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METEOROLOGISKA INSTITUTET
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Lagrangian Convolutional Neural Network for Radar-Based Precipitation Nowcasting

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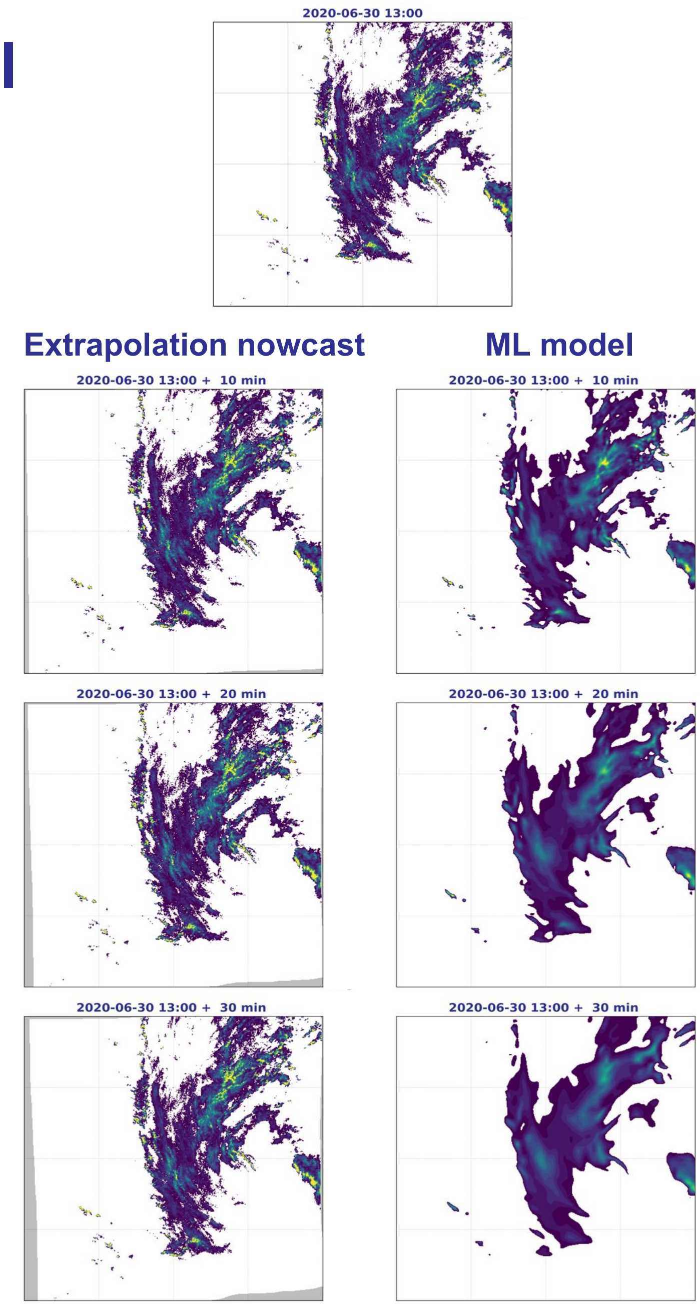
L-CNN: Lagrangian Convolutional Neural Network

- Machine learning (ML) methods have shown promise in rainfall nowcasting
- However, ML nowcasting methods
  - suffer from blurring and underestimation of rainfall
  - have lower skill than state-of-art persistence-based methods especially at higher rain rates
- In L-CNN, a convolutional neural network is used to model the growth and decay of rainfall by removing advection with Lagrangian transform
- This results in improved forecast skill in high-intensity, small-scale rainfall compared to reference models



Reference models: RainNet & LINDA

RainNet

- U-net for precipitation nowcasting developed by Ayzel et al. (2020)
- RainNet also used as neural network in L-CNN
- Input 4 timesteps of 512 x 512 images
- Trained by minimizing log-cosh loss over nowcasts for 5...30 minutes

LINDA

- Lagrangian Integro-Difference equation model with Autoregression developed by Pulkkinen et al. (2021)
- Designed to model growth and decay of convective precipitation in Lagrangian coordinate system
- Implementation from PySteps library

Pulkkinen, S., Nerini, D., Pérez Hortal, A. A., Velasco-Forero, C., Seed, A., Germann, U., and Foresti, L.: Pysteps: An Open-Source Python Library for Probabilistic Precipitation Nowcasting (v1.0), Geoscientific Model Development, 2019, 12, 1–68, https://doi.org/10/gf38m5, 2019.
Pulkkinen, S., Chandrasekar, V., and Niemi, T.: Lagrangian Integro-Difference Equation Model for Precipitation Nowcasting, Journal of Atmospheric and Oceanic Technology, 38, 2125–2145, https://doi.org/10.1175/JTECH-D-21-0013.1, 2021.
Ayzel, G., Scheffer, T., and Heistermann, M.: RainNet v1.0: a convolutional neural network for radar-based precipitation nowcasting, 13, 2631–2644, https://doi.org/10/gmr9n5, 2020.

