On the challenge of precipitation nowcasting in the Canary Islands

David Quintero Plaza, AEMET, Spain. European Nowcasting Conference (ENC2022), March 21-25th, 2022

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- The islands have a complex, mountainous and fastly changing terrain, with the so called local "micro-climates".

- Even High Resolution Models (Harmonie & gSREPS at 2.5 Km) still show limitations for the islands (not to mention models with less resolution).

- Affected by middle latitudes and tropical phenomena.


Canary Islands
Spain
provincia capital
city
town
airport
ATLANTIC OCEAN
La Palma
Santa Cruz de la Palma
Tenerife
Santa Cruz de Tenerife
La Gomera
San Sebastian de la Gomera
El Hierro
Valverde
Provincia de Santa Cruz de Tenerife
Provincia de Las Palmas
Gran Canaria
Las Palmas de Gran Canaria
Lanzarote
Arrecife
Isla de Alegranza
Isla de Montaña Clara
Isla Graciosa
Isla de Lobos
Fuerteventura
Puerto del Rosario
18°
17°
16°
15°
14°
29°
28°

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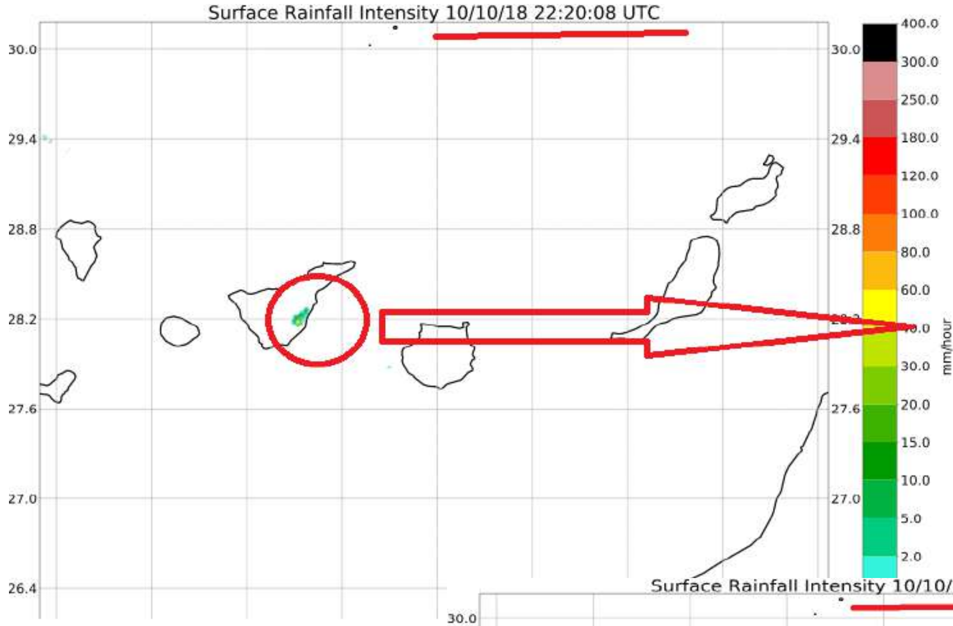

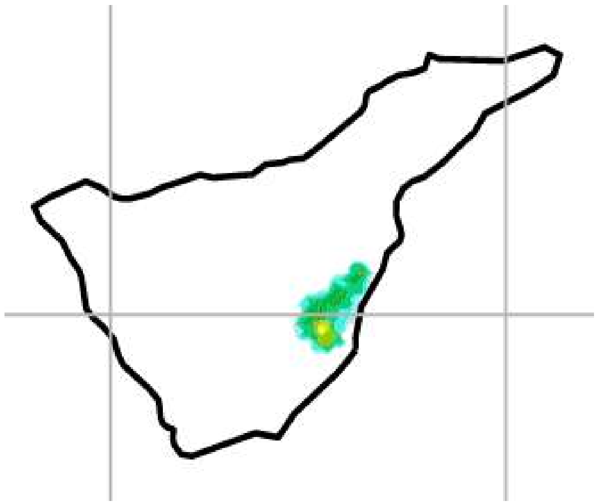

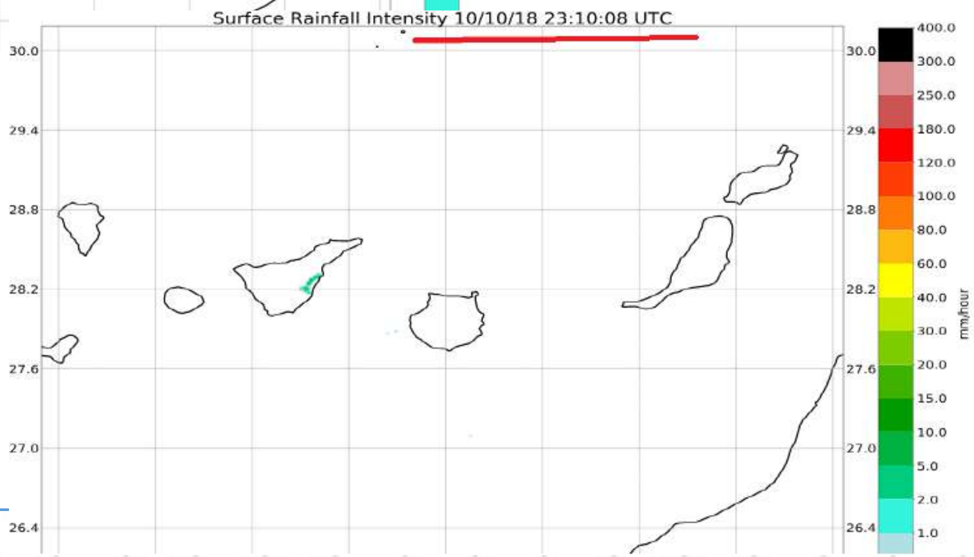

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- Regarding the nowcasting: 3 possibilities,
    - Fast Integration Models.
    - Optical Flow.
    - **Neural Networks and other Deep Learning approaches.**

- Some evidence that Machine Learning/Deep Learning is on equal terms (and sometimes beating) more *classical* options...

