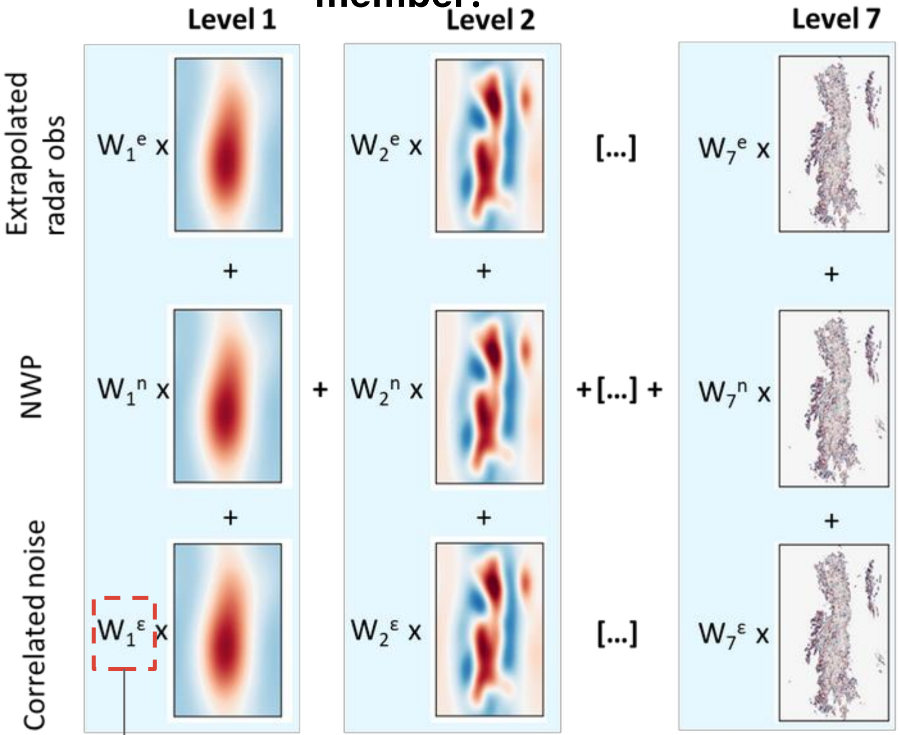
A scale-dependent blending method

Fast-Fourier transform to different spatial scales



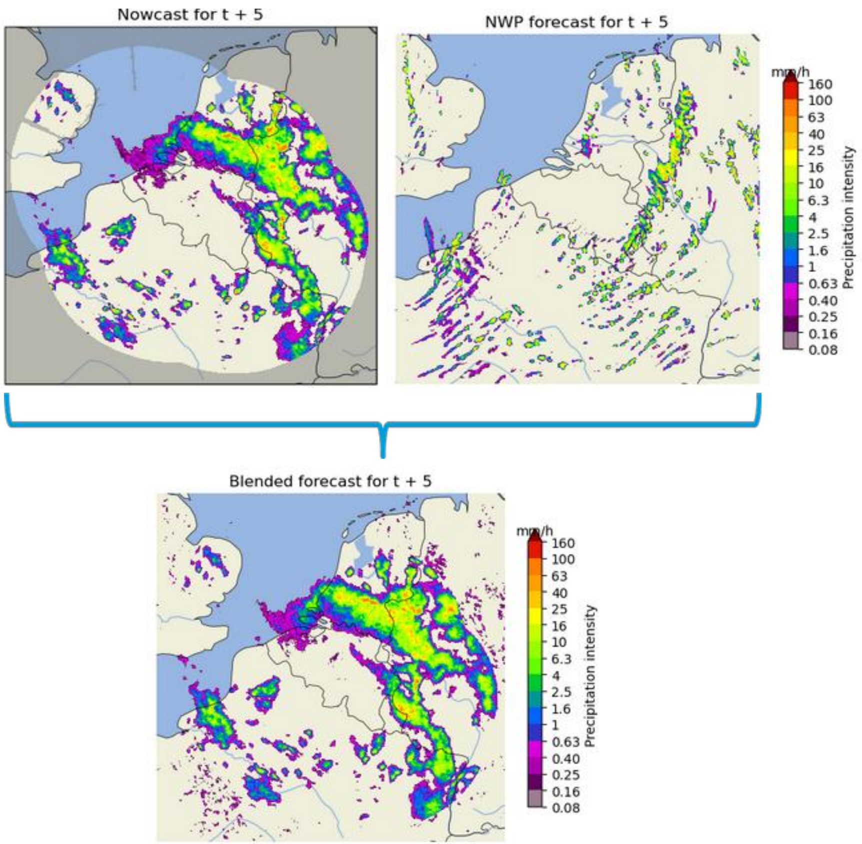
Pulkkinen et al., 2019

Per ensemble member:



Blending weights depend on initial and expected future skill

A scale-dependent blending method



Functionalities added to original concept:

- Skill NWP component regresses to skill of the past days
- Multiple weights determination methods
- Option to blend multiple NWP ensemble members / models
- To constrain rain (dis)appearance in the ensemble to regions around rainy areas:
  - Lagrangian blended probability matching scheme
  - Incremental masking strategy

