



Toward an ARPEGE-based aviation turbulence combined diagnosis

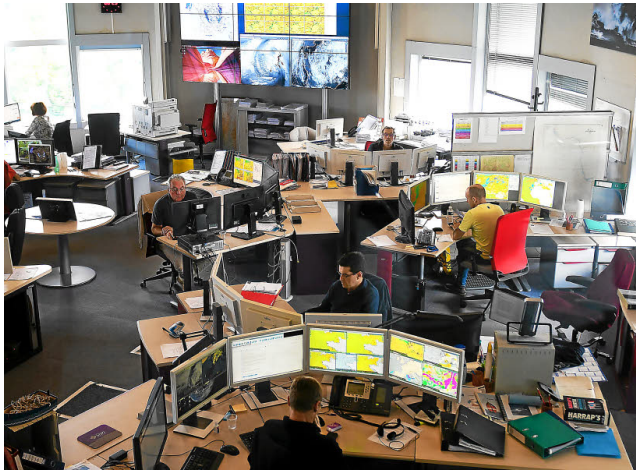
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Météo-France – DSM/AERO, Toulouse, France
NCAR/RAL Boulder, USA

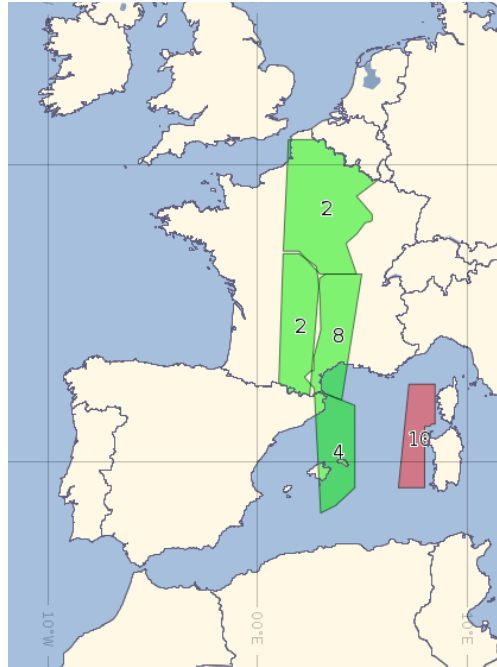
Phoenix - ARAM 19th conference - 2019

Aviation turbulence forecasting at Météo-France

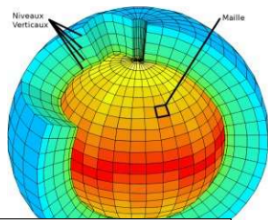
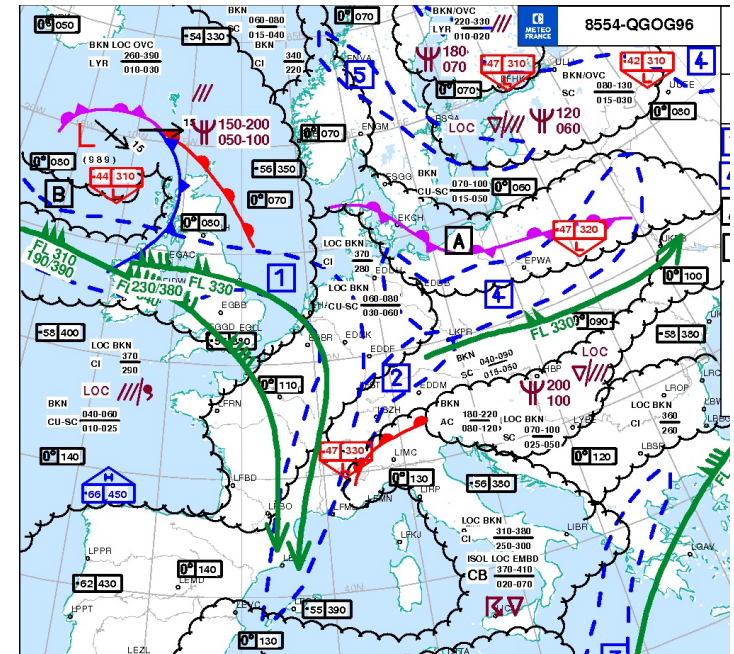
Interactions with French en-route air traffic control



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



French and European **SIGWX** charts (3H freq)