MetNet: A Neural Weather Model for Precipitation Forecasting. https://arxiv.org/abs/2003.12140

Convcast: An embedded convolutional LSTM based architecture for precipitation nowcasting using satellite data. PLoS ONE 15(3): e0230114. https://doi.org/10.1371/journal.pone.0230114

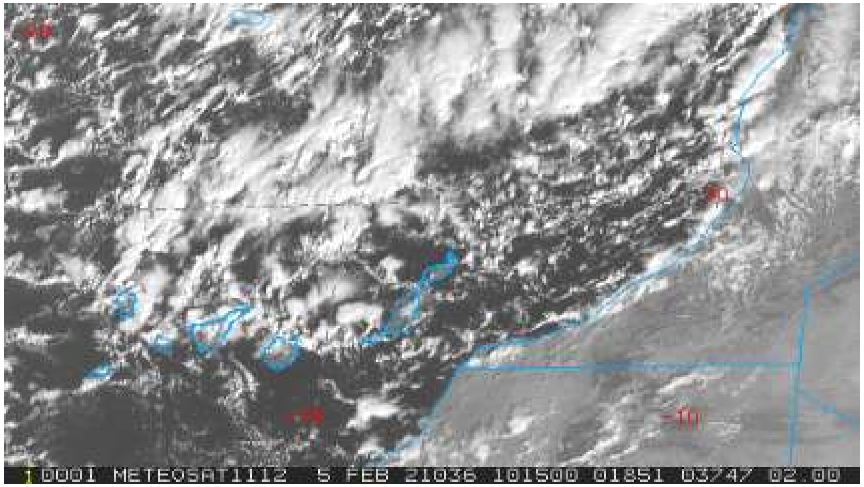
Skilful precipitation nowcasting using deep generative models of radar. Nature volume 597, pages 672–677 (2021). Nature volume 597, pages 672–677 (2021). https://doi.org/10.1038/s41586-021-03854-z

GOBIERNO DE ESPAÑA VICEPRESIDENCIA CUARTA DEL GOBIERNO MINISTERIO PARA LA TRANSICIÓN ECOLÓGICA Y EL RETO DEMOGRÁFICO

AEMet Agencia Estatal de Meteorología

- The variable chosen was **SRI (Surface Rainfall Intensity)**, an estimated value of the instantaneous precipitation using data from all the vertical, as offered by the IRIS SIGMET-VAISALA **radar, each 10 minutes, in mm/hour**. 1 Km of resolution, 480x480 points.

- Beware of the **limitations**: radar located at 1778 meters above sea level! Sparse dataset (few rain & many times very local).



- *rainymotion*: optical flow. Run in AEMET headquarters.

- *conda* installation of different libraries, especially NumPy and wradlib (for radar data reading).

- *rainymotion: Ayzel, G., Heistermann, M., and Winterrath, T.: Optical flow models as an open benchmark for radar-based precipitation nowcasting (rainymotion v0.1), Geosci. Model Dev., 12, 1387-1402, https://doi.org/10.5194/gmd-12-1387-2019, 2019.*

- ***rainymotion*** inner working:

Estimate motion between 2 small instants of time. Assume conservation of brigthness:

$$I(x, y, t) = I(x + \Delta x, y + \Delta y, t + \Delta t)$$

Taylor expanding at first order and taking limits: $$\frac{\partial I}{\partial x} V_x + \frac{\partial I}{\partial y} V_y + \frac{\partial I}{\partial t} = 0$$

One equation, 2 unknowns (V's, *aperture problem*): extra assumptions needed. Typical assumption: *Lucas-Kanade* => flow constant in some region. The problem now has more equations that unknowns (over-determined). Solved with least squares.

$$\begin{aligned} I_x(q_1)V_x + I_y(q_1)V_y &= -I_t(q_1) \\ I_x(q_2)V_x + I_y(q_2)V_y &= -I_t(q_2) \\ &\vdots \\ I_x(q_n)V_x + I_y(q_n)V_y &= -I_t(q_n) \end{aligned}$$

$$\begin{bmatrix} V_x \\ V_y \end{bmatrix} = \begin{bmatrix} \sum_i I_x(q_i)^2 & \sum_i I_x(q_i)I_y(q_i) \\ \sum_i I_y(q_i)I_x(q_i) & \sum_i I_y(q_i)^2 \end{bmatrix}^{-1} \begin{bmatrix} -\sum_i I_x(q_i)I_t(q_i) \\ -\sum_i I_y(q_i)I_t(q_i) \end{bmatrix}$$

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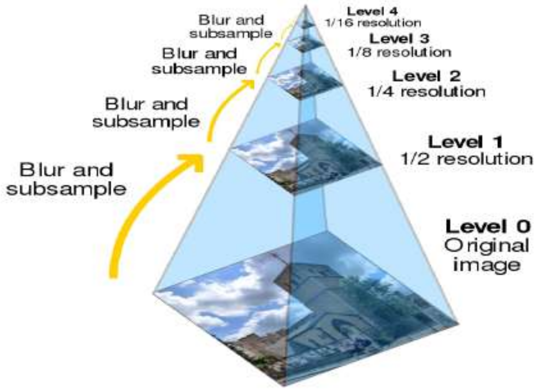
- ***rainymotion*** inner working:

2 approaches: Sparse and Dense. Sparse: look for corners and evaluate and propagate velocity through Lucas-Kanade.



Dense (Kroeger et al., 2016): from coarse to fine (pyramid):

1) Create regular grid with overlapping patches
2) Find velocity of displacement (Lucas-Kanade)
3) Weighted averaging of displacements
(λ = 1 means overlap between patch i and point x, d measures difference of intensities)
4) Variational "energy" minimization of U
(ψ(E) α E)

$$\mathbf{U}_s(\mathbf{x}) = \frac{1}{Z}\sum_i^{N_s} \frac{\lambda_{i,\mathbf{x}}}{\max(1, ||d_i(\mathbf{x})||_2)} \cdot \mathbf{u}_i \qquad Z = \sum_i \lambda_{i,\mathbf{x}} / \max(1, ||d_i(\mathbf{x})||_2) \qquad E(\mathbf{U}) = \int_\Omega \sigma\Psi(E_I) + \gamma\Psi(E_G) + \alpha\Psi(E_S)\, d\mathbf{x}$$

$$E_I = \mathbf{u}^T \bar{\mathbf{J}}_0 \mathbf{u} \qquad \nabla_3 = (\partial x, \partial y, \partial z)^T \qquad \bar{\mathbf{J}}_0 = \beta_0 (\nabla_3 I)(\nabla_3^T I) \qquad E_G = \mathbf{u}^T \bar{\mathbf{J}}_{xy} \mathbf{u} \qquad E_S = ||\nabla u||^2 + ||\nabla v||^2$$

$$\bar{\mathbf{J}}_{xy} = \beta_x (\nabla_3 I_{dx})(\nabla_3^T I_{dx}) + \beta_y (\nabla_3 I_{dy})(\nabla_3^T I_{dy})$$