L-CNN model

Advection equation

$$\frac{\partial \psi}{\partial t} + \mathbf{v} \cdot \nabla \psi = S$$

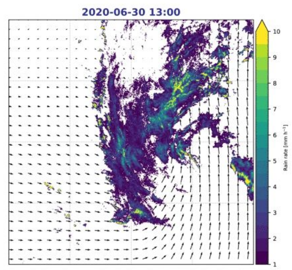
In Lagrangian coordinate system

$$\mathbf{v} \cdot \nabla \widetilde{\psi} = 0 \quad \Rightarrow \quad \frac{\partial \widetilde{\psi}}{\partial t} = S$$

Growth / decay term

$$S = \frac{\partial \widetilde{\psi}}{\partial t} \approx \Delta \widetilde{\psi}_t = \widetilde{\psi}_t - \widetilde{\psi}_{t-i}$$

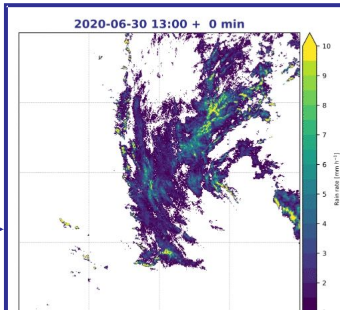
***n + 1* rain rate fields**



Optical flow

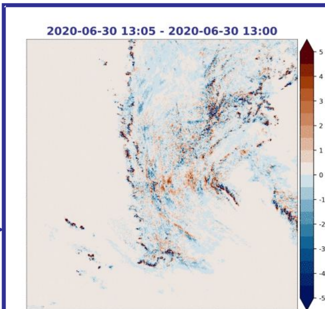
Advection field

Transform to Lagrangian coordinates



n + 1 fields
(Lagrangian coordinates)

Discretize time derivative



n differenced fields
(Lagrangian coordinates)

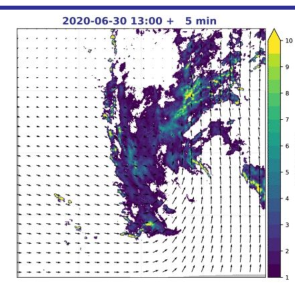
RainNet trained with RMSE loss

Integrate back to original time series

m predicted fields
(Lagrangian coordinates)

Transform to Eulerian coordinates

***m* nowcast rain rate fields**



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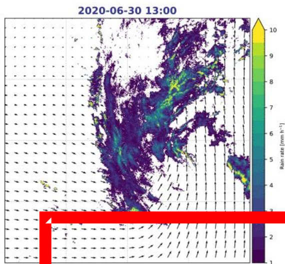
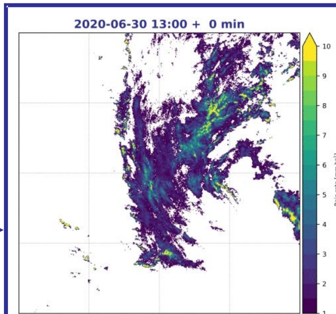
n + 1 **rain rate fields**



Optical flow

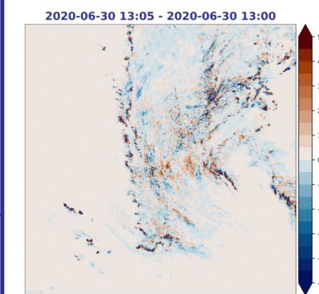
Advection field

Transform to Lagrangian coordinates



n + 1 fields
(Lagrangian coordinates)

Discretize time derivative



n differenced fields
(Lagrangian coordinates)

RainNet trained with RMSE loss

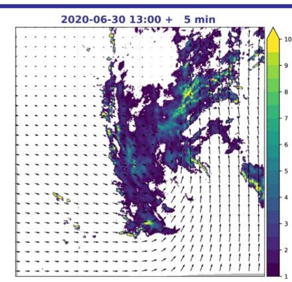
...ack to original time series

(Lagrangian coordinates)

