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Towards thunderstorm nowcasting by applying machine learning to a multi-sensor observation and NWP model database

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Motivation

Severe convective systems can lead to hail, heavy rain, gale-force wind gusts, lightning, and flash floods. Hence, forecasting them accurately is crucial. But numerical weather prediction models face difficulties in predicting the exact position and strength of these systems. As a consequence, thunderstorm nowcasting in the first few hours is mostly based on current observations. Today's nowcasting systems primarily rely on a series of threshold tests. We plan to additionally exploit the potential of machine learning techniques to automatically extract information on the typical development of thunderstorms from a multi-sensor database and thus further improve the very short-term forecasts.

Satellite-based rainfall retrival

Methodology

Data

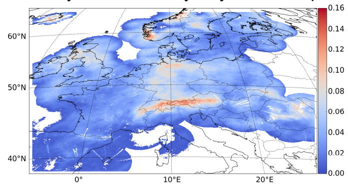
- June - August 2017: Training (800 time slots), validation (400), and test set (400)

Input Features

- MSG SEVIRI IR channels + differences
- NWCSAF products
- Local solar time, coordinates, topography, land-sea mask, satellite viewing geometry

Ground Truth

- Quality-controlled Odyssey radar composite rain rates



Fraction of time during which radar product is available and rain rate >= 0.3 mm h^{-1}

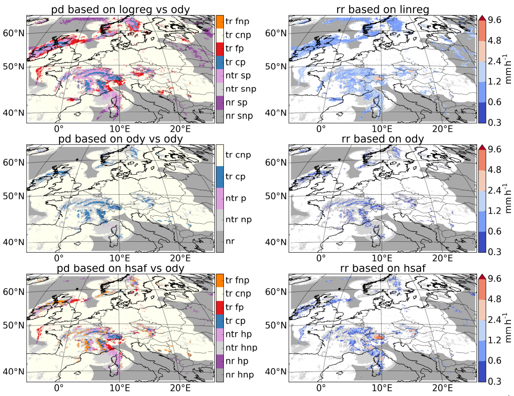
Model

- Precip detection: logistic regression (logreg), SVM
- Rain rate: linear regression (+ probability matching)

Performance compared to

- HSAF precip product

Case study: 12 UTC 09 July 2017



Precip detection

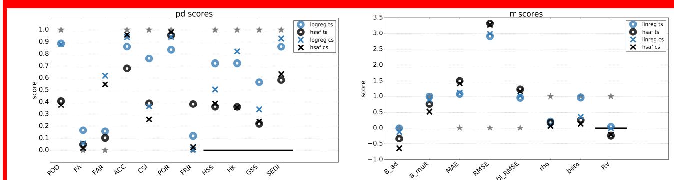
- Logreg: hardly any misses, many false alarms
- HSAF: more misses, fewer false alarms

Rain rate

- Linreg: mostly predict low values close to mean
- HSAF: overestimation over large areas
- Both: fine-scale structure of radar is not captured

***Left**: precip detection; **Right**: rain rate on the predicted precip region in mm h^{-1};*
***Legend**: nr: no radar, ntr: not trusted radar, tr: trusted radar, p: precip, np: no precip, snp/hnp: satellite / hsaf predicted no precip, sp/hp: satellite / hsaf predicted precip, cp: correct predicted precip, fp: false predicted precip, cnp (ivory): correct predicted NO precip, fnp: false predicted NO precip*

Verification



*Scores for the test set (ts) and the case study above (cs); **Left**: precip detection, circles = 0.8 mio random cloudy pixels (balanced) scores; **Right**: rain rate retrieval, circles = 0.4 mio random rainy pixels scores; **Both**: crosses = case study scores, stars = optimal scores, black horizontal line = 0 skill line*

POD = Probability of Detection, FA = False Alarm Rate, FAR = False Alarm Ratio, ACC = Accuracy, CSI = Threat Score, POR = Probability of Rejection, FRR= False Rejection Ratio, HSS = Heidke Skill Score, HK = Hanssen-Kuipers Discriminant, GSS = Gilbert Skill Score, SEDI = Symmetric Extremal Dependence Index
B_ad = Additive Bias, B_mult = Multiplicative Bias, MAE = Mean Absolute Error, RMSE = Root Mean Squared Error, debi_RMSE = Debiased Root Mean Squared Error, rho = Linear Correlation Coefficient, beta = Linear Regression Slope, RV = Reduction of Variance

- High case-to-case variability in performance of the algorithm
- Many scores strongly dependent on test set distribution -> which one to optimize?