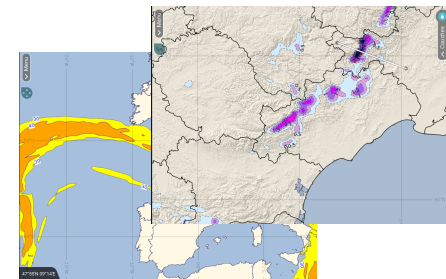


ARPEGE
Météo-France

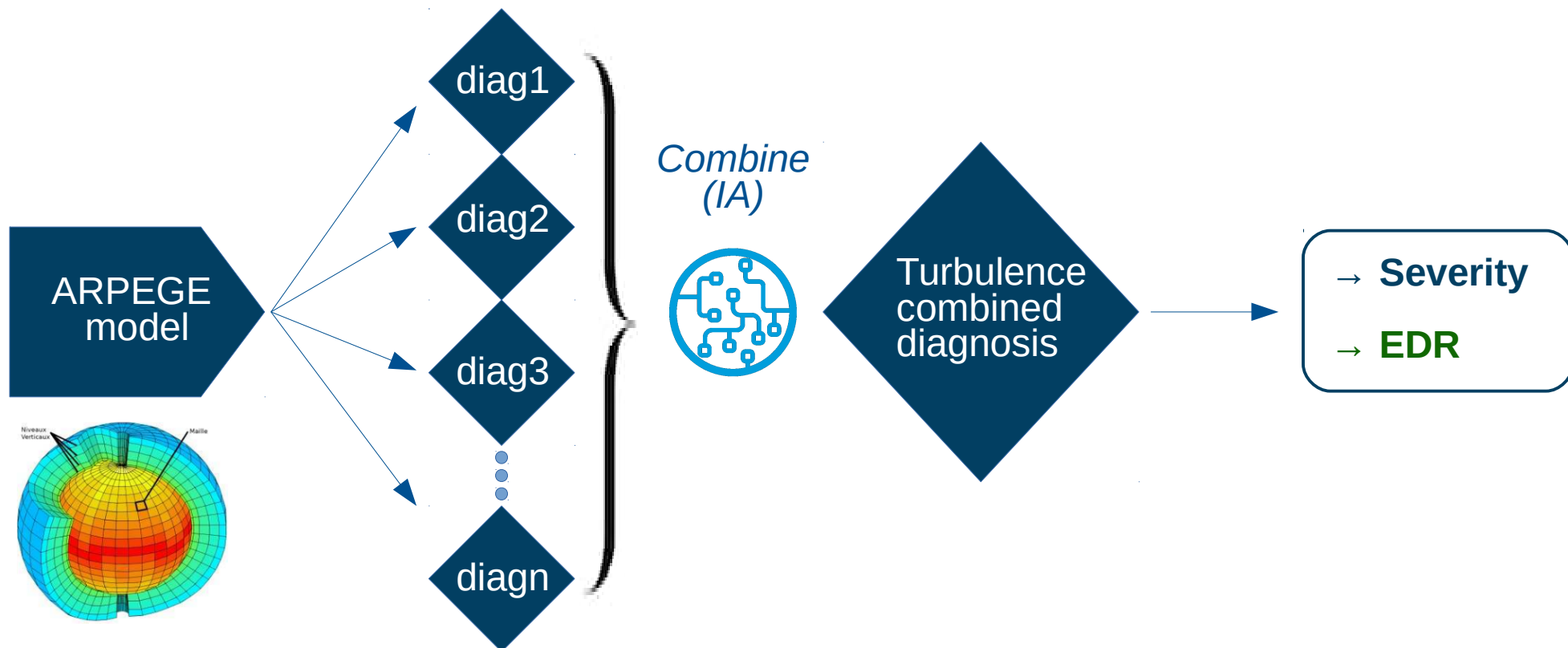
→ T, Wind, etc... →

Individual aviation turbulence diagnoses

Severity maps, contours



Goal: Computation of diagnoses within the ARPEGE model + combination.



- Catch several sources of turbulence
- Final result is $EDR = \epsilon^{1/3}$

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.

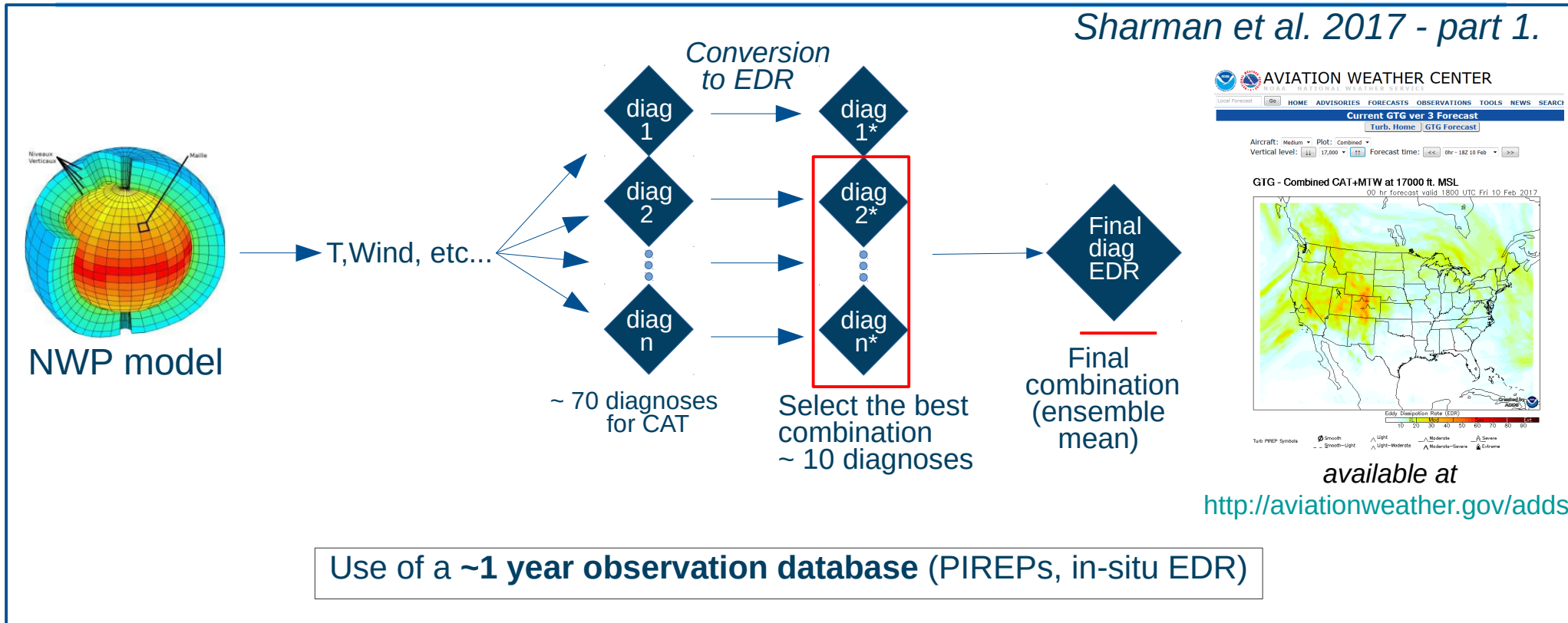
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Combining aviation turbulence diagnoses

The GTG methodology – NCAR / RAL

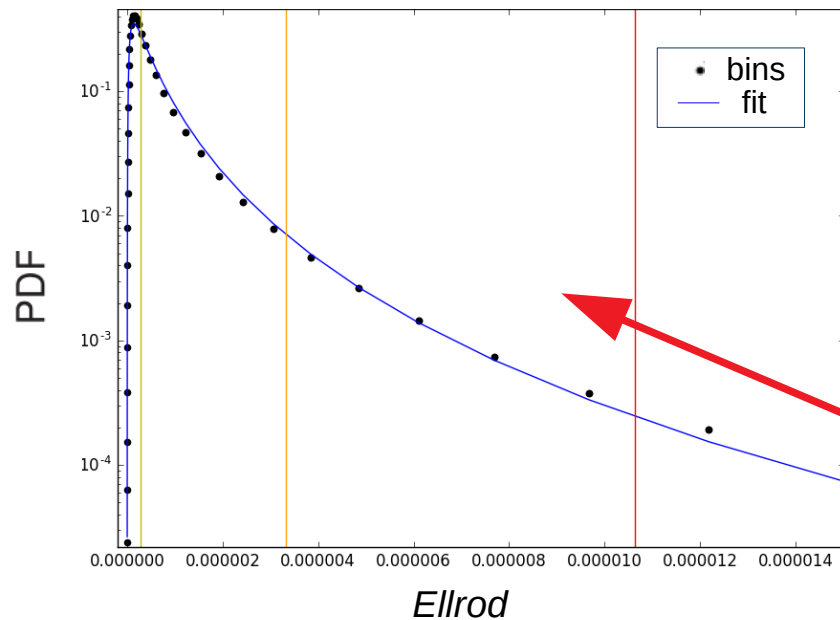
Sharman et al. 2017 - part 1.



