Toward an ARPEGE-based aviation turbulence combined diagnosis

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Phoenix - ARAM 19th conference - 2019
Aviation turbulence forecasting at Météo-France

Interactions with French en-route air traffic control

SIGMETs for French territories including French Antilles, Polynesia,..

French and European SIGWX charts (3H freq)

Arpege Météo-France

Severity maps, contours

Individual aviation turbulence diagnoses

T, Wind, etc...
Goal: Computation of diagnoses within the ARPEGE model + combination.

- Catch several sources of turbulence
- Final result is $\text{EDR} = \varepsilon^{1/3}$
  - $\varepsilon = \text{Energy Dissipation Rate of eddies.}$
Météo-France & NCAR collaboration

- Use GTG methodology on ARPEGE outputs
- Explore other combination & selection methodologies

**Model:** ARPEGE 0.25° grid with native vertical levels.

**Observations:** 1 year PIREPs and EDR (2017) **above USA.**

**Preliminary results**

**CAT** at upper levels (FL > 200) in US & Europe.
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- Use GTG methodology on ARPEGE outputs

- Explore other combination & selection methodologies
Combining aviation turbulence diagnoses
The GTG methodology – NCAR / RAL

Use of a ~1 year observation database (PIREPs, in-situ EDR)

- Same process for different sources: CAT, MTW, CIT, LLT, at low mid & upper levels
- Final combinations directly computed in operational mode
- Aims to be used by Washington and London WAFC for SIGWx charts production (Kim et al. 2018)

Sharman et al. 2017 - part 1.

Conversion to EDR

Select the best combination
~ 10 diagnoses

Final combination (ensemble mean)

Final diag EDR

~ 70 diagnoses for CAT

NWP model

T, Wind, etc...

Available at
http://aviationweather.gov/adds
1. GTG pre-processing step:
Conversion of individual diagnoses to EDR

Ex: Ellrod turbulence diag climatology – year 2017
ARPEGE - CONUS 0.25°

→ Conversion to EDR by using a *lognormal to lognormal* transformation.

\[ D_{\text{Ellrod}} \rightarrow \text{edr} = e^a D_{\text{Ellrod}}^b \]
1. GTG pre-processing step: Conversion of individual diags to EDR

Distribution fitting for the other diagnoses: Log-log visualization
### 2. GTG feature selection & combination step

- **Selection**: iterative forward selection.
- **Combination**: ensemble mean of **EDR-scaled diagnoses**.
- **Metric**: Area Under ROC Curve score (AUC) for Moderate Or Greater turbulence events (MOG) i.e. EDR> $0.22 \, \text{m}^{2/3} \, \text{s}^{-1}$.

<table>
<thead>
<tr>
<th>ARPEGE 0.25 Combination</th>
<th>Sharman et al. 2017 (GFS 0.25)</th>
<th>Kim et al 2018 (WAFC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>NCSU2/Ri</td>
<td>NCSU2/Ri</td>
<td>NCSU2/Ri</td>
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<tr>
<td>Fth/Ri</td>
<td>Fth/Ri</td>
<td>Fth/Ri</td>
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<td>DEFSQ</td>
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<tr>
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<td>EDRLUN</td>
<td>EDRLUN</td>
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<td>wsq</td>
<td>wsq/Ri</td>
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<td>EDRLL</td>
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<td>RTKE</td>
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<td>DIV</td>
<td>/Ri</td>
</tr>
<tr>
<td>-NVA</td>
<td>Ellrod3</td>
<td>TEMPG/Ri</td>
</tr>
<tr>
<td></td>
<td>iawind</td>
<td>Ellrod3</td>
</tr>
<tr>
<td></td>
<td>PVGRAD</td>
<td>iawind ...</td>
</tr>
</tbody>
</table>
3. Scores – MOG turbulence events – ROC curves

Applying GTG methodology with ARPEGE0.25 calibrated with US observations shows that:
- performance is improved for USA compared to individual diagnoses
- results remain consistent above Europe.
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- Use GTG methodology on ARPEGE 0.25° outputs

- Explore other combination & selection methodologies
Machine learning (ML) algorithms

- **Previous works:** e.g. J.K. Williams et al.
  - Show good results for several ML methods (eg. Random Forests)

- **To handle operational constraints**
  - Restriction of diagnoses number is needed ~ 10 diags
  - Calibration should be “easy” to perform
  - How to convert Machine Learning outputs to EDR?

