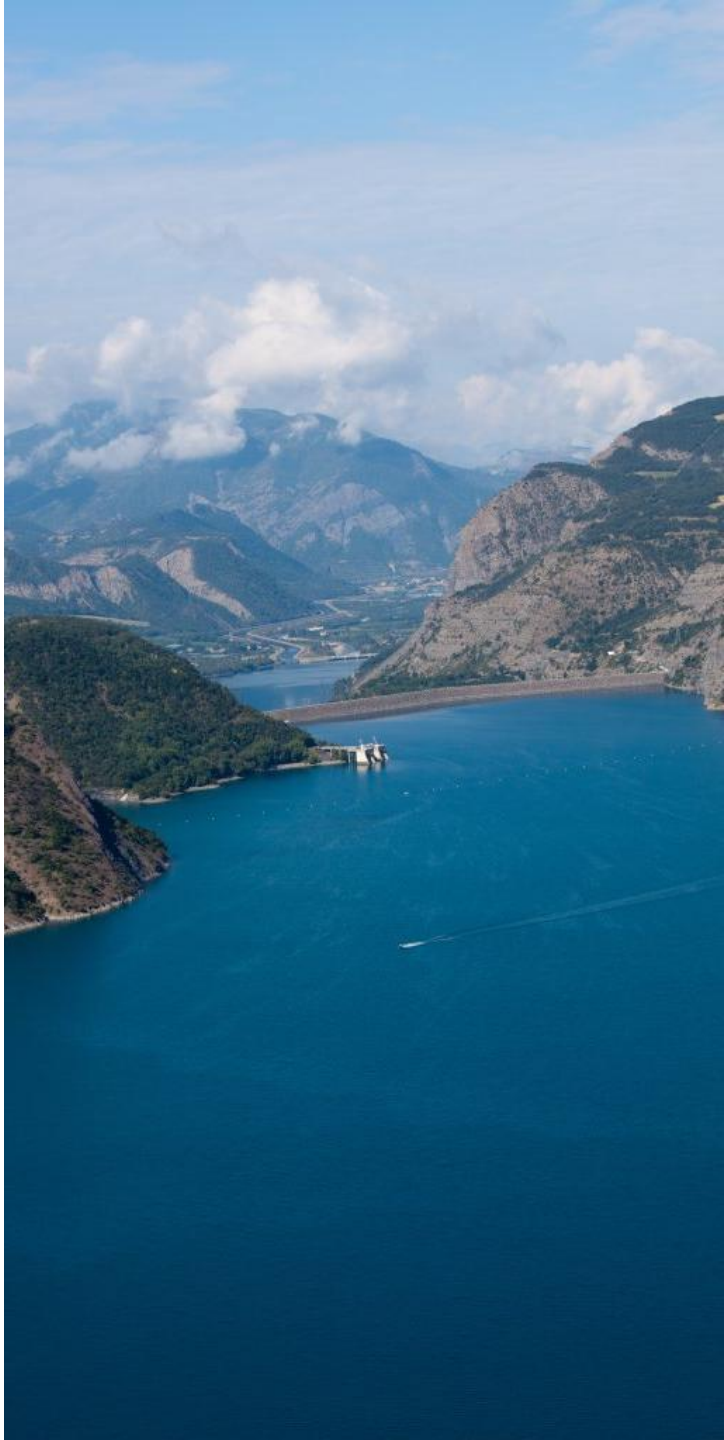
Operational use of ensemble hydrometeorological forecasts at EDF (french producer of energy)



***M. Le Lay**, P. Bernard, J. Gailhard, R. Garçon, T. Mathevet & EDF forecasters*

matthieu.le-lay@edf.fr

SBRH Conference – 2013/11/18

Outlines of the talk

- The weather-sensitive context of a national energy company
- EDF Ensemble forecasting System : an expertised semi-automatic ensemble forecasting chain
- Our experience after 3 years of daily operationnal forecasts

EDF : a weather sensitive company

Energy Consumption & Production

Air Temperature
Nebulosity

Power consumption

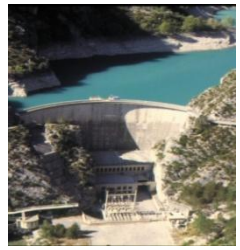
Consumption

Wind

Wind energy
Production (~3%)

Precipitation
(Air Temperature)

Hydroelectric production
(~12%)



Water
Temperature

Nuclear production
(~80%)

Production

EDF : a weather sensitive company

Natural Hazards

Loire at Grangent, november 2008.