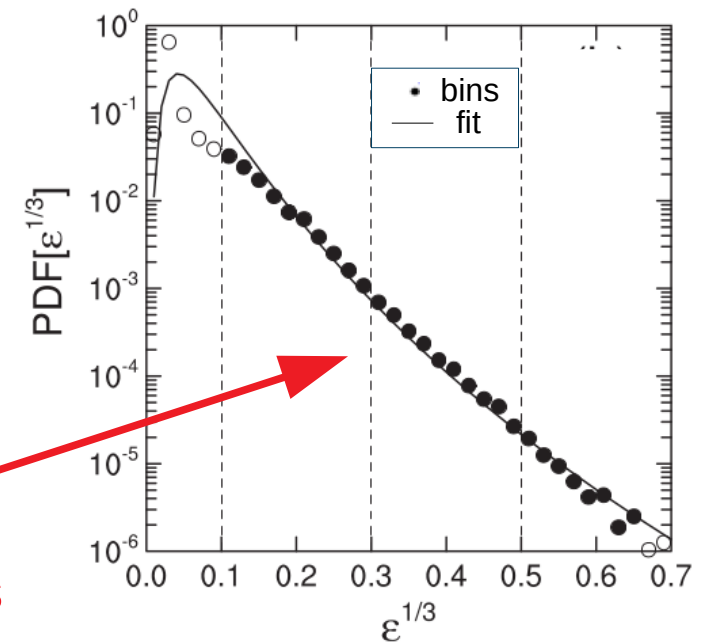
- Same process for different sources: CAT, MTW, CIT, LLT, at low mid & upper levels
- Final combinations directly computed in operational mode
- Aims to be used by Washington and London WAFC for SIGWX charts production (Kim et al. 2018)

1. GTG pre-processing step: Conversion of individual diagnoses to EDR

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



In-situ EDR climatology
Sharman et al. 2014



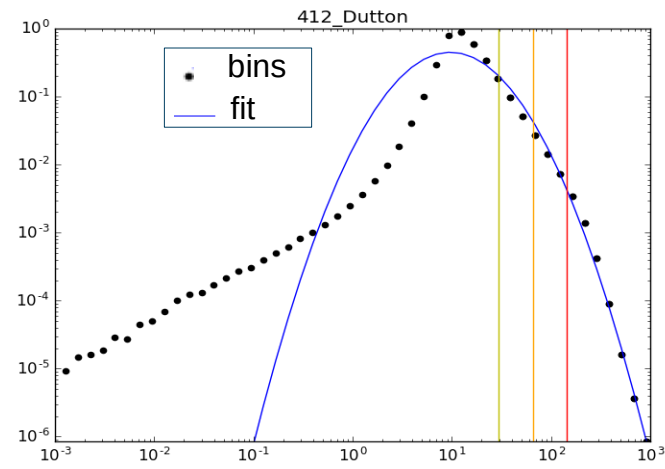
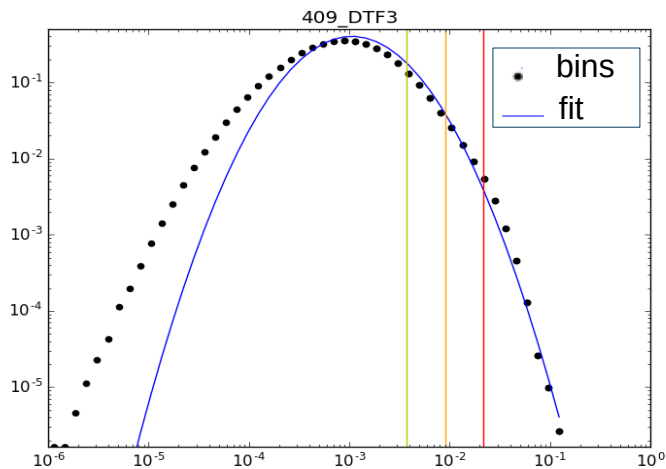
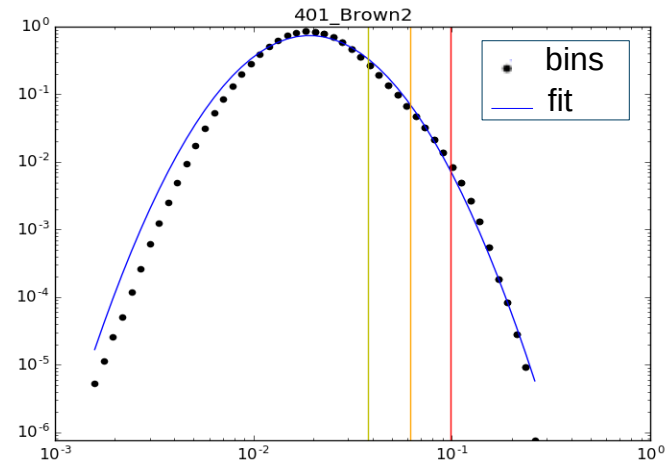
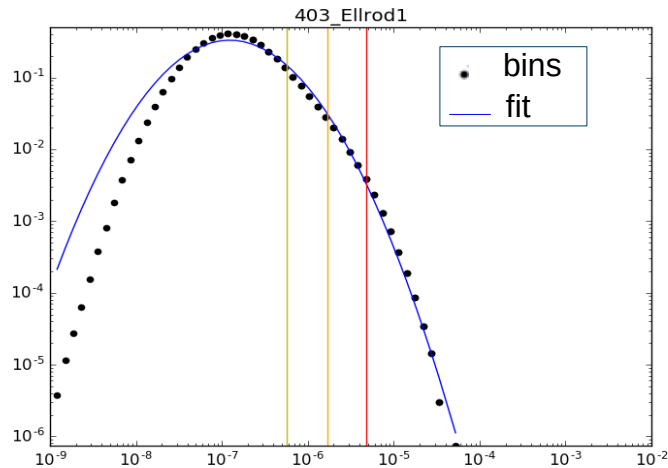
Lognormal
distributions

