An observation operator for geostationary lightning imager data assimilation in storm-scale numerical weather prediction systems

Pauline COMBARNOUS[1,3] Felix ERDMANN[2] Olivier CAUMONT[1] Eric DEFER[3]

[1]CNRM, Université de Toulouse, Météo-France, CNRS, Toulouse, France

[2]Royal Meteorological Institute of Belgium, Brussels, Belgium

[3]LAERO, Université de Toulouse, UT3, CNRS, IRD, Toulouse, France

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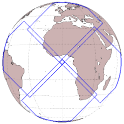
Motivations

- Improve the prediction accuracy of deep convection
- Launch of Meteosat Third Generation (MTG) satellite in 2022 with the lightning imager (LI) onboard
- Assimilation of total lightning data in the French storm-scale regional AROME NWP system
  - Synthetic MTG-LI data (*Erdmann et al., in revision for JTECH*)
  - A lightning observation operator is required to convert the model variables into a product comparable to the observations

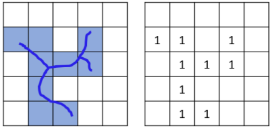
Outline

(Synthetic) MTG-LI observations

- The MTG satellite: continuous observations over Europe, the Mediterranean Sea, The Atlantic Ocean and a small part of South America
- Spatial resolution of a few kilometers
- Gridded product of the count of flashes passing in a grid cell over a certain accumulation period (flash extent accumulation, FEA)

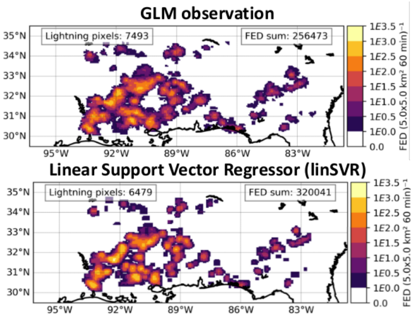


LI coverage



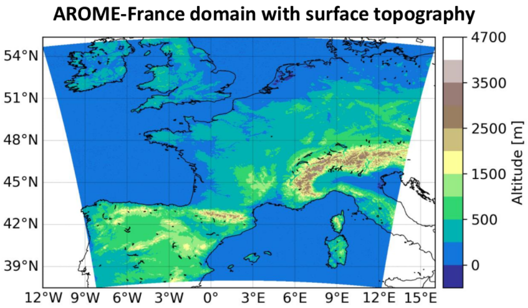
FEA exemple

- Synthetic MTG-LI observations generated from the Meteorage ground-based lightning detection system (*Erdmann et al., in revision for JTECH*)
- Machine learning algorithm of the lightning generator trained with the US NLDN and GLM



AROME-France

- 1 hour forecasts
- 90 vertical layers
- Deep convection resolved
- Microphysical scheme ICE3
  - cloud water
  - Rain
  - Ice crystals
  - Snow
  - Graupel and hail
- 27 stormy days of 2018



Proxies

- Integral of graupel mass above −5 °C (*Deierling and Petersen, 2008*) in kg
- Ice Water Path (IWP, *Petersen et al., 2005*): precipitating ice mass for levels above −10 °C, in kg m^{-2}
- F2 (*McCaul et al., 2009*): columnar mass of graupel, snow, and ice, in kg m^{-2}
- Rimed particle column (*Figueras i Ventura et al., 2019*): thickness of predominating graupel, in m
- Lightning potential index (LPI, *Yair et al., 2010*) measures charge separation potential, in J kg^{-1}
- F1 (*McCaul et al., 2009*): graupel vertical flux at −15°C, in m s^{-1}
- w_{max} (*Price and Rind, 1992*): maximum vertical speed, in m s^{-1}
- Updraft volume (*Deierling and Petersen, 2008*), i.e., where $w > 2.5$ m s^{-1} and $t <$ −5 °C, in m^3

Methodology - Regression

- Dataset split into training (25 days) and validation (2 days)
- Proxies projected on the FEA grid (7x7km)
- Data processed as a sorted distribution over the whole domain (no pixel-to-pixel comparison)
- Machine learning models:
  - Linear regression
  - Linear support vector machine
  - Multilayer perceptron (20 layers)
  - Random forest (20 trees)

Methodology - Evaluation of the regression

- R^2 (coefficient of determination) regression score $R^2 = 1 - \frac{\sum_{i=1}^{n}(FEA_i^o - FEA_i^m)^2}{\sum_{i=1}^{n}(FEA_i^o - \overline{FEA_i^o})^2}$
- Mean absolute error $MAE = \frac{1}{n}\sum_{i=1}^{n}|FEA_i^o - FEA_i^m|$

Where FEA_i^m is the modelled value of the i-th sample and FEA_i^o is the corresponding observed value

Methodology - Fraction skill score

Fraction skill score (*Roberts and Lean, 2008*): a neighborhood verification method

For a given spatial window size (neighborhood), a perfect forecast has the same frequency of events as the observation

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$$FSS = 1 - \frac{\frac{1}{N}\sum_{i=1}^{N}(f_m - f_o)^2}{\frac{1}{N}\sum_{i=1}^{N} f_m^2 + \frac{1}{N}\sum_{i=1}^{N} f_o^2}$$

Where N is the number of windows in the domain,
f_m and f_o are respectively the forecast and observed fractions of the i-th window

Exemple of a perfect FSS:

1	0	1
0	0	1
0	1	0

Observation

0	1	1
1	0	0
0	1	0

Forecast

Methodology - Fraction skill score

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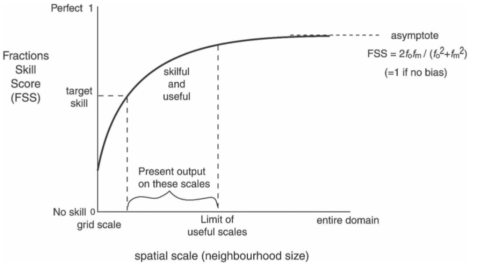
Observation

0	1	1
1	0	0
0	1	0

Forecast

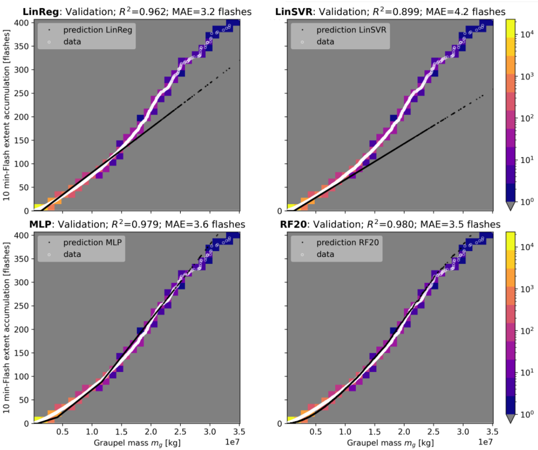
FSS computed for a large range of window sizes

Determination of the scale at which FSS reaches the target skill of $0.5 + \frac{f_o}{2}$

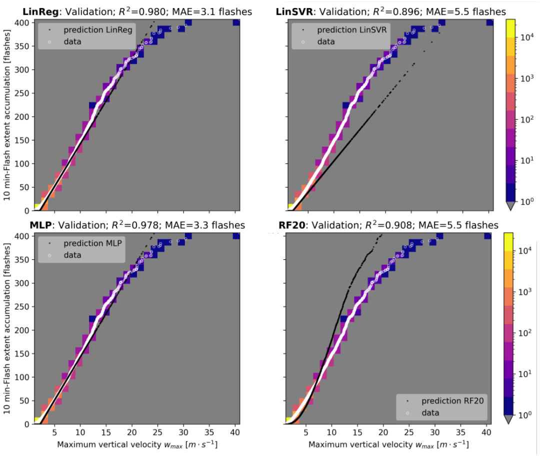


From *Roberts and Lean (2008)*

Results - Regression models



Graupel mass



wmax

LinReg Linear regression; **LinSVR** Linear support vector machine; **MLP** Multilayer perceptron; **RF20** Random forest

Rank-ordered proxies according to their R^2 score for the random forest model for validation (2 stormy days of August):

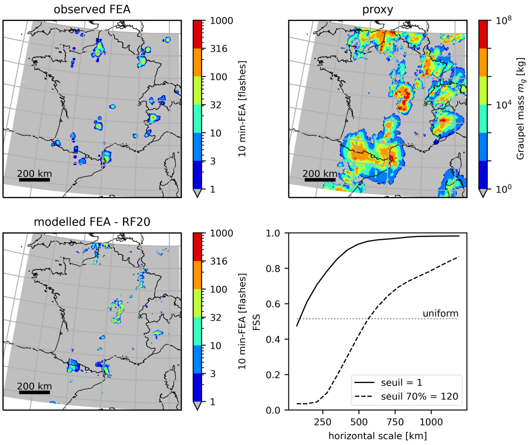
Proxy	R^2	MAE (flashes)
Graupel mass	0.980	3.5
IWP	0.974	3.3
F2	0.967	4.3
Rimed particle column	0.958	4.8
wmax	0.908	5.5
Updraft volume	0.888	7.0
LPI	0.846	7.3
F1	0.842	7.7

Grey: microphysics-based proxies

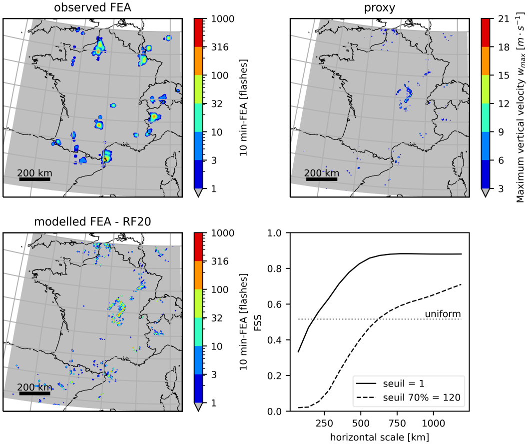
White: velocity-based proxies

The microphysics-based proxies yield higher R^2 scores and lower MAEs than the velocity-based proxies.

Modelled FEA vs observations for a typical 1h forecast (19:00 UTC on 2018.08.07):



Graupel mass



wmax

Velocity-based modelled FEA is more scattered whereas microphysics-based modelled FEA has a better spatial distribution

Conclusions and perspectives

Conclusions:

- Microphysics-based proxies perform better than velocity-based proxies for the representative database used here
- For a given proxy the main differences brought by the different regression models lie in the amplitude of simulated FEA
- Metrics on simulated distributions not sufficient: need to study the FSS on simulated FEA fields

Perspectives:

- Investigate sensitivity to the accumulation period (currently 10 min)
- Investigate multivariate regression models
- Rank the most explanatory proxies