Forecasting storms with insight (FORESIGHT)

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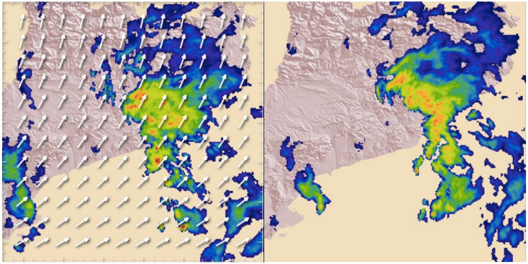
Radar nowcasting

Predict future rainfall over the next 0-6 hours based on Lagrangian persistence, AR(1) or AR(2) models of past radar observations.



Source: Project HAREN "Hazard Assessment based on Rainfall European Nowcasts" (Berenguer et al. 2013)

Pros:

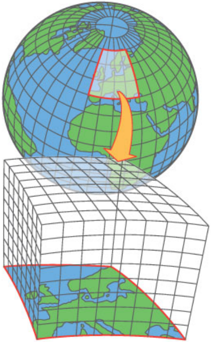
- Fast, robust and simple
- High-resolution
- Hard to beat!

Cons:

- Lacks physics
- No growth & decay
- Lags behind true state
- Noise & artifacts

Numerical weather prediction (NWP)

Numerically solve large systems of coupled differential equations describing the laws of the atmosphere.



Pros:

- Physics based
- Can predict non-linear changes

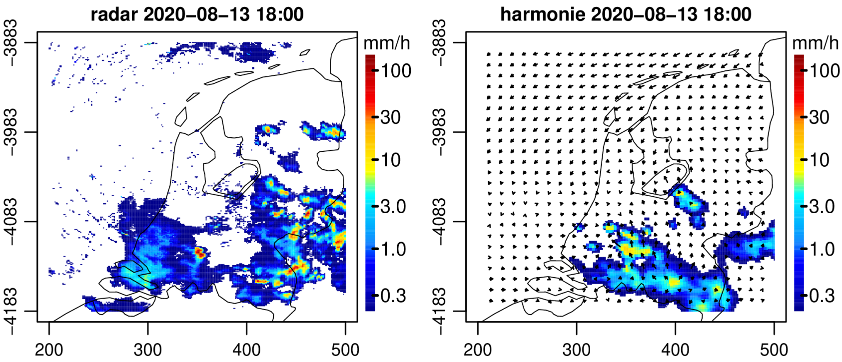
Cons:

- Computationally expensive
- Initial & boundary conditions
- Lacks small-scale details
- Not always consistent with radar!

Modern, high-resolution convection-permitting NWPs have become better at predicting rain. But their skill during the first hours is still lower than radar forecasts.

Example for the Netherlands:

August 13, 2020 at 18:00 UTC



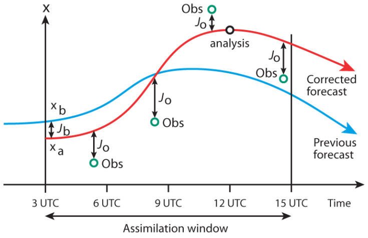
On the left, the rainfall intensity as seen by the radar. On the right, the surface predictions by the HARMONIE model (based on the latest data assimilated at 18 o'clock).

Data assimilation

Approaches:

- Variational methods (3D-Var, 4D-Var)
- Kalman Filters (EnKF, LETKF)

Data assimilation schemes for convective scales are still in their infancy. Direct assimilation of radar into NWPs remains challenging.



Challenges:

- Nonlinear operators
- Computationally expensive
- High update frequency
- Noise
- Rain-no-rain issue

"Even the most sophisticated currently available NWP models with the best data assimilation techniques still do not perform better than radar-based forecasts during the first few hours (Radhakrishnan and Chandrasekar, 2020)"

References

- Gustafsson, N. et al. 2018 "Survey of data assimilation methods for convectivescale numerical weather prediction at operational centres". Q J R Meteorol Soc., 144, 1218-1256.
- Radhakrishnan, C., and V. Chandrasekar, 2020: "CASA Prediction System over Dallas-Fort Worth Urban Network: Blending of Nowcasting and High-Resolution Numerical Weather Prediction Model". J. Atmos. Oceanic Technol., 37, 211-228.