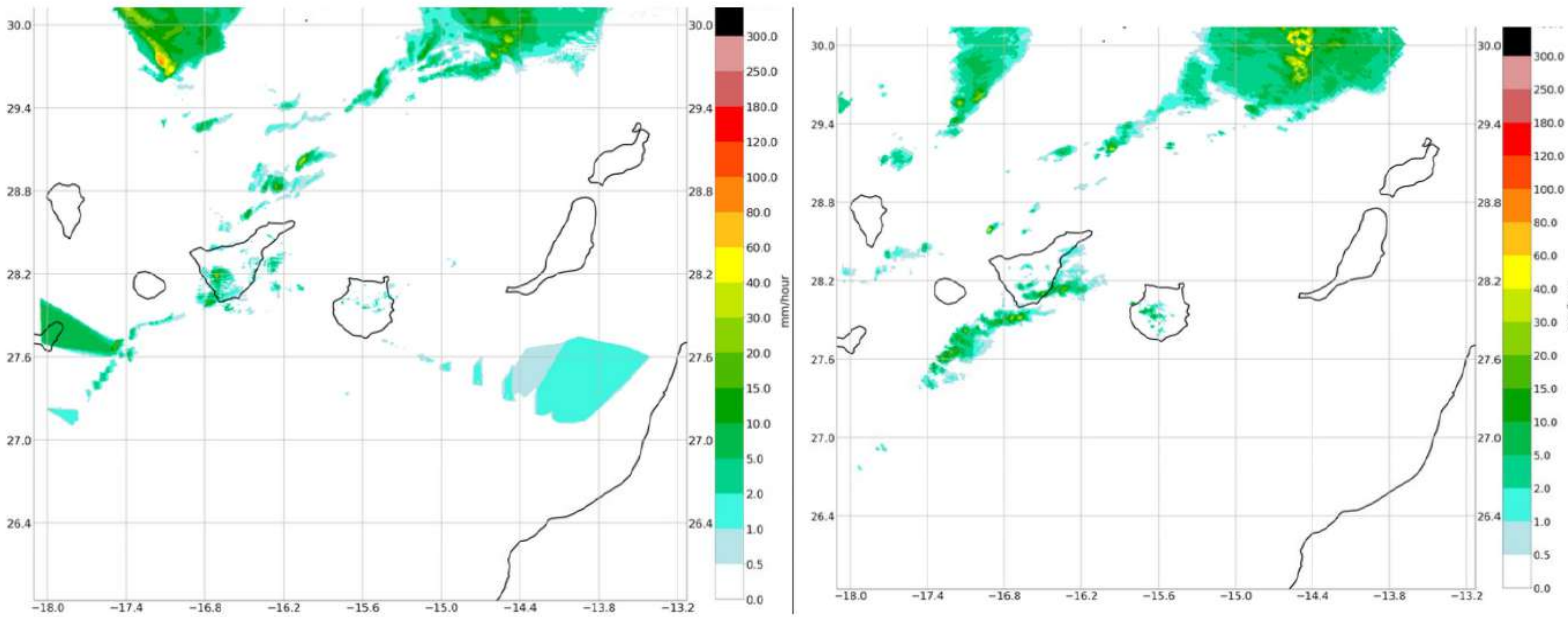
- *rainymotion* inner working:

Dense propagates velocity allowing for rotation (semi-Lagrangian field) or with a constant vector, using times *t* and *t-1*.

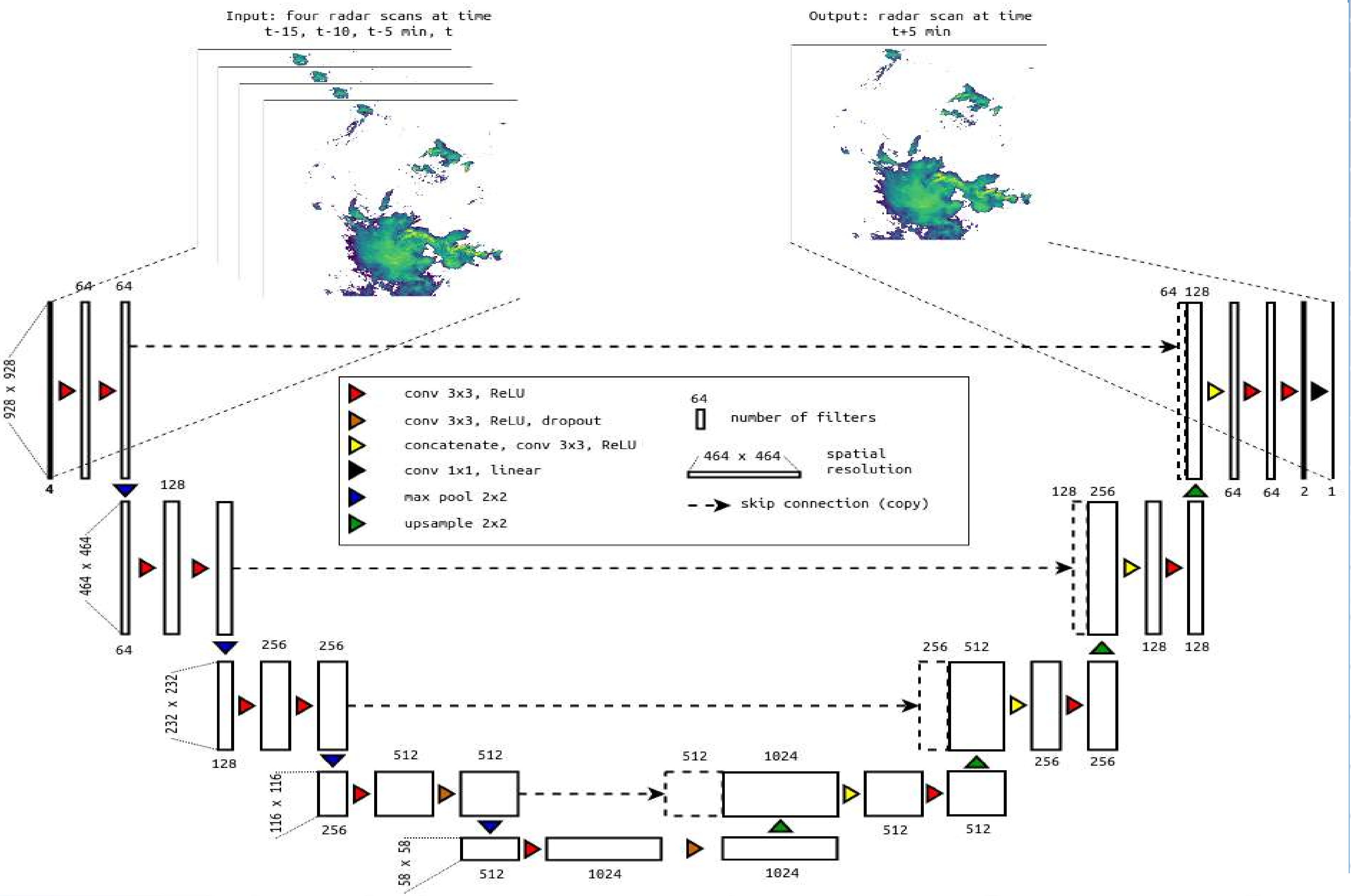
After propagating pixels to *t+n*, with the calculated velocities, new intensities are interpolated between *t* and *t+n* with **inverse distance weighting**.