Transform to E... coordinates

Lagrangian transform is key part of the model!
(Ask for details)

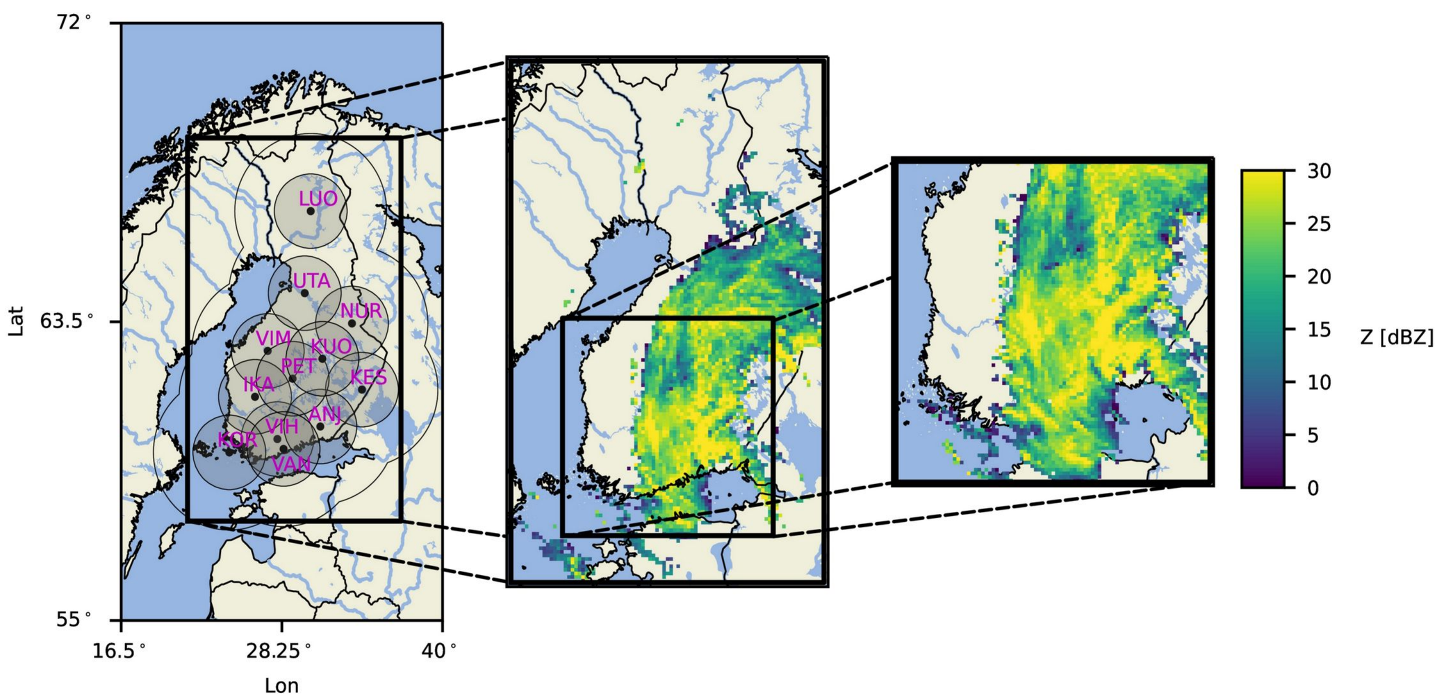
m **nowcast rain rate fields**



Data sets from the Finnish radar composite

- Full radar composite (1 km resolution) cropped to 512 x 512 km
- Rain rate thresholded at 0.1 mm/h to remove non-precipitating echoes
- Cases selected from rainy days from summers 2019 - 2021