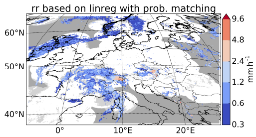
Conclusions

Precip detection

- Very satisfactory results with logistic regression
- SVM slightly inferior performance + much larger computational time (not shown)

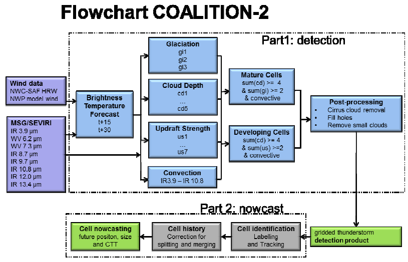
Rain rate

- Difficult task
- Ground truth from different instrument
- Instantaneous rain rates highly skewed
- Predictions close to mean favored: prob. matching?



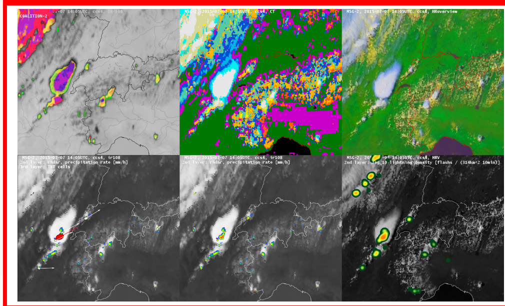
Thunderstorm nowcasting

COALITION-2 algorithm



Threshold test for «convective initiation»	Category
WV6.2µm – IR10.8µm	Cloud depth
WV6.2µm – WV7.3µm	Cloud depth
IR10.8µm	Cloud depth
WV7.3µm – IR13.4µm	Cloud depth
IR6.2µm – IR9.7µm	Cloud depth
IR8.7µm + IR12.0µm – 2xIR10.8µm	Glaciation indicator
IR8.7µm – IR10.8µm	Glaciation indicator
IR12.0µm – IR10.8µm	Glaciation indicator
d(WV6.2µm – WV7.3µm) / 30min	Updraft strength
d(IR10.8µm) / 15min	Updraft strength
d(IR10.8µm) / 30min	Updraft strength
d(WV6.2µm – WV7.3µm) / 15min	Updraft strength
d(IR9.7µm – IR13.4µm) / 30min	Updraft strength
d(WV6.2µm – IR10.8µm) / 30min	Updraft strength
d(WV6.2µm – IR12.0µm) / 15min	Updraft strength
IR3.9µm – IR10.8µm	Small ice crystals

COALITION-2 product suit

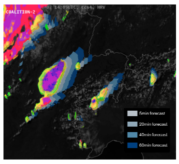


Available Products

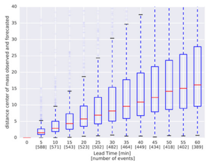
From upper left to lower right:

- COALITION-2
- NWCSAF cloud type
- High resolution overview
- TRT cell rank
- Precip rate
- Lightning rate

Nowcasting of thunderstorm position and properties



Cell-based thunderstorm nowcast applying Lagrangian persistence + linear extrapolation of the area trend for various lead times

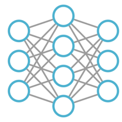


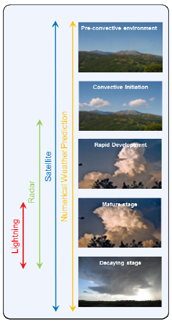
Verification of the forecasted cell position for cells with a history > 30 min for various lead times against the observed position with the error in km

Outlook

Rainfall retrieval

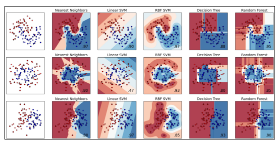
- Test potential of Artificial Neural Networks (+ possibly other machine learning algorithms) for rainfall retrieval

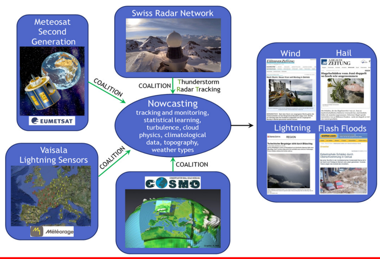




Thunderstorm nowcasting

- Create thunderstorm data set in Lagrangian coordinates with variables used so far + include radar, NWP, and lightning information
- Employ machine learning methods to nowcast thunderstorm evolution
- Develop real-time, multi-sensor, seamless, quantitative, end-to-end, localized, robust, and customer-oriented products





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