rainymotion offers other options and tweaking of the parameters.

- To give an example: SRI from *rainymotion* at 09:10 UTC, 2021-01-07, with SRI calculated from 07:50 and 08:00; predicted at 09:10 (left); observed SRI at 09:10 (right).



- RainNet (Gyorgy Ayzel):



- Our dataset has holes, is sparse and has low signal (due to the radar altitude).

- Training has to be done with a temporal set of files without holes (temporal ordering is important).

- Workflow:

1) Download historical data (SRI) from the radar until a hole appears.

2) Training (early stopping, model checkpoint).

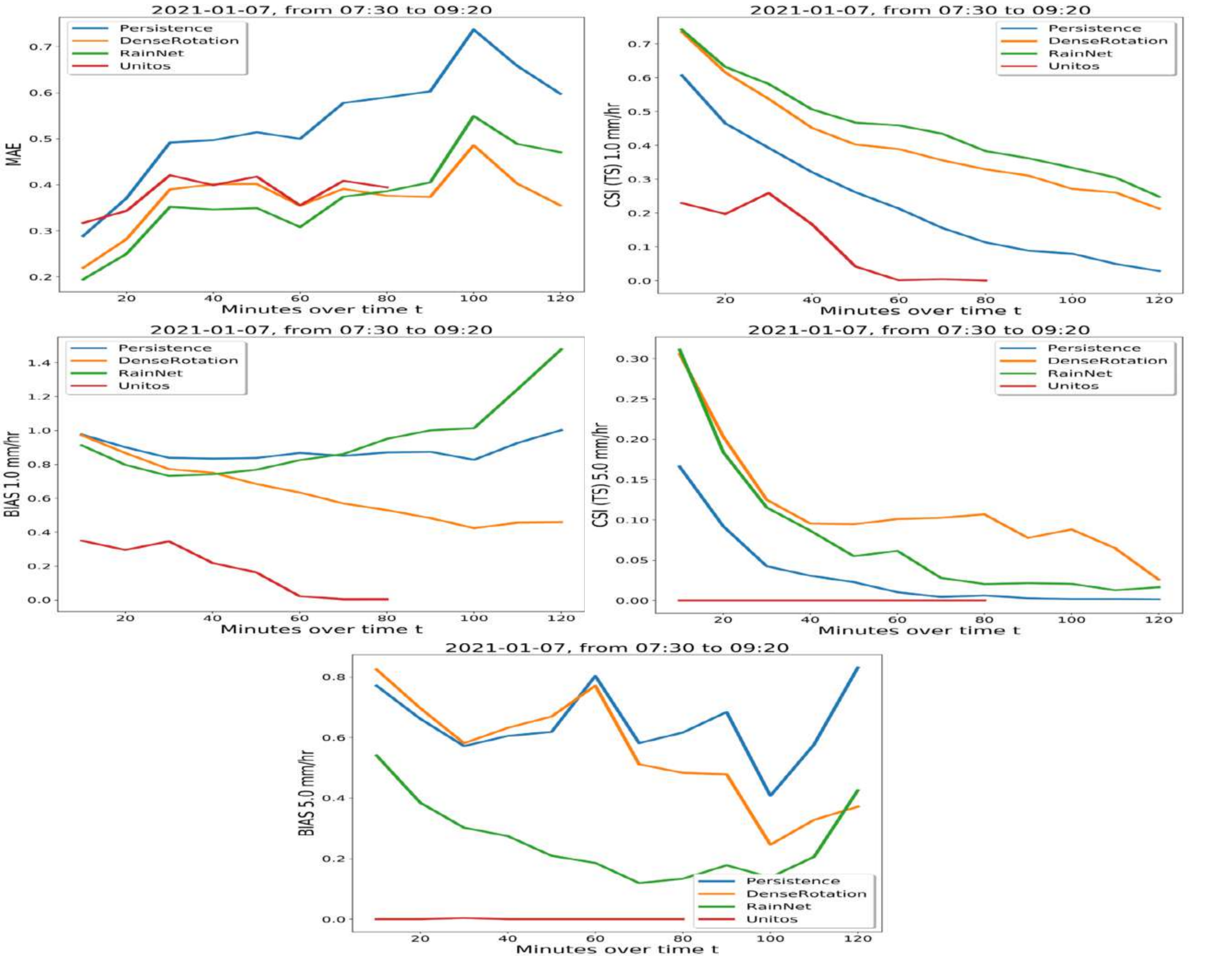
3) Go back to 1 and repeat.