→ 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 visualisation



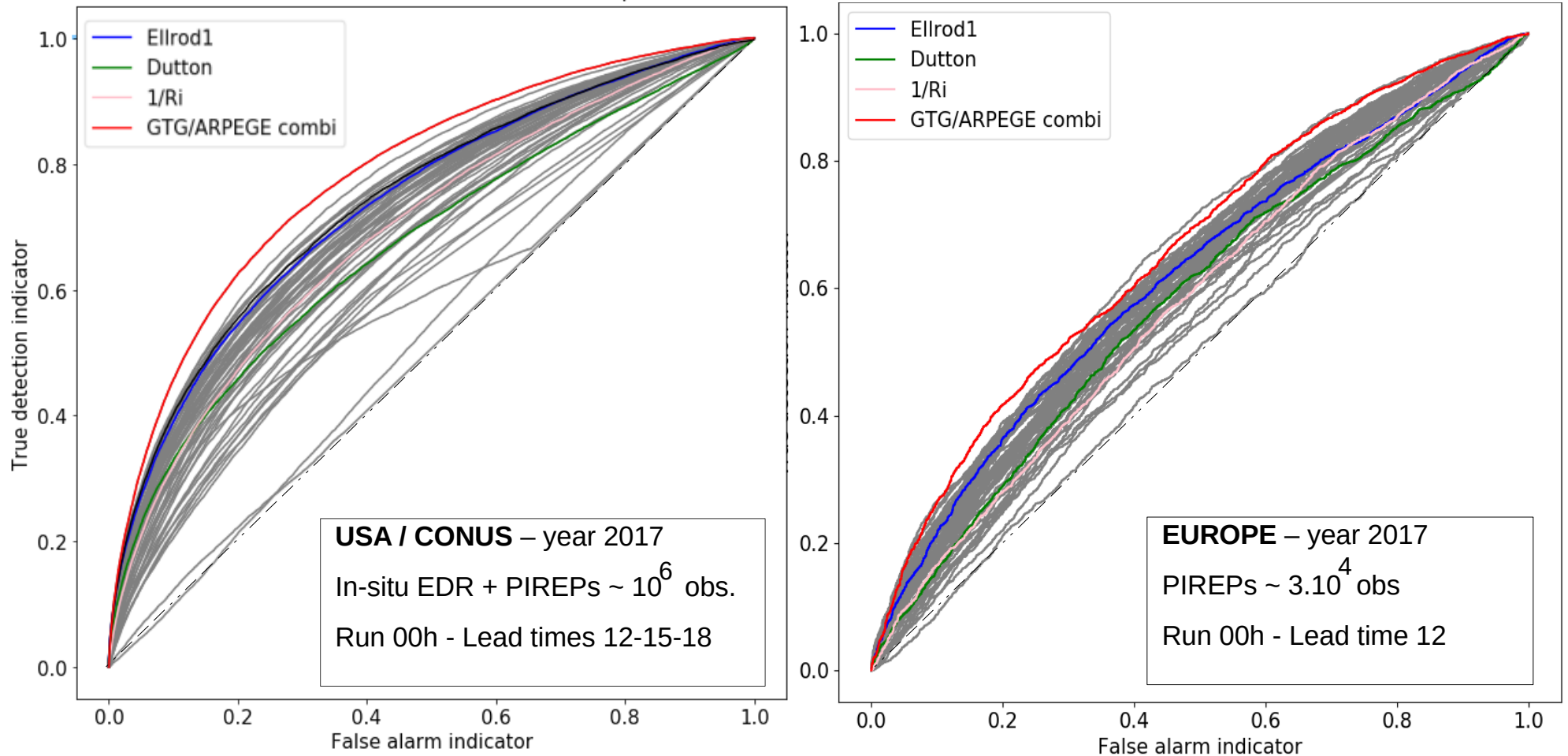
2. GTG feature selection & combination step

- **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. $EDR > 0.22 \text{ m}^{2/3} \text{ s}^{-1}$.

Selection
Selected individual
diags (previously
scaled to EDR).

ARPEGE 0.25 Combination	Sharman et al. 2017 (GFS 0.25)	Kim et al 2018 (WAFC)
NCSU2/Ri	NCSU2/Ri	NCSU2/Ri
Fth/Ri	Fth/Ri	Fth/Ri
DEFSQ	DEFSQ	DEFSQ
EDRLUN	EDRLUN	EDRLUN
wsq	wsq/Ri	wsq/Ri
RTKE	EDRLL	EDRLL
1/RiTW	UBF/Ri	RTKE
DIV /Ri	TEMPG/Ri	UBF/Ri
-NVA	Ellrod3	TEMPG/Ri
	iawind	Ellrod3
	PVGRAD	iawind ...

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.

Météo-France & NCAR collaboration

- 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 → L1 penalization on coefficients

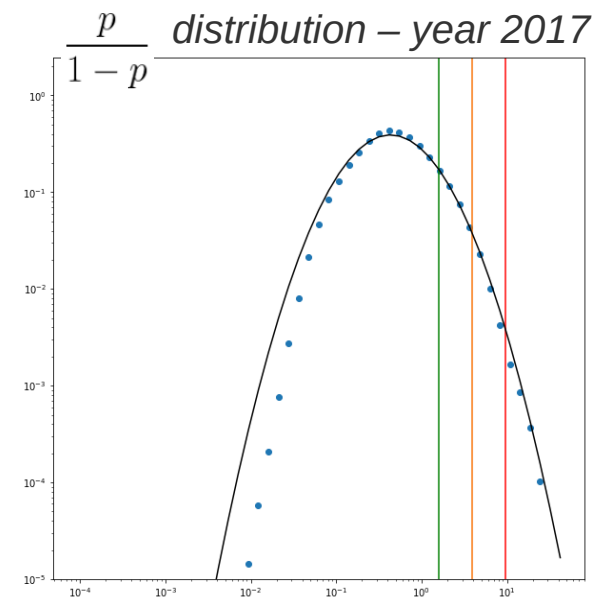
$$\log \left(\frac{p}{1-p} \right) = \beta_0 + \sum_{j=1}^m \beta_j \bar{D}_j \quad \leftarrow \text{Normalized diagnoses } \sim \mathcal{N}(0, 1)$$

p = probability of MOG event

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

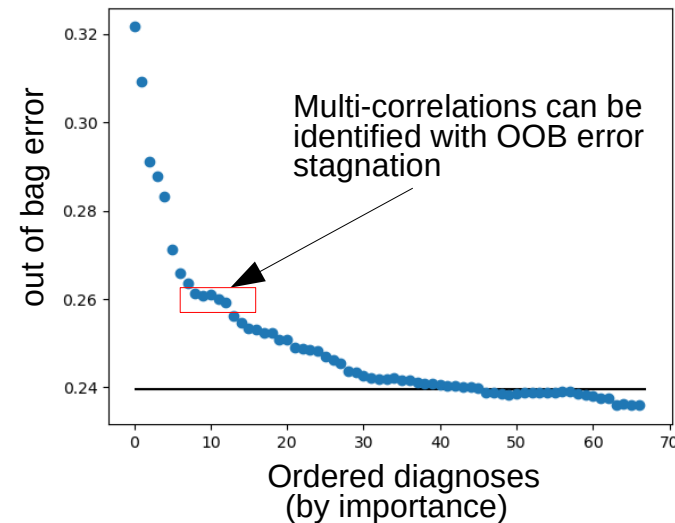
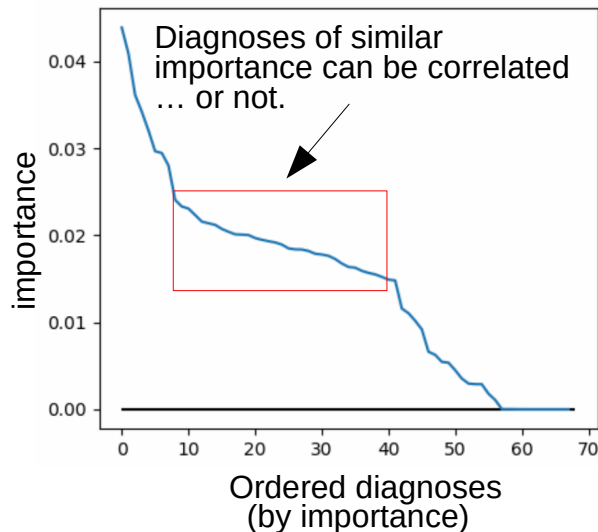
- Conversion to EDR