Blending of radar and NWP

Option 1: Simple weighted merging with lead time

- Hyperbolic tangent curve HTW (Wang et al. 2015)
- Salient cross-dissolve Sal CD (Radhakrishnan and Chandrasekar, 2020)

Option 2: performance-dependent weights

- In STEPS, the forecasts are combined based on the most recent skill of radar and NWP for each lead time and spatial scale (Bowler et al. 2006)

Other options:

- Image registration, Kalman filters, Baysian methods, machine learning, etc..

References:

- Bowler, N. E., Pierce, C. E., and Seed, A. W. (2006): "STEPS: A probabilistic precipitation forecasting scheme which merges an extrapolation nowcast with downscaled NWP", Q. J. Roy.Meteorol. Soc., 132, 2127-2155
- Radhakrishnan, C., and V. Chandrasekar, 2020: "CASA Prediction System over Dallas-Fort Worth Urban Network: Blending of Nowcasting and High-Resolution Numerical Weather Prediction Model". J. Atmos. Oceanic Technol., 37, 211-228.
- Wang, G., W.-K. Wong, Y. Hong, L. Liu, J. Dong, and M. Xue (2015): Improvement of forecast skill for severe weather by merging radar-based extrapolation and storm-scale NWP corrected forecast. Atmos. Res., 154, 14-24

The idea behind FORESIGHT:

"Instead of artificially forcing NWPs to comply with radar, why not use the guidance from a NWP to improve radar forecasts?"

Approach:

1. Extract key atmospheric variables from a NWP (e.g., temperature, pressure, wind speed, rainfall rates, etc...)
2. Compare previous NWP predictions to the actual evolution of rainfall in radar images
3. Train a machine learning model to predict future radar observations based on the latest radar data and NWP predictions!

Problem formulation

$$\underbrace{R(\mathbf{x}, t+\tau)}_{\text{Future rainfall}} = \underbrace{\hat{R}_t^{\mathrm{Lag}}(\mathbf{x}, t+\tau)}_{\text{Lagrangian forecast}} + \underbrace{f(\mathbf{x}, t+\tau, \Theta_t)}_{\text{Prediction error}} + \underbrace{\varepsilon(\mathbf{x}, t+\tau)}_{\text{Irreducible error}} \quad (1)$$

where $f(\mathbf{x}, t+\tau, \Theta)$ is a function for predicting deviations from Lagrangian persistence at location $x \in \mathbb{R}^2$ and lead time τ

$\Theta_t =$ all features extracted from radar and NWP data until time t.

We can use machine-learning to approximate f by training on past observations and NWP predictions.

$$\underbrace{\hat{R}(\mathbf{x}, t+\tau)}_{\text{Prediction}} = \underbrace{\hat{R}_t^{\mathrm{Lag}}(\mathbf{x}, t+\tau)}_{\text{Lagrangian forecast}} + \underbrace{\hat{f}(\mathbf{x}, t+\tau, \Theta_t)}_{\text{Predicted error}} \quad (2)$$

Feasibility study for the Netherlands

+2 hours lead times
24 events from February to September 2020

Radar data: KNMI radar nowcasts (no bias adjustment)
NWP model: HARMONIE-AROME cy40 (surface parameters only)

Model	Radar	HARMONIE
Resolution	1 km	2.5 km
Update time	5 min	6 hours

Features Θ:
- Wind speed & direction
- Pressure, temperature
- Relative humidity
- Cloud cover
- Rain rate (HARMONIE)
- Rain rate (Radar)
- Lagrangian forecast