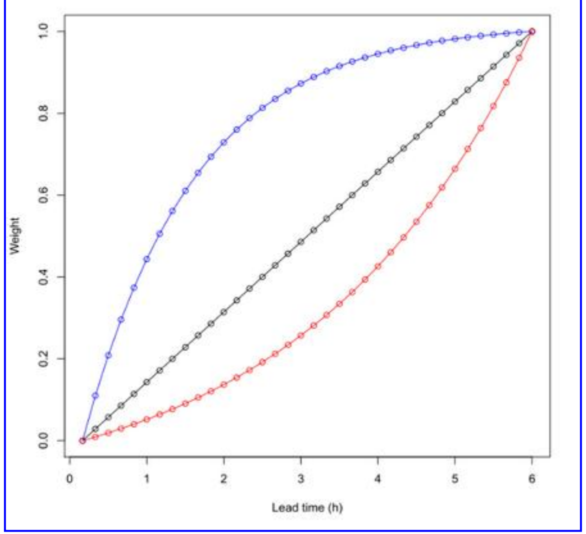
Step 5b: Weighted Blending with NWP

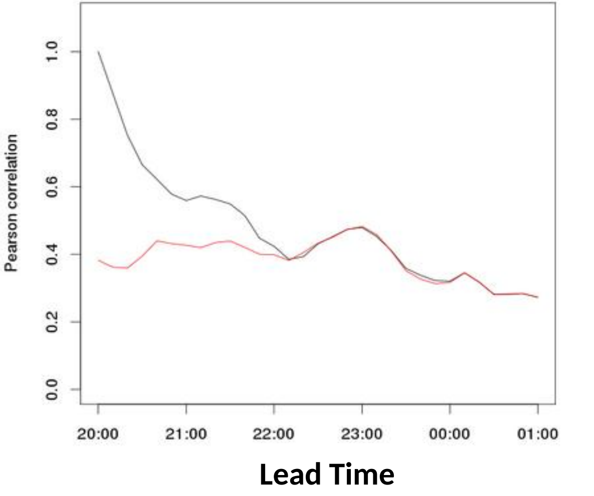
1 Merging of the nowcast with the NWP takes place employing a formula which is based on weights of the two components.

2 How fast the merging will take place depends on the correlation of the NWP with recent observations.

When NWP correlates well with the recent observations the merging takes place faster.

$$R = (1 - w_i)F + w_i M$$

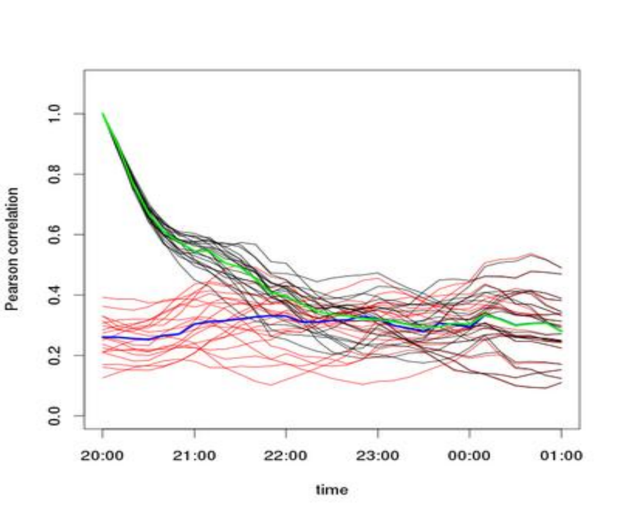




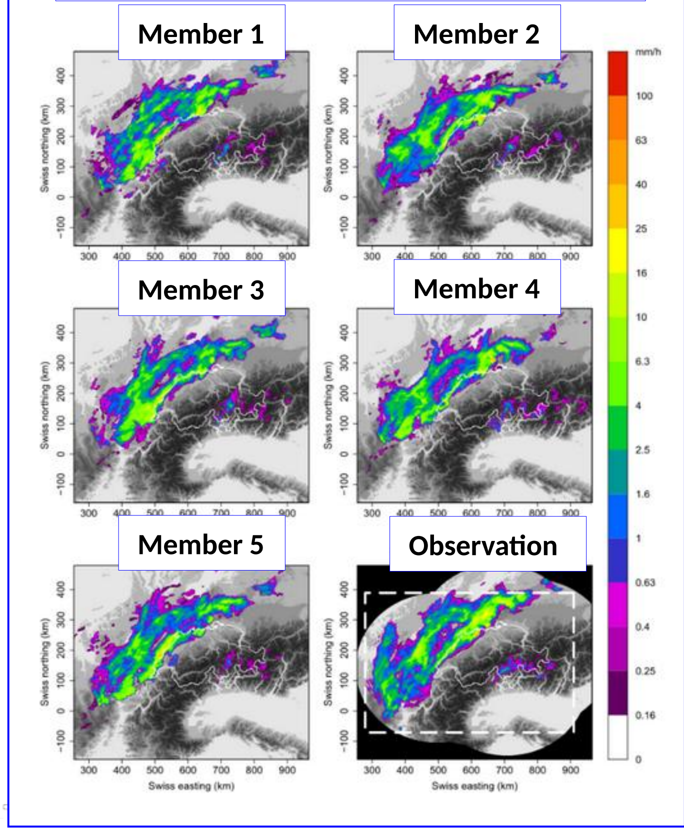
Step 5: Probabilistic Blending with NWP

- Designed to use stochastic noise: it can produce an ensemble of possible scenarios
- Each nowcasting scenario can merge seamlessly with one of the members of the NWP output
- Real time ensemble production will take place in the future

Black curves: correlation of NowPrecip nowcasts with time.
Red curves: correlation with time of the COSMO ensemble members. Green and blue curves represent mean values.



NowPrecip Ensemble



Summary

- Nowcasting: Statistical prediction for now to a few hours ahead
- Step 1: Optical flow and extrapolation
- Step 2: Cascade decomposition
- Step 3: Growth and decay
- Step 1+2+3: Convolutional Neural Network / U-net, recurrent CNNs
- Step 4: Uncertainty estimation and spatio-temporal structures
- Step 4: Generative Models GAN or latend diffusion models
- Step 5: Blending with NWP

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