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



2. Random Forests with selection

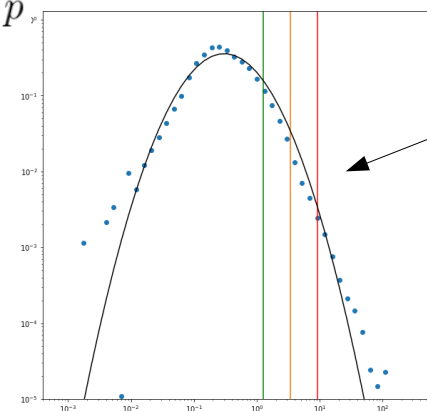
- Genuer et al. 2015 – Feature selection with Random Forests based on
 - ▶ **Diag importance** in the tree growing process
 - ▶ **Out of the bag error (OOB)**



- Conversion to EDR

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

$\frac{p}{1-p}$ distribution – year 2017



Answer seems to be « **Yes** »

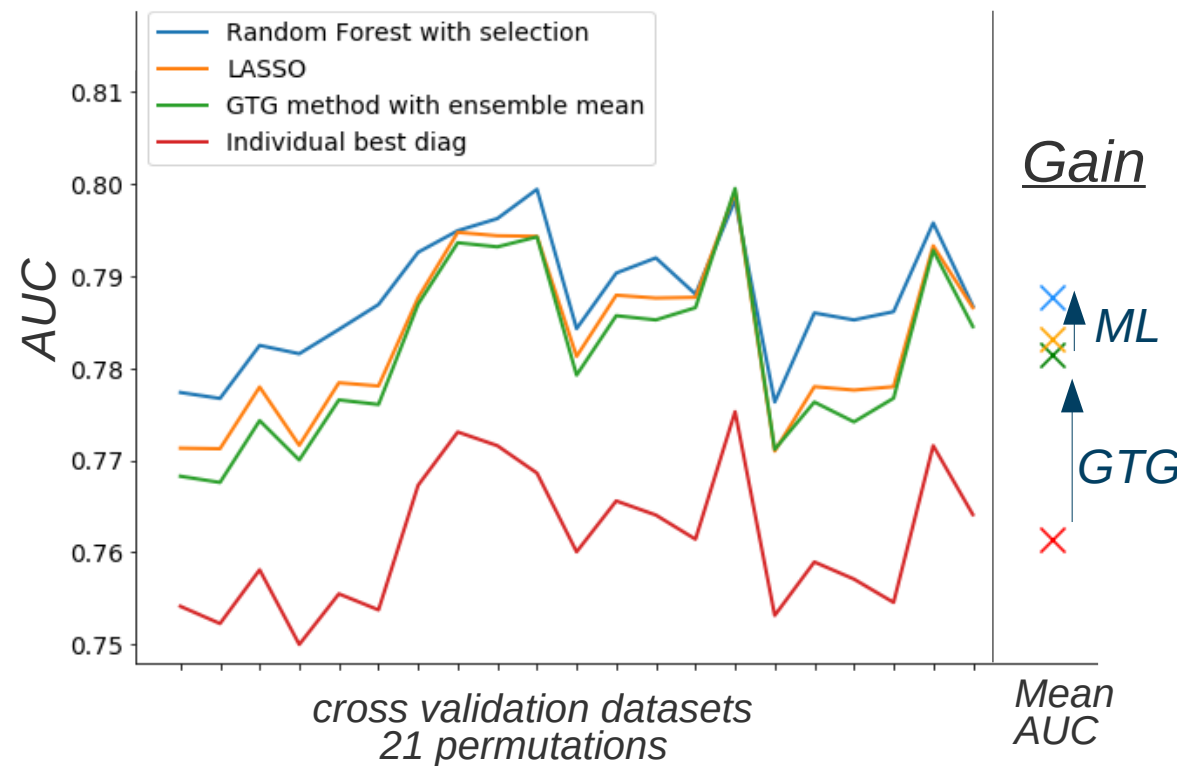
Results

Cross validation: feature selection

GTG Fwd selection + Ensemble mean	LASSO regression	RF with selection
NCSU2/Ri 21	NCSU2/Ri 21	NCSU2/Ri 21
Fth/Ri 21	Fth/Ri 21	RTKE 21
RTKE 21	RTKE 21	DEFSQ/Ri 21
1/RiTW 21	1/RiTW 21	RTKE/Ri 21
DEFSQ 16	EDRLL 21	F3D/Ri 21
EDRLL 16	-NVA 21	1/RiTW 20
Wsq 20	EDR 21	SPEED 20
+ others	Brown1 21	F2D/Ri 20
	SGSTKE/Ri 21	DIV /Ri 17
	LAZ 16	Fth/Ri 17
	+ others	+ others

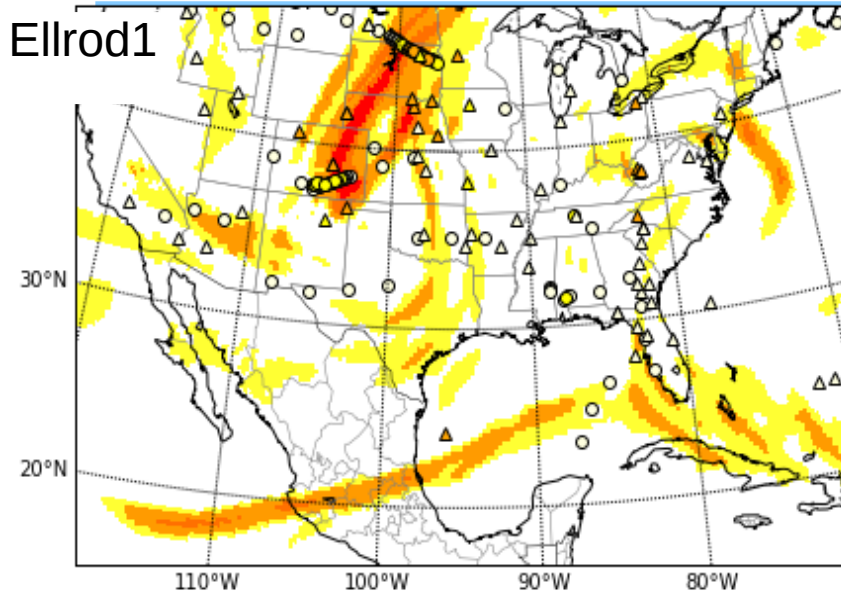
Yellow: 3 common selections
Pink: 2 common selections