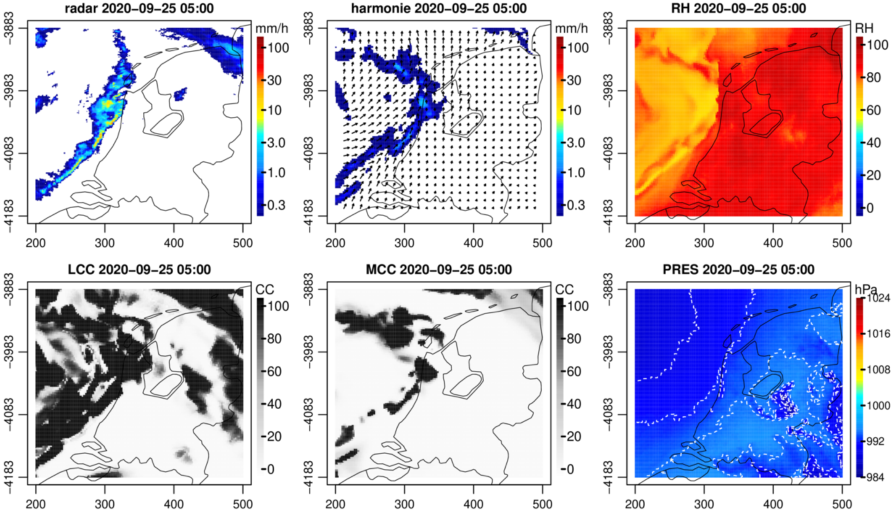
Considered models:
1) HARMONIE only
2) Radar only (Lagrangian)
3) Blended (radar + HARMONIE)
4) Adjusted forecast (Random forest)

Validation is performed using the radar observations as the reference.

Example 1

September 25-26, 2020

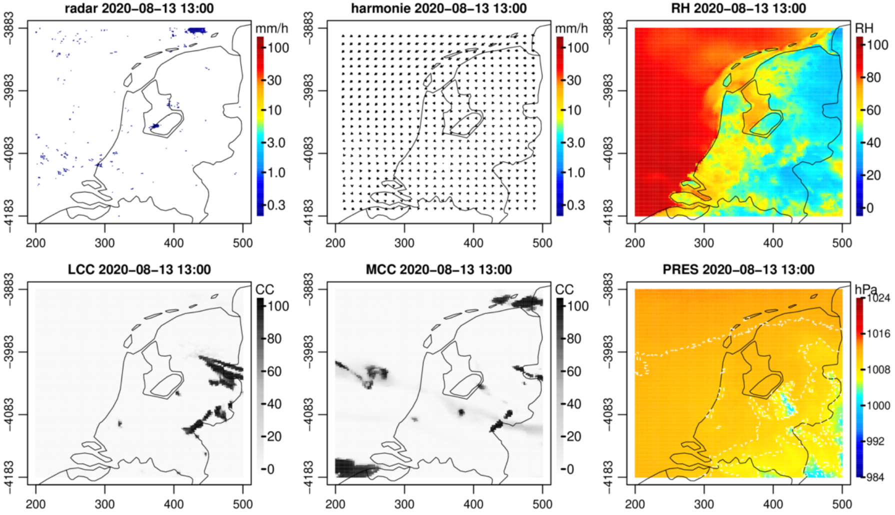
Low pressure system with strong winds, lots of rain and strong forcing



Example 2

August 13-14, 2020

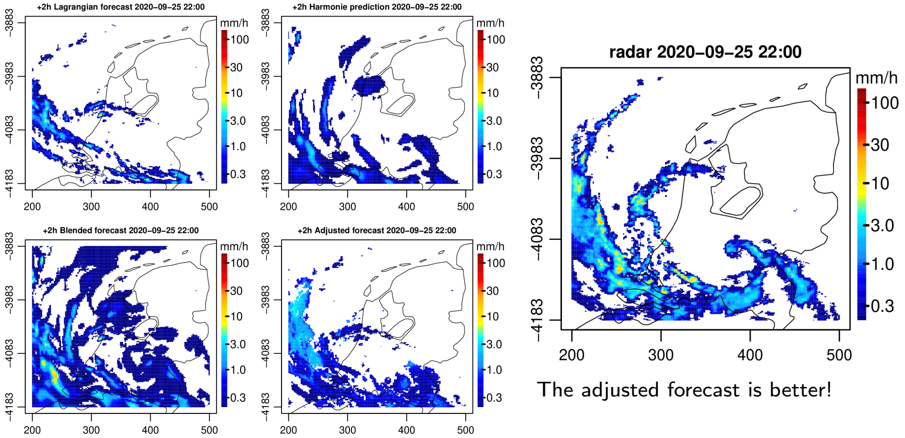
Strong localized evening thunderstorms, weak forcing