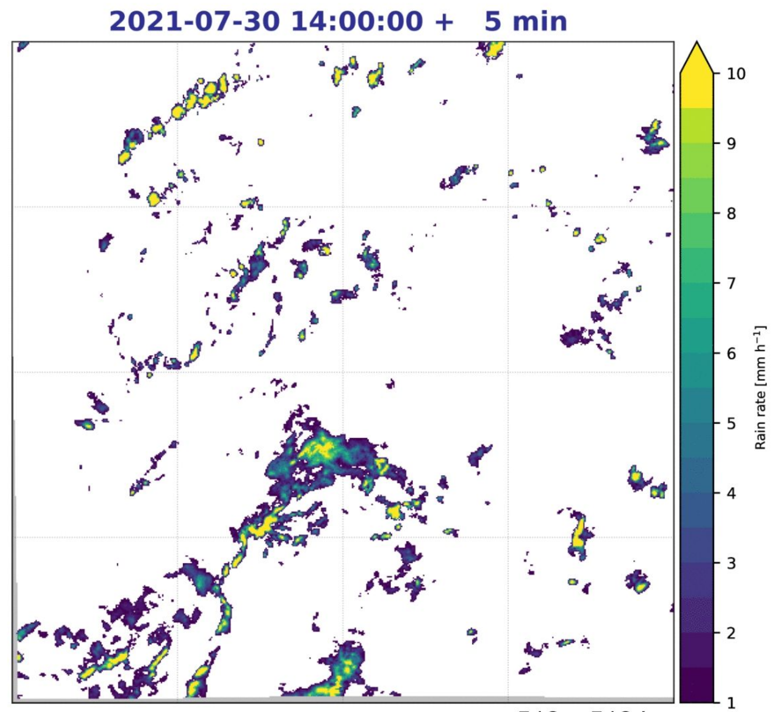
Data set	No. of timestamps
Training	15 840
Validation	2664
Verification	2448



Saltikoff, E., Huuskonen, A., Hohti, H., Koistinen, J., and Järvinen, H.: Quality assurance in the FMI Doppler Weather Radar Network, Boreal Environment Research, 15, 579–594, 2010.

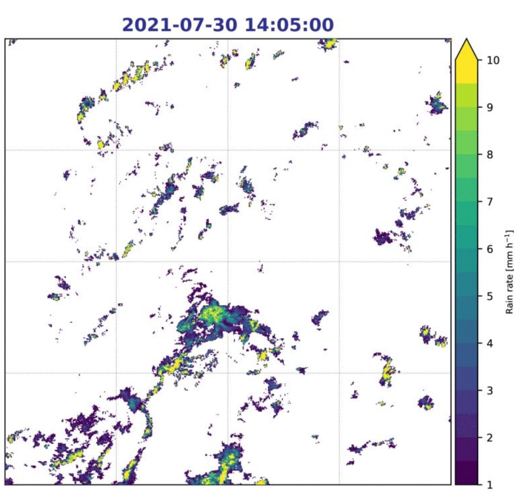
Example: Convective rain with growth and decay

Compared to RainNet, **L-CNN**
- retains both high- and lower intensity rainfall longer
- has less blurring