Severe drought

Snow storm

Natural Hazards (Floods, drought, storms, …) affect our installations

EDF : a weather sensitive company

Hydrometeorological forecasts

- **Hydrometeorological forecasts are necessary to :**
  - Ensure safety & security of installations
  - Meet environmental standards
  - Improve water resources management
  - Optimize the powerplants production

  → *End-users = Dam operators & Optimization teams of EDF*

- In this industrial context, **estimation & communication of uncertainties to end-users is of first importance for** improving water resources management & decision-making

  → *It is why I am here today!*

Hydrometeorological forecasts at EDF

History

- **A long tradition … since 50’s**
  - Dam inflow (50’s : statistical model)
  - Rainfall (70’s : Analog method)
  - Streamflow (90’s : subjective forecasts)
  - Water temperature (2004, post 2003 heat wave)
  - Wind (2008)
  - Sediment (2009)

- **… Up today, based on meteorological ensembles**
  - Rainfall and Air Temperature (2010)
  - Streamflow (2010)

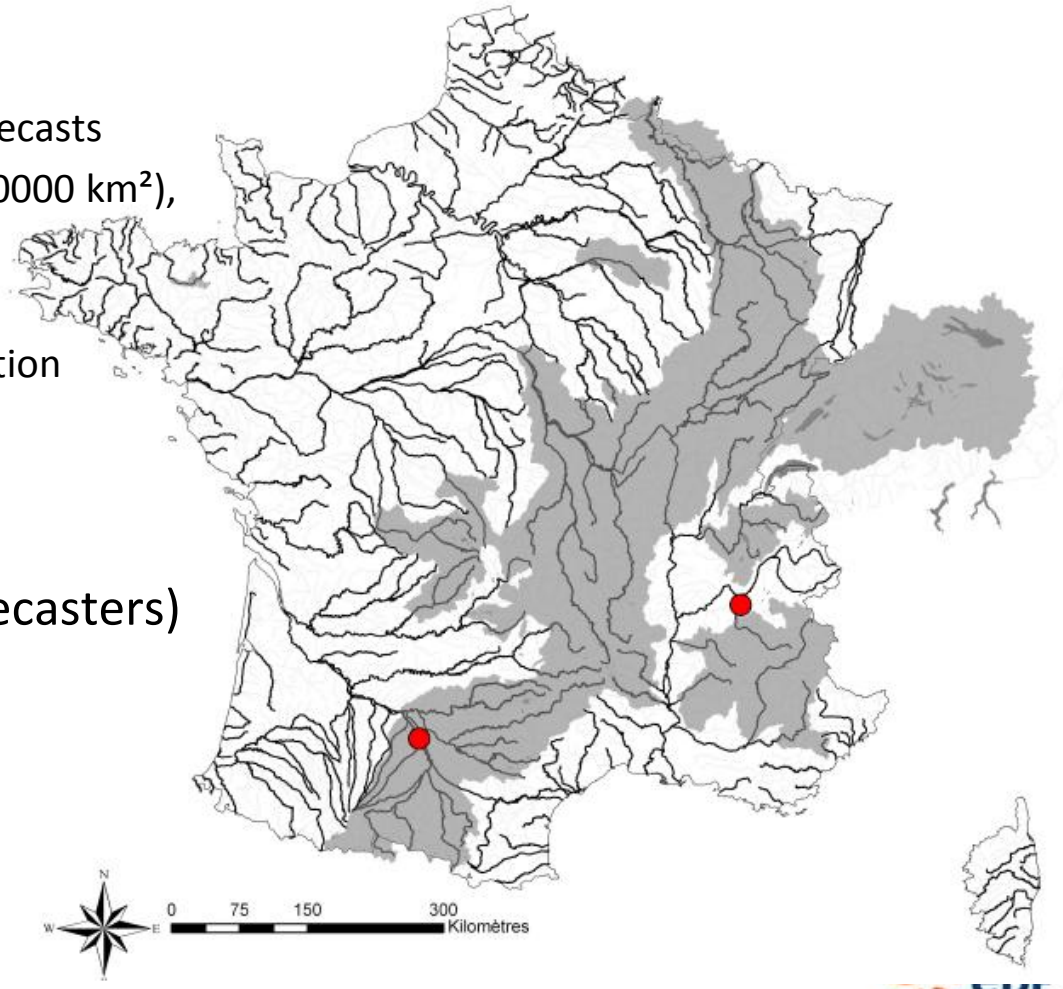
Hydrometeorological forecasts at EDF

Organization

- **Streamflow forecasts**
  - Daily short-term to long-term forecasts
  - ~ 130 watersheds (from ~10 to 50000 km²), mainly in mountainous areas
  - ~ 250 000 