- **Test of two ML methods which provide selection**
  - Logistic regression LASSO
  - Random Forests with predictor selection
Machine learning (ML) algorithms

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**Test of two ML methods which provide selection**

- Logistic regression LASSO
- Random Forests with predictor selection
1. Logistic LASSO regression

- Logistic LASSO Regression $\rightarrow$ L1 penalization on coefficients

$$\log \left( \frac{p}{1 - p} \right) = \beta_0 + \sum_{j=1}^{m} \beta_j \bar{D}_j \quad \text{Normalized diagnoses } \sim \mathcal{N}(0, 1)$$

$p = \text{probability of MOG event}$

**Property:** Maximization of L1-penalized log likelihood provides variable selection ($\beta_j = 0$)

- Conversion to EDR

$$\frac{p}{1 - p} \sim \log \mathcal{N}(\mu, \sigma) \rightarrow \text{convertible to EDR}$$

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2. Random Forests with selection

- Genuer et al. 2015 – Feature selection with Random Forests based on
  - **Diag importance** in the tree growing process
  - **Out of the bag error (OOB)**

  Diagnoses of similar importance can be correlated … or not.

  Multi-correlations can be identified with OOB error stagnation

- Conversion to EDR

  is \( \frac{p}{1 - p} \) fitting a lognormal distribution?

  Answer seems to be «Yes»
Results

Cross validation: feature selection

<table>
<thead>
<tr>
<th>GTG</th>
<th>LASSO regression</th>
<th>RF with selection</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fwd selection + Ensemble mean</td>
<td>NCSU2/Ri 21</td>
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<td>Fth/Ri 21</td>
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<td>DEFSQ 16</td>
<td>EDRLL 21</td>
<td>F3D/Ri 21</td>
</tr>
<tr>
<td>EDRLL 16</td>
<td>-NVA 21</td>
<td>1/RiTW 20</td>
</tr>
<tr>
<td>Wsq 20</td>
<td>EDR 21</td>
<td>SPEED 20</td>
</tr>
<tr>
<td>+ others</td>
<td>Brown1 21</td>
<td>F2D/Ri 20</td>
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<tr>
<td></td>
<td>SGSTKE/Ri 21</td>
<td></td>
</tr>
<tr>
<td></td>
<td>LAZ 16</td>
<td>Fth/Ri 17</td>
</tr>
<tr>
<td>+ others</td>
<td></td>
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</tr>
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</table>

Yellow: 3 common selections
Pink: 2 common selections

Cross validation: AUC scores - USA
Case-study

30th April 2017 – FL340 – Run 00UTC – Lead time 15UTC

Ellrod1

Ensemble mean

Observations

Time window +/- 30 min

Levels +/- 20 FL

LASSO

Random Forest
Case-study

30th April 2017 – FL340 – Run 00UTC – Lead time 15UTC

Observations

Time window +/- 30 min

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GTG - Ensemble mean

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LASSO regression

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Time window +/- 30 min
Levels +/- 20 FL
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30th April 2017 – FL340 – Run 00UTC – Lead time 15UTC

Random Forest

Observations

Time window
+/- 30 min

Levels
+/- 20 FL
Conclusion

- GTG methodology applied with ARPEGE model:
  - Improvement compared to individual diagnoses
  - Diagnosis selection depends on NWP model (but common selected diagnoses appear)

- LASSO regression and Random Forests methods:
  - can be used to combine diagnoses while providing selection
  - have their output convertible to EDR
  - RF method improves AUC score ↔ more complex to implement
Thank you. Questions?

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