Results - Event 1

Model	FSS	RMSE	CC	B
Lagrangian	0.43	1.07	0.11	-0.05
Harmonie	0.45	0.88	0.11	-0.12
Blended	0.47	1.14	0.12	0.06
Adjusted	0.55	0.88	0.23	0.00

The table on the left shows the performance metrics for the entire event

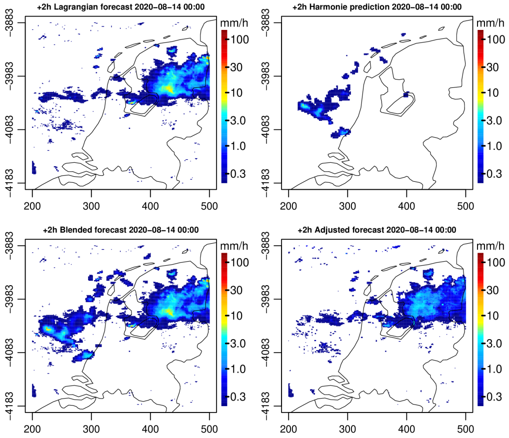


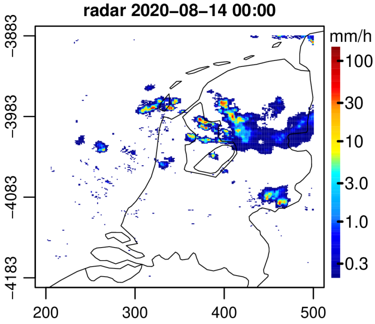
The adjusted forecast is better!

Results - Event 2

Model	FSS	RMSE	CC	B
Lagrangian	0.44	2.30	0.04	0.01
Harmonie	0.20	1.64	0.00	-0.11
Blended	0.40	2.55	0.03	0.11
Adjusted	0.46	1.80	0.10	0.00

The table on the left shows the performance metrics for the entire event





The adjusted forecast is worse...

Main challenge: dealing with conflicting information

Radar and NWP information can be
a) complementary
b) redundant
c) contradictory

"The hard part is to determine when/where to trust the radar and NWP predictions and how to best exploit the information they provide"

Possible solutions:
- Use a series of stacked models (e.g., decision tree followed by neural network)
- Use fixed thresholds (e.g., only adjust when NWP has enough skill)
- Keep track of previous performance and learn from mistakes

Overall performance

+2 hours lead times ; 24 events from February to September 2020

Model	Radar	Adjusted	Difference
Fraction skill score (FSS)	0.53	0.62	+ 17 %
Root mean square error (RMSE)	0.38	0.32	- 16%
Correlation coefficient (CC)	0.17	0.31	+82%

We see clear improvements compared with radar nowcasts!

Note: These results were obtained using simple models and surface parameters only. There is still lots of room for improvement!

Conclusions and outlook

FORESIGHT = adjust radar nowcasts based on information about future storm dynamics from NWPs.

"By linking physical forecasts with radar observations, we aim to teach computers to develop an intuitive understanding of storm dynamics"

Advantages:
- Faster than data assimilation
- High spatial resolution
- High update frequency

Challenges:
- Conflicting information
- Large performance fluctuations
- Prediction uncertainty?

There's many different ways to approach this problem!
Please ask a question or share your thoughts with me!
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