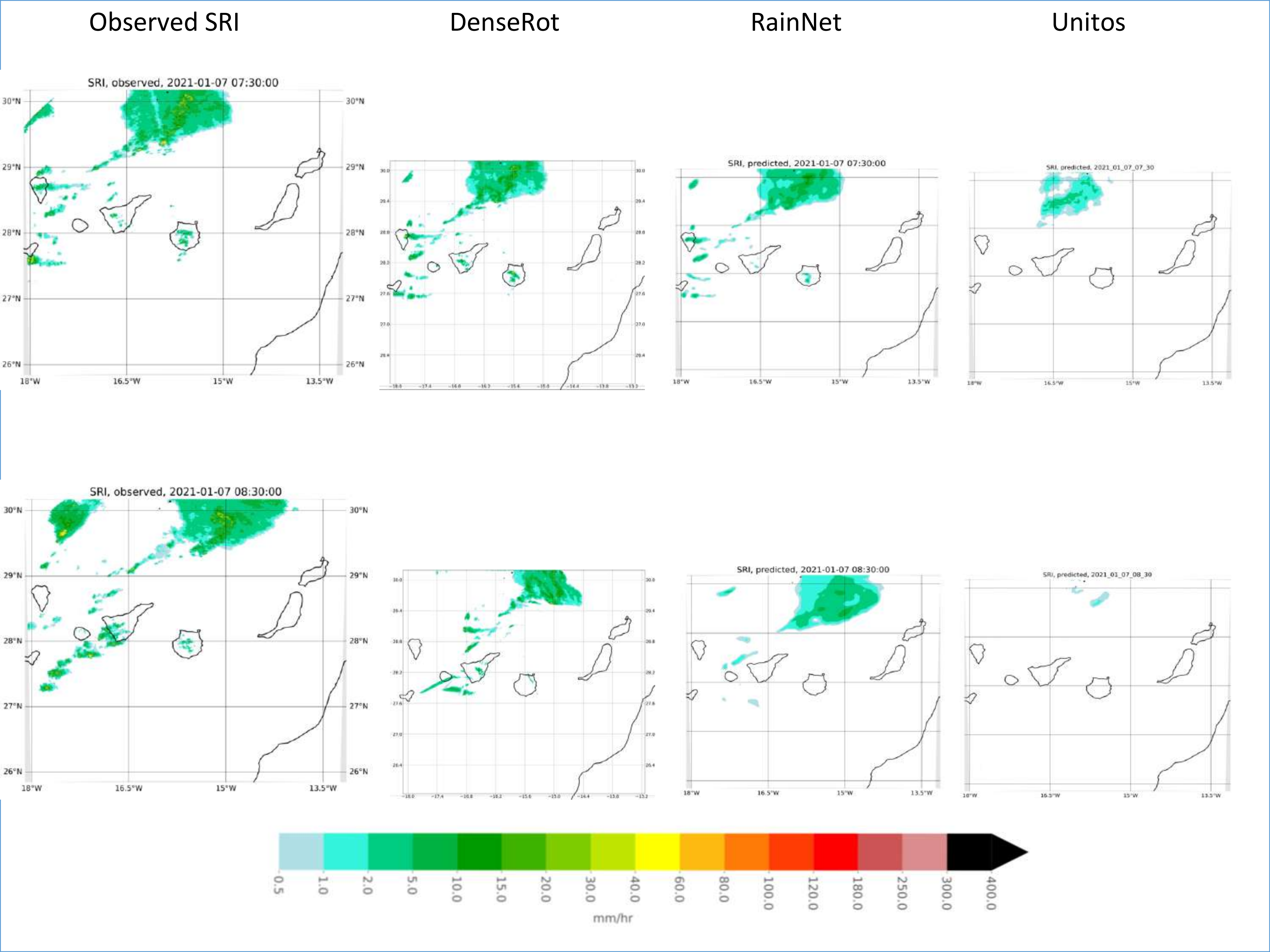
- Roughly 10 000 samples of training.

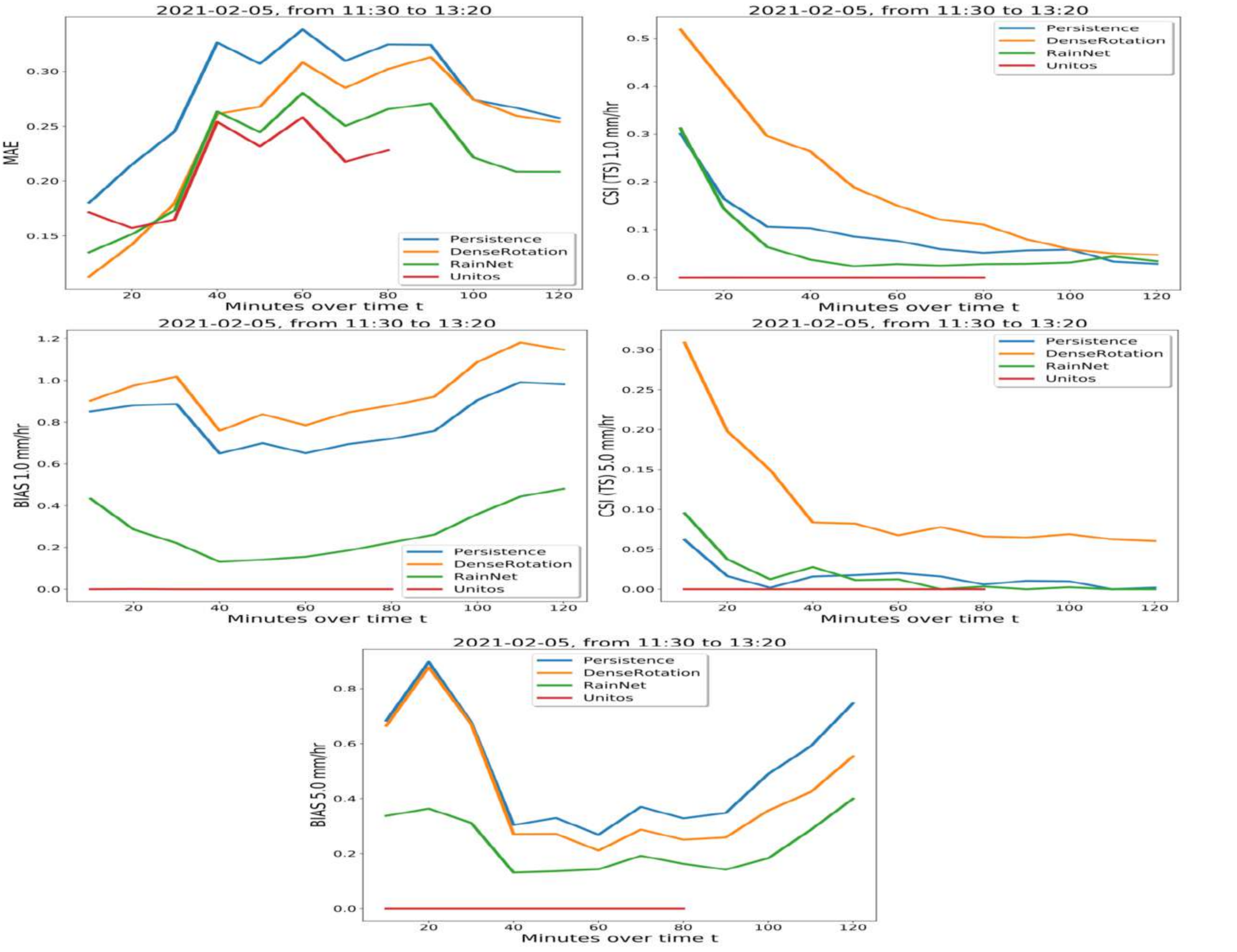
- Others, less successful approaches…:

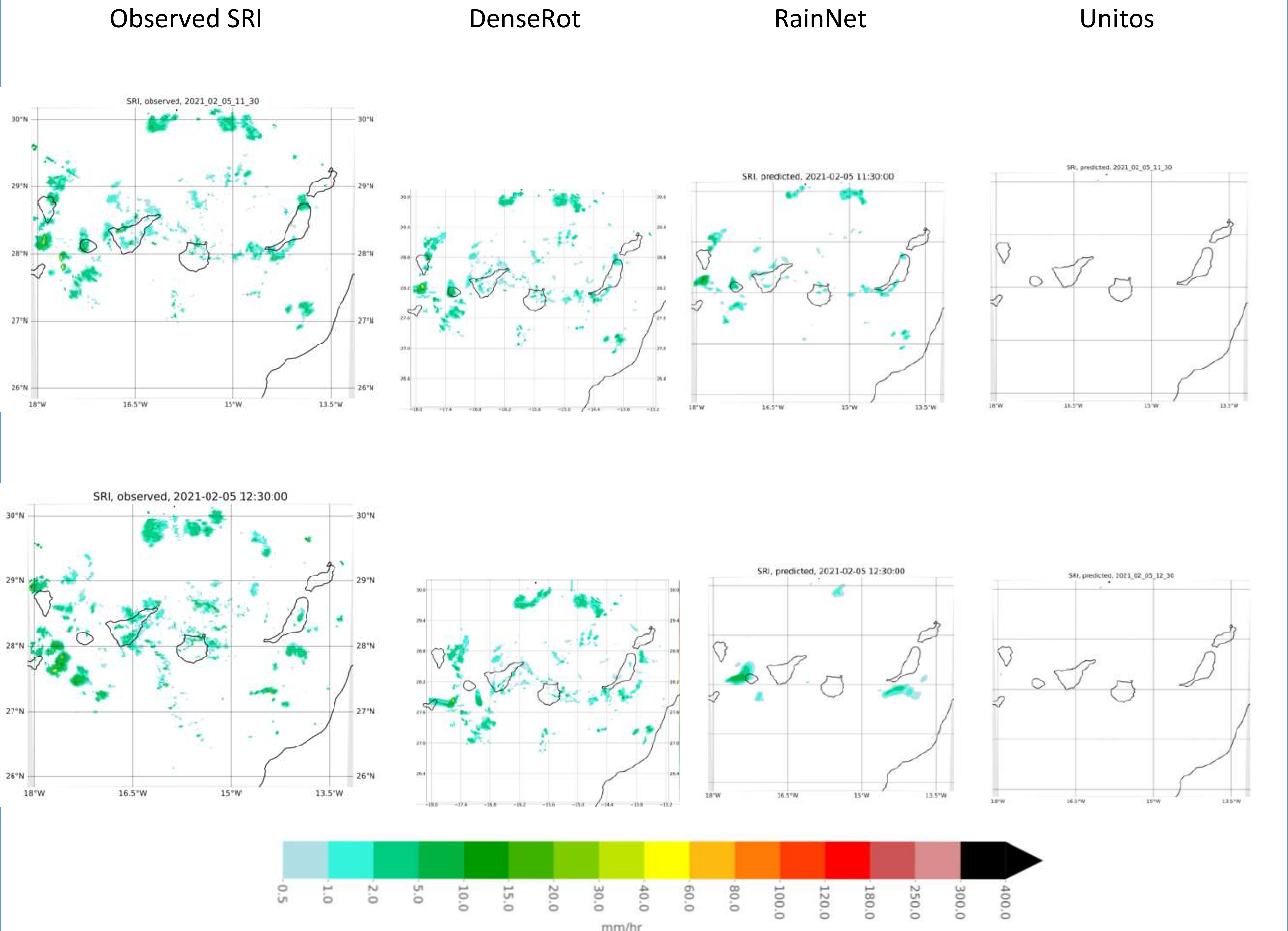
- A **"Convcast stlye"** net (https://journals.plos.org/plosone/article/file?id=10.1371/journal.pone.0230114&type=printable): stack of ConvLSTMs type of neurons, in theory good for grabbing spatial + temporal patterns, although hard to train and slightly unstable numerically.

- A **"unitos style"** net (https://is.muni.cz/th/p3fuc/fi-pdflatex.pdf): very similar to RainNet; a combination of U-Net + SegNet, but most Convs substituted by ConvLSTMs. Better than "convcast style" but clearly behind RainNet.

