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

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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
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**Outline**

1. Data
2. Methodology
3. Results
4. Conclusions and perspectives
(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)

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 $-5^\circ C$ (*Deierling and Petersen, 2008*) in kg
- **Ice Water Path** (IWP, *Petersen et al., 2005*): precipitating ice mass for levels above $-10^\circ C$, 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 $-15^\circ C$, 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 $t < -5^\circ C$, 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)
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Methodology - Evaluation of the regression

$R^2$ (coefficient of determination) regression score $R^2 = 1 - \frac{\sum_{i=1}^{n} (FEA_i^o - FEA_i^m)^2}{\sum_{i=1}^{n} (FEA_i^o - \bar{FEA}_i^o)^2}$

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.
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

\[
FSS = 1 - \frac{1}{N} \sum_{i=1}^{N} (f_m - f_o)^2 \left( \frac{1}{N} \sum_{i=1}^{N} f_m^2 + \frac{1}{N} \sum_{i=1}^{N} f_o^2 \right)
\]

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:

<table>
<thead>
<tr>
<th></th>
<th>0</th>
<th>1</th>
<th>0</th>
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</thead>
<tbody>
<tr>
<td>0</td>
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Observation

<table>
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<tr>
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<th>1</th>
<th>1</th>
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<tbody>
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<td>1</td>
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<td>0</td>
<td>1</td>
<td>0</td>
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</tbody>
</table>

Forecast
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

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

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:

<table>
<thead>
<tr>
<th>Observation</th>
<th>Forecast</th>
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<tbody>
<tr>
<td>1 0 1</td>
<td>0 1 1</td>
</tr>
<tr>
<td>0 0 1</td>
<td>1 0 0</td>
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<tr>
<td>0 1 0</td>
<td>0 1 0</td>
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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

**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):

<table>
<thead>
<tr>
<th>Proxy</th>
<th>$R^2$</th>
<th>MAE (flashes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graupel mass</td>
<td>0.980</td>
<td>3.5</td>
</tr>
<tr>
<td>IWP</td>
<td>0.974</td>
<td>3.3</td>
</tr>
<tr>
<td>F2</td>
<td>0.967</td>
<td>4.3</td>
</tr>
<tr>
<td>Rimed particle column</td>
<td>0.958</td>
<td>4.8</td>
</tr>
<tr>
<td>wmax</td>
<td>0.908</td>
<td>5.5</td>
</tr>
<tr>
<td>Updraft volume</td>
<td>0.888</td>
<td>7.0</td>
</tr>
<tr>
<td>LPI</td>
<td>0.846</td>
<td>7.3</td>
</tr>
<tr>
<td>F1</td>
<td>0.842</td>
<td>7.7</td>
</tr>
</tbody>
</table>

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

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

wmax

Maximum vertical velocity $w_{max}$ [m s$^{-1}$]
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