Cross validation: AUC scores - USA

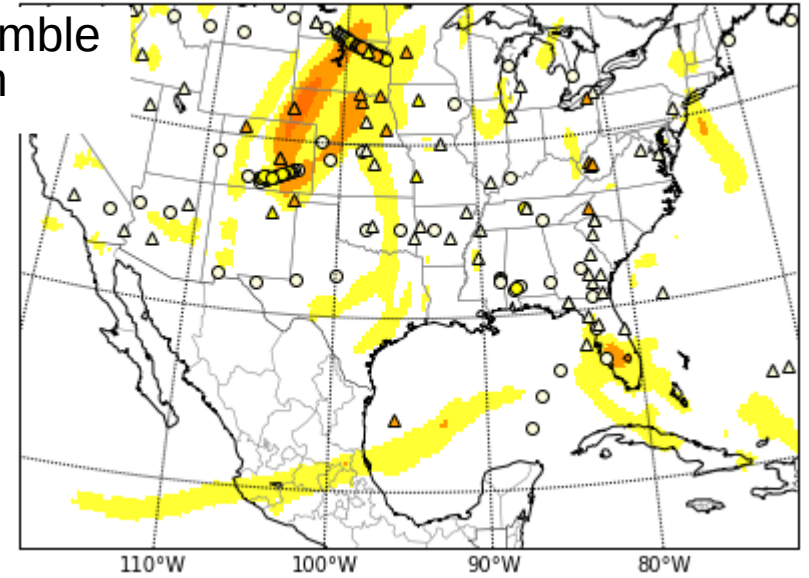


Case-study

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



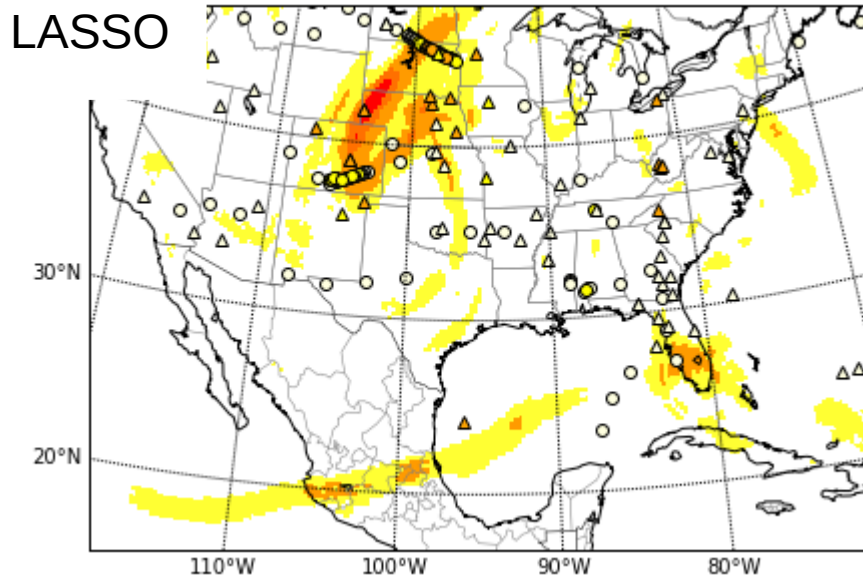
Ensemble mean



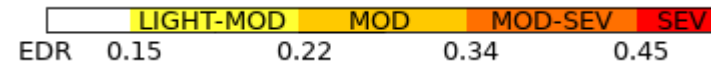
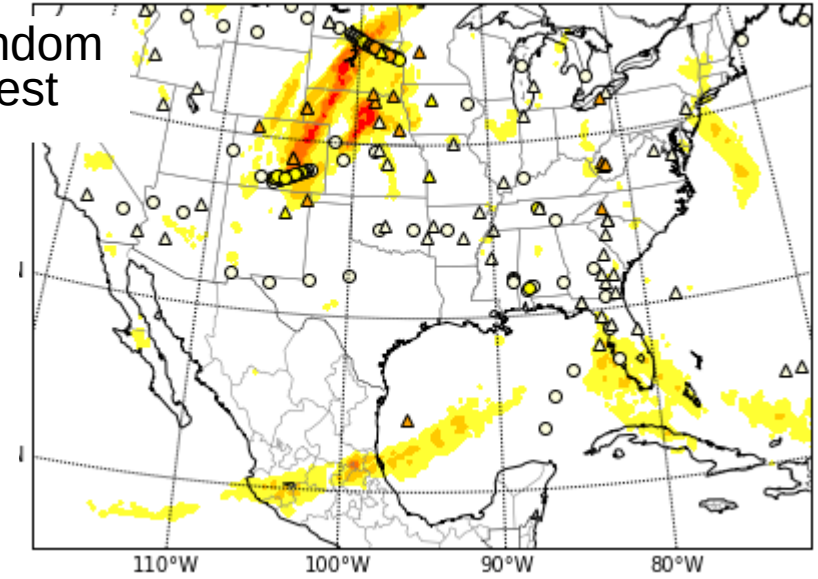
Observations