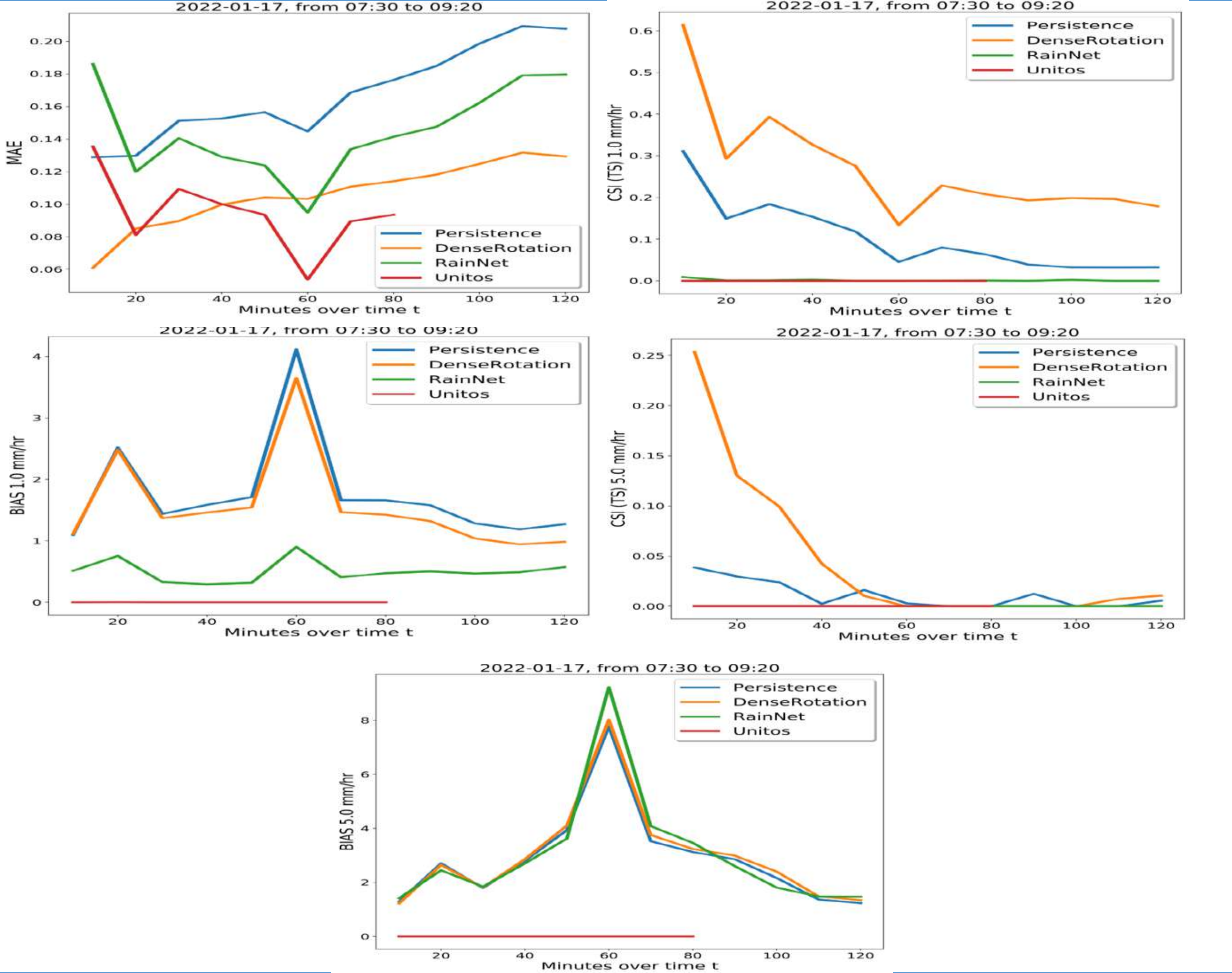

2021-01-07, from 07:30 to 09:20
Persistence
DenseRotation
RainNet
Unitos
MAE
CSI (TS) 1.0 mm/hr
BIAS 1.0 mm/hr
CSI (TS) 5.0 mm/hr
BIAS 5.0 mm/hr
Minutes over time t