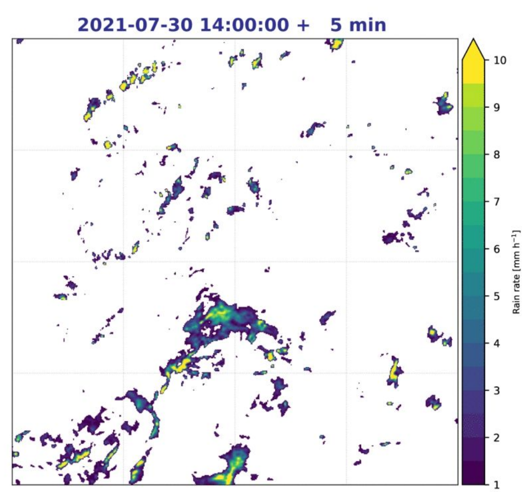


512 x 512 km

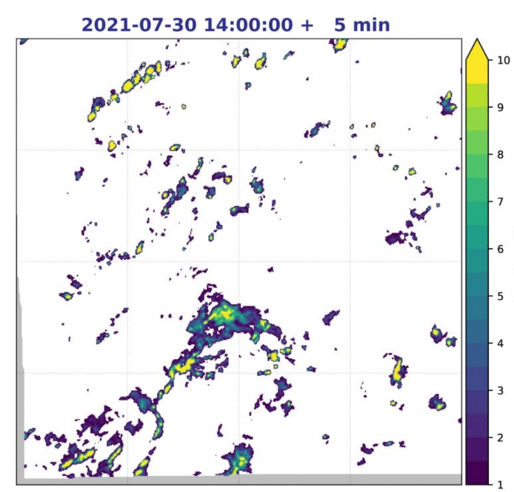
Observations



RainNet



LINDA



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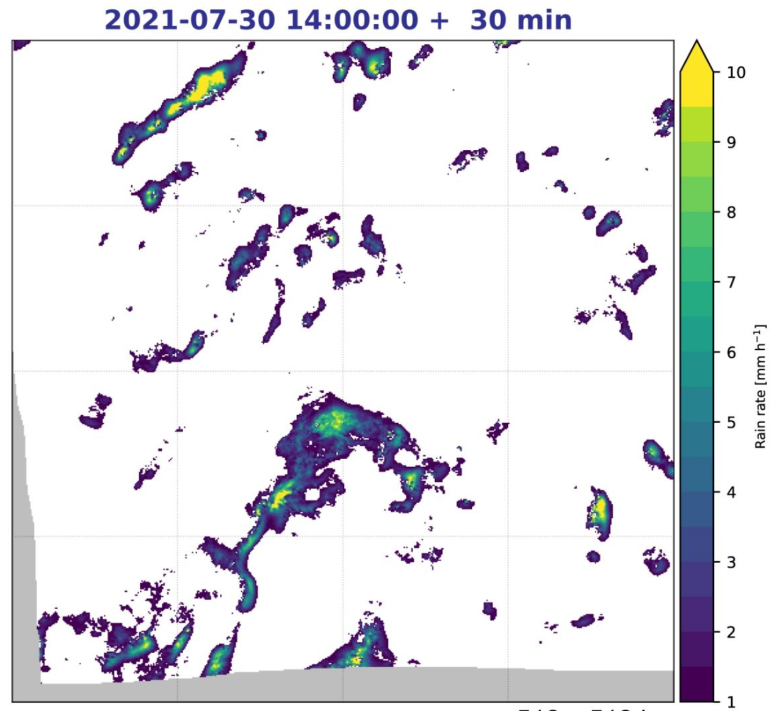
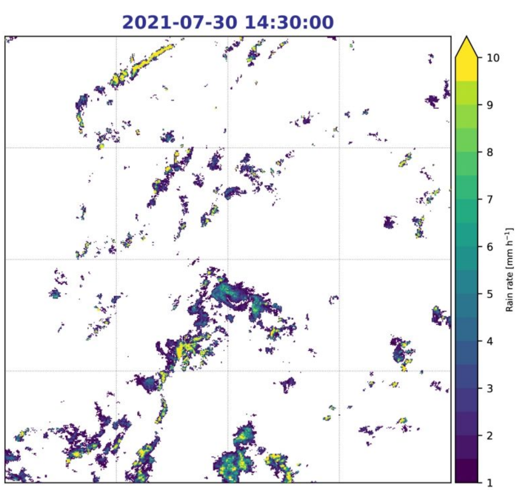
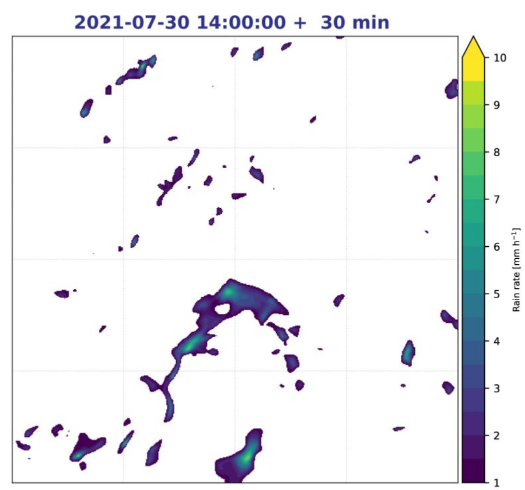


512 x 512 km

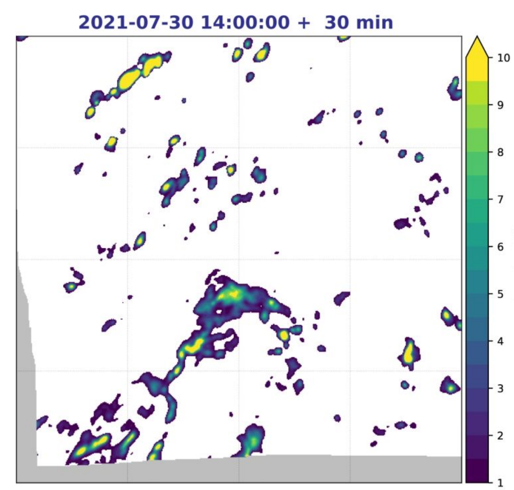
Observations



RainNet



LINDA



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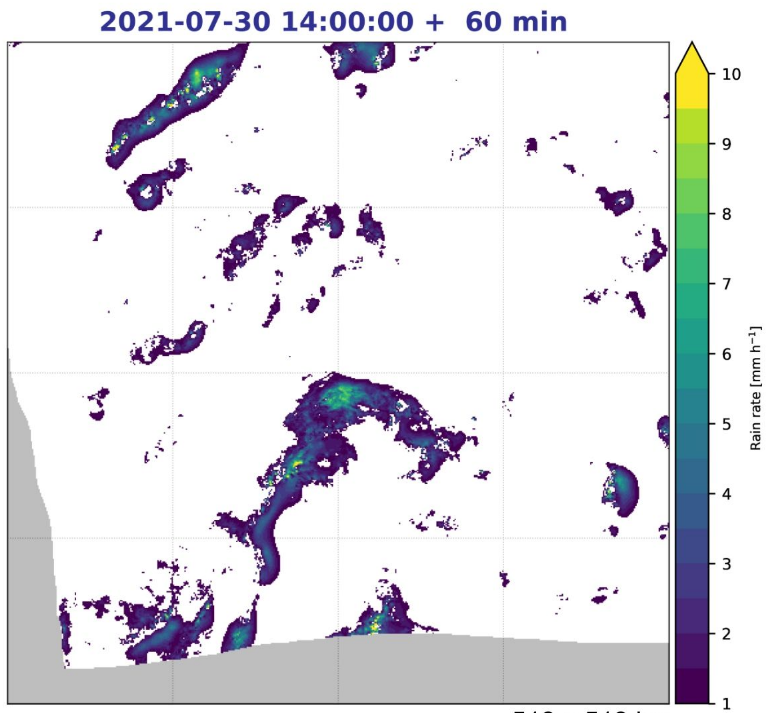
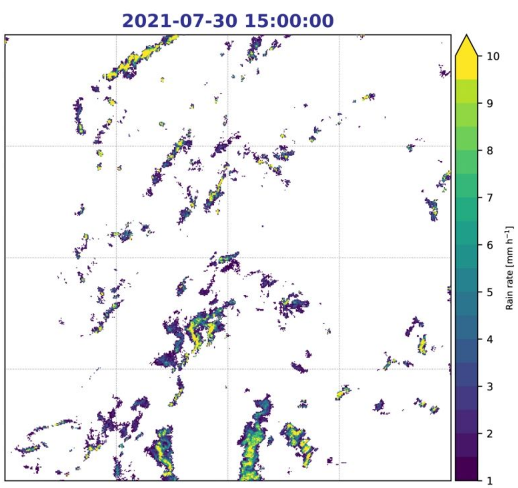
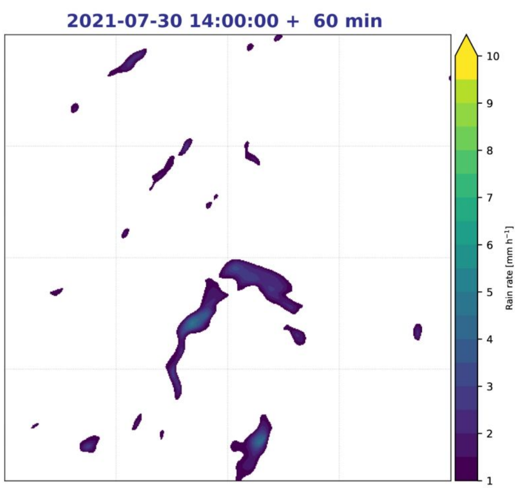


512 x 512 km

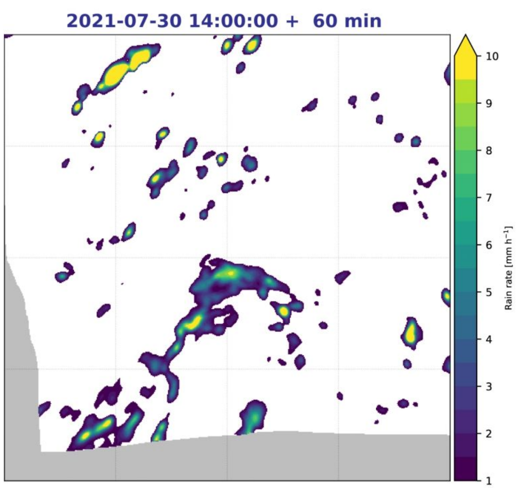
Observations



RainNet

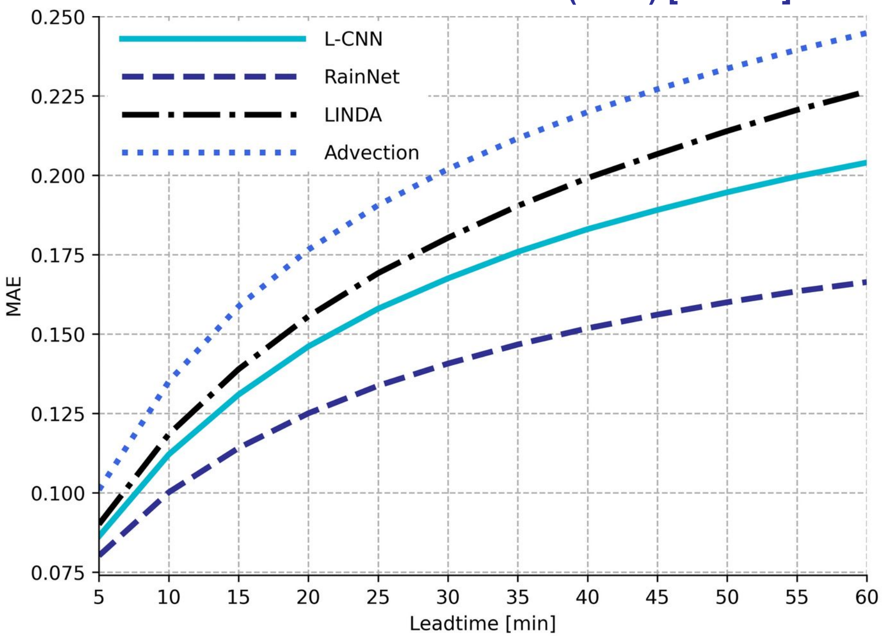


LINDA

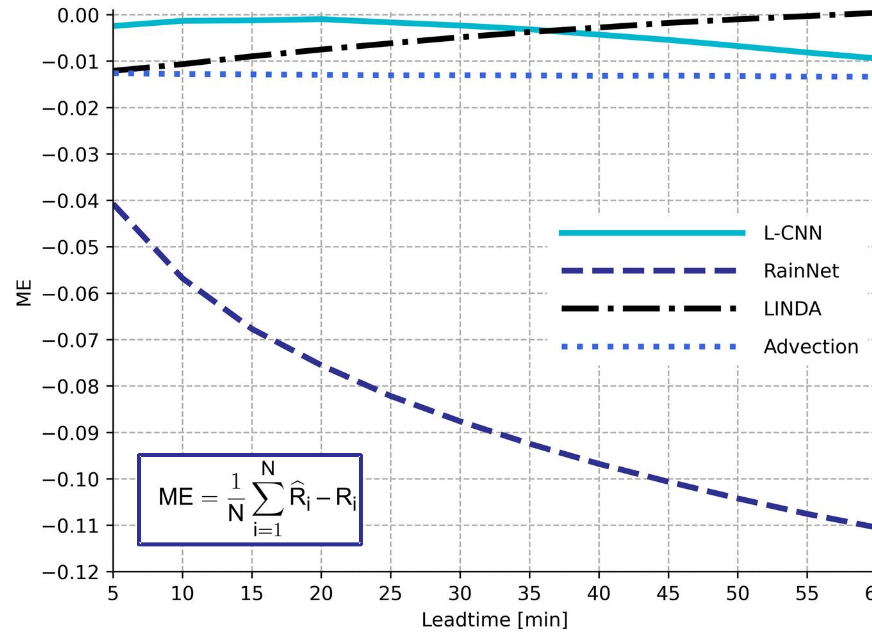


L-CNN over- and underestimates rainfall less than reference models

MEAN ABSOLUTE ERROR (MAE) [mm h-1]



MEAN ERROR (ME) [mm h-1]



- RainNet has lowest mean absolute error, because the log-cosh loss function minimizes MAE
- L-CNN has lower MAE than LINDA

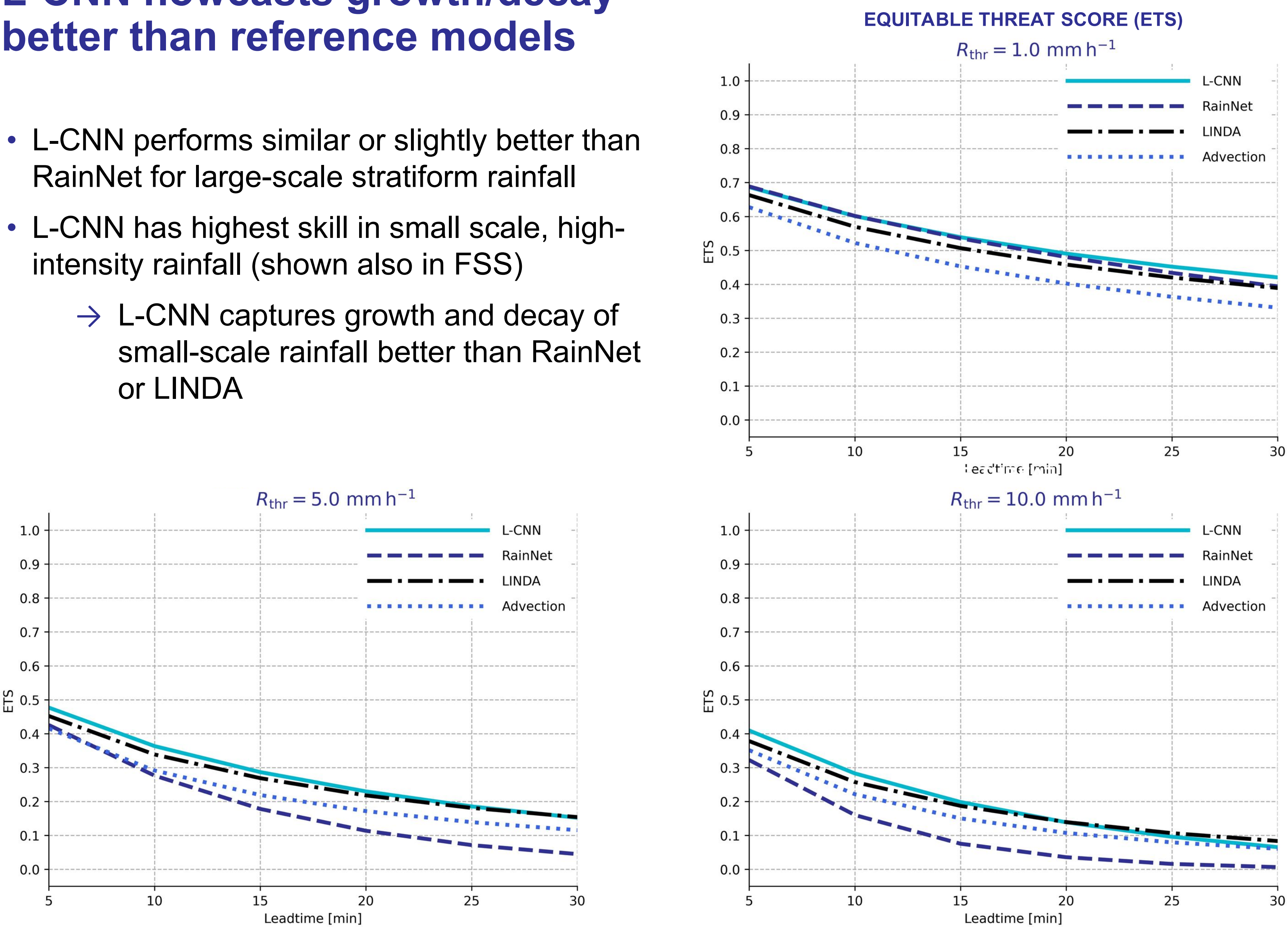
  → L-CNN shows less overestimation of high intensities than LINDA

- L-CNN has smallest mean bias

  → L-CNN underestimates rainfall less than RainNet and LINDA

L-CNN nowcasts growth/decay better than reference models

- L-CNN performs similar or slightly better than RainNet for large-scale stratiform rainfall
- L-CNN has highest skill in small scale, high-intensity rainfall (shown also in FSS)
  → L-CNN captures growth and decay of small-scale rainfall better than RainNet or LINDA



Conclusions

- L-CNN uses temporal differencing in Lagrangian coordinates to model growth and decay of rainfall
- This results in improved forecast skill at high rain rate thresholds compared to reference models
    - → L-CNN captures growth and decay of small-scale rainfall better than reference models