Time window
+/- 30 min

Levels
+/- 20 FL



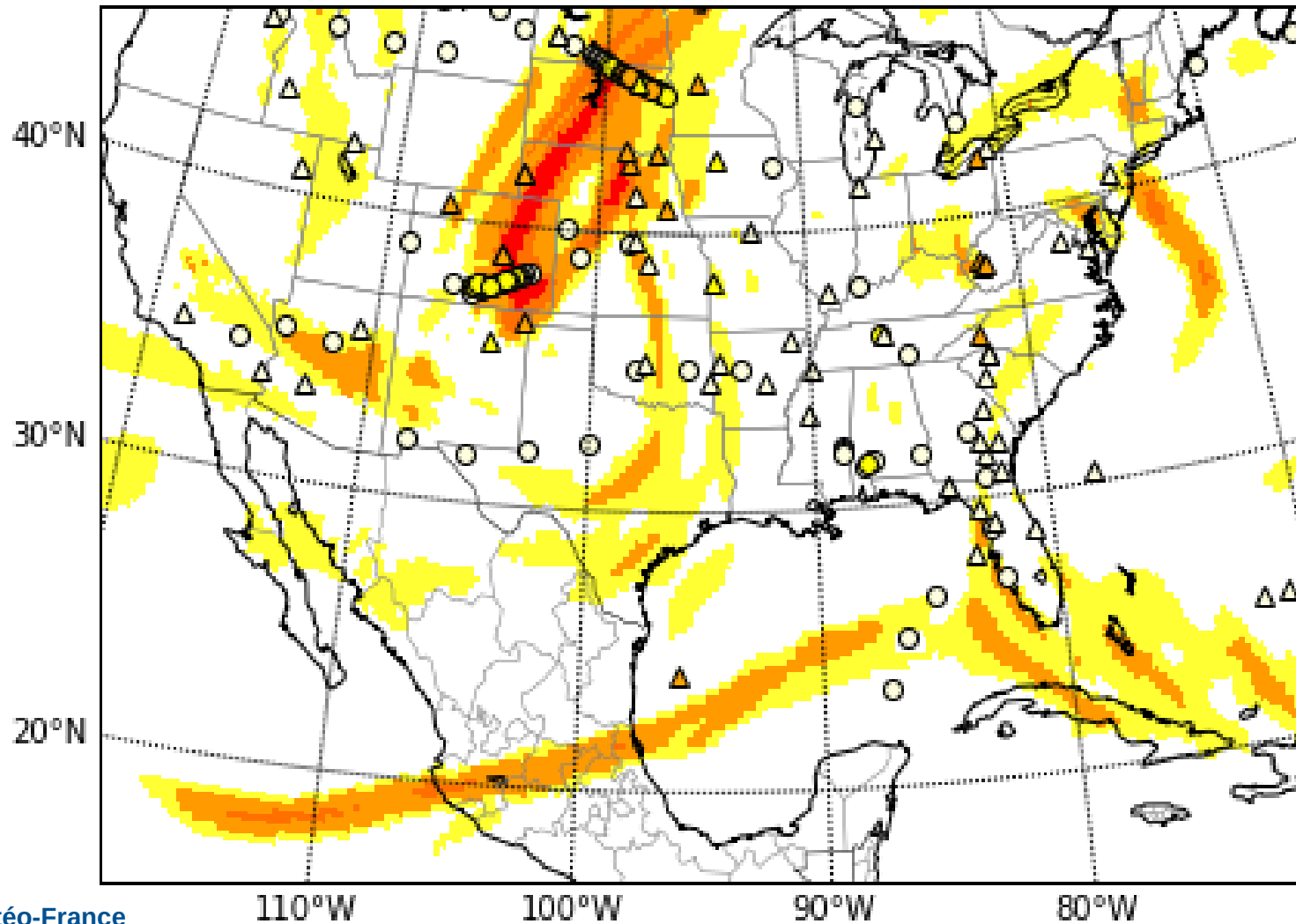
Random Forest



Case-study

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

Ellrod1



Observations

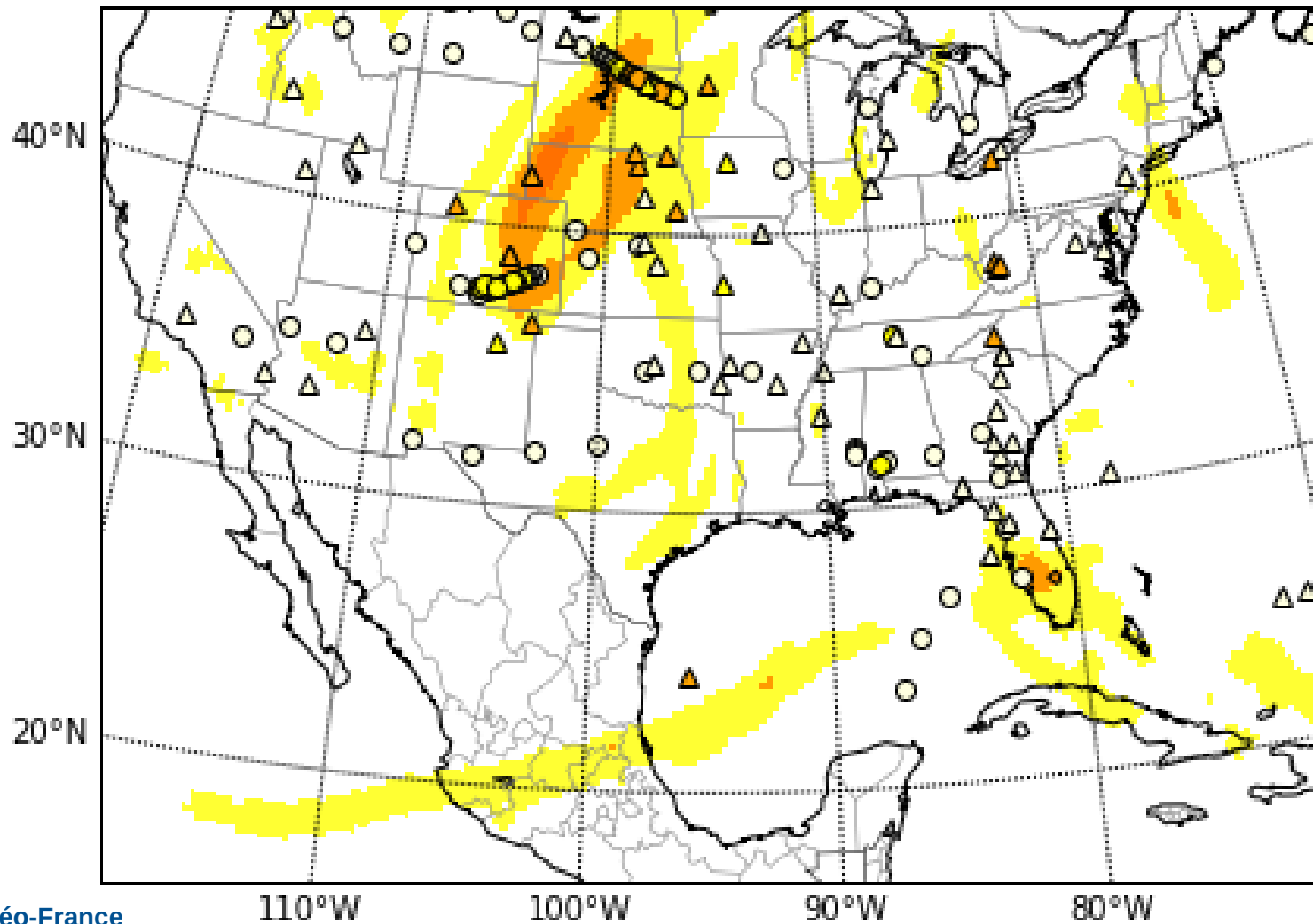
Time window
+/- 30 min

Levels
+/- 20 FL

Case-study

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

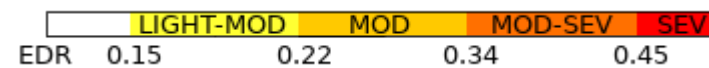
GTG - Ensemble mean



Observations

Time window
+/- 30 min

Levels
+/- 20 FL