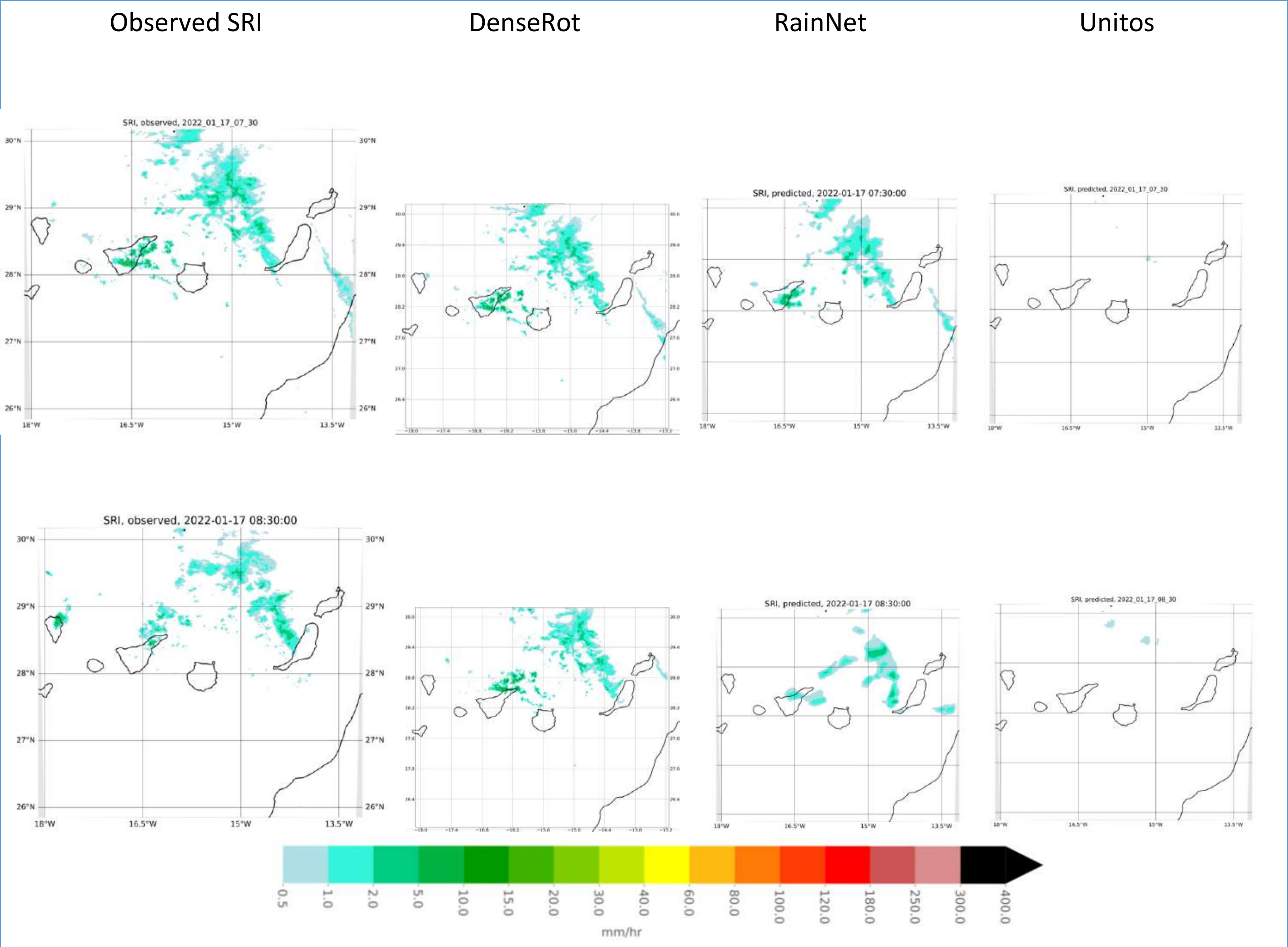

Observed SRI
DenseRot
RainNet
Unitos
SRI, observed, 2021-01-07 07:30:00
SRI, predicted, 2021-01-07 07:30:00
SRI, predicted, 2021_01_07_07_30
SRI, observed, 2021-01-07 08:30:00
SRI, predicted, 2021-01-07 08:30:00
SRI, predicted, 2021_01_07_08_30
30°N
29°N
28°N
27°N
26°N
18°W
16.5°W
15°W
13.5°W
0.5
1.0
2.0
5.0
10.0
15.0
20.0
30.0
40.0
60.0
80.0
100.0
120.0
180.0
250.0
300.0
400.0
mm/hr


2021-02-05, from 11:30 to 13:20
MAE
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos
2021-02-05, from 11:30 to 13:20
CSI (TS) 1.0 mm/hr
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos
2021-02-05, from 11:30 to 13:20
BIAS 1.0 mm/hr
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos
2021-02-05, from 11:30 to 13:20
CSI (TS) 5.0 mm/hr
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos
2021-02-05, from 11:30 to 13:20
BIAS 5.0 mm/hr
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos



Observed SRI
DenseRot
RainNet
Unitos
SRI, observed, 2021_02_05_11_30
SRI, predicted, 2021-02-05 11:30:00
SRI, predicted, 2021_02_05_11_30
SRI, observed, 2021-02-05 12:30:00
SRI, predicted, 2021-02-05 12:30:00
SRI, predicted, 2021_02_05_12_30
30°N
29°N
28°N
27°N
26°N
18°W
16.5°W
15°W
13.5°W
0.5
1.0
2.0
5.0
10.0
15.0
20.0
30.0
40.0
60.0
80.0
100.0
120.0
180.0
250.0
300.0
400.0
mm/hr


2022-01-17, from 07:30 to 09:20
MAE
Minutes over time t
Persistence
DenseRotation
RainNet
Unitos
CSI (TS) 1.0 mm/hr
BIAS 1.0 mm/hr
CSI (TS) 5.0 mm/hr
BIAS 5.0 mm/hr


Observed SRI
DenseRot
RainNet
Unitos
SRI, observed, 2022_01_17_07_30
SRI, predicted, 2022-01-17 07:30:00
SRI, predicted, 2022_01_17_07_30
SRI, observed, 2022-01-17 08:30:00
SRI, predicted, 2022-01-17 08:30:00
SRI, predicted, 2022_01_17_08_30
30°N
29°N
28°N
27°N
26°N
18°W
16.5°W
15°W
13.5°W
0.5
1.0
2.0
5.0
10.0
15.0
20.0
30.0
40.0
60.0
80.0
100.0
120.0
180.0
250.0
300.0
400.0
mm/hr

4

- Conclusions and the future:

- **RainNet's original paper:** RainNet improves CSI (TS) at 1 and 5 mm/hr thresholds for up to 1 hour. Rainymotion better in higher thresholds. **In our case:** rainymotion better for 5 mm/hr, and sometimes even for 1 mm/hr! **Using Rainymotion** with Dense Rotation, perhaps just Dense is slightly better.

- We aren't criticizing designs that did work for other cases! We just state they are not valid for us. DL is probably the tool to go except in few, weird cases (ours?)!

- **Our problems:**
  - complex orography => sometimes very local effects,
  - sparse dataset & perhaps under-detected (only 1 radar & at high altitude),
  - tropical effects? (forecast in Tropics tends to be harder, most DL in midlatitudes).

- Keep trying, yes. Perhaps GANs?

References:

P. 3: Left image: By Iven Gummelt - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=4040284

Central image: By Jens Steckert - Own work, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=765158

Right image: By Daniel Gaínza (Tenerife) - Own work, CC BY-SA 4.0, https://commons.wikimedia.org/w/index.php?curid=4555690

P. 4: By Oona Räisänen (Mysid) - Self-made in Inkscape by w:User:Mysid. Based on SRTM data as edited by CGIAR-CSI. Place names based on the Open Streetmap., Public Domain, https://commons.wikimedia.org/w/index.php?curid=2499704

P. 8: Icon EWCloud from https://www.europeanweather.cloud/

Icon rainymotion: https://github.com/hydrogo/rainymotion

P. 9: Optical flow: https://en.wikipedia.org/wiki/Optical_flow. Lucas-Kanade: https://en.wikipedia.org/wiki/Lucas%E2%80%93Kanade_method

P. 10: Kroeger T., Timofte R., Dai D., Van Gool L. (2016) Fast Optical Flow Using Dense Inverse Search. In: Leibe B., Matas J., Sebe N., Welling M. (eds) Computer Vision – ECCV 2016. ECCV 2016. Lecture Notes in Computer Science, vol 9908. Springer, Cham. https://doi.org/10.1007/978-3-319-46493-0_29

Image: Von Cmglee - Eigenes Werk, CC BY-SA 3.0, https://commons.wikimedia.org/w/index.php?curid=42549151

P. 13: RainNet description: https://github.com/hydrogo/rainnet