Case-study

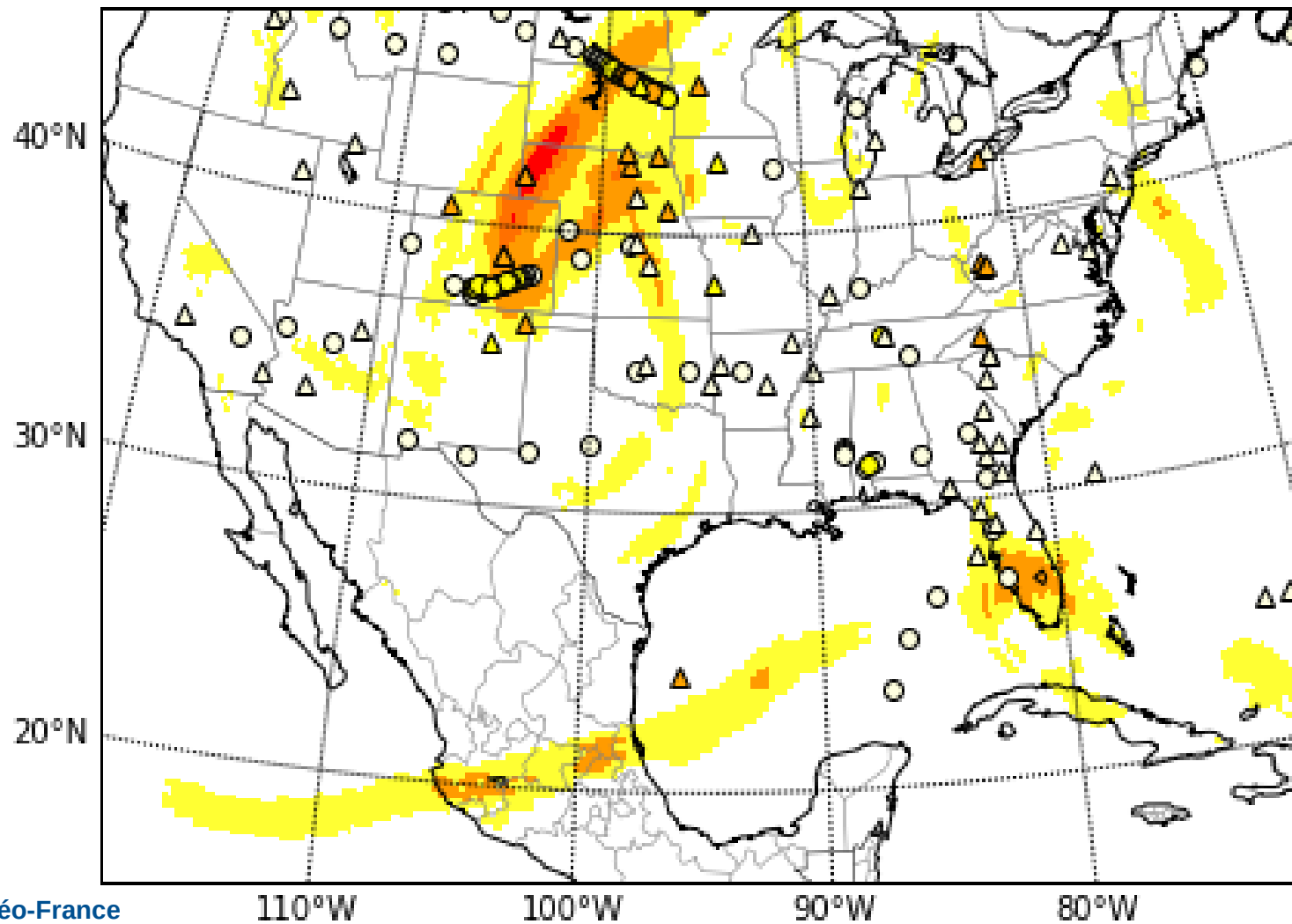
30th April 2017 – FL340 – Run 00UTC – Lead time 15UTC

LASSO regression

Observations

Time window
+/- 30 min

Levels
+/- 20 FL



Case-study

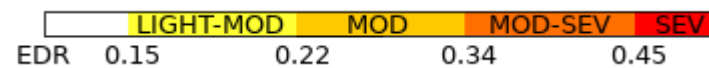
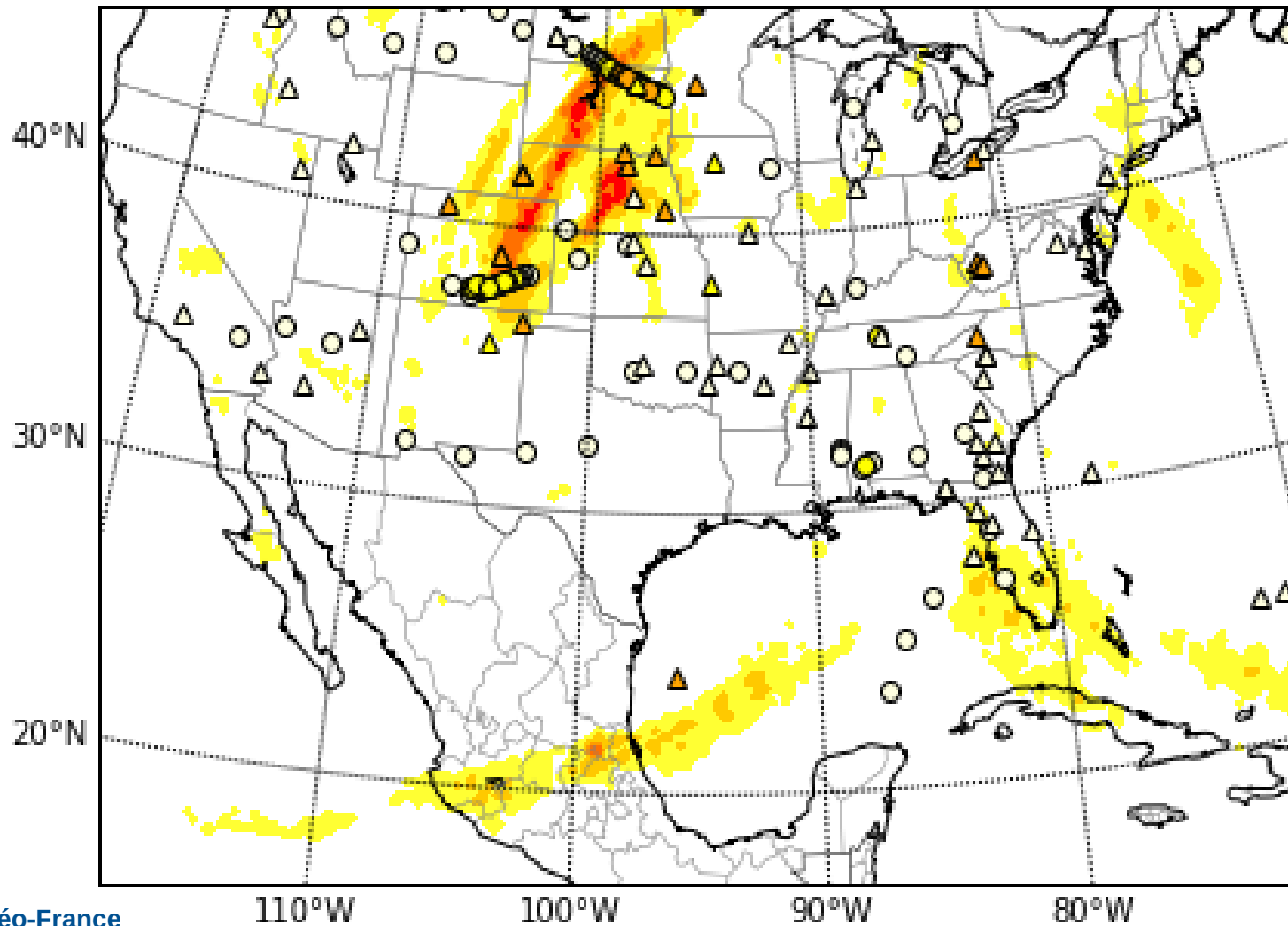
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Random Forest

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 ?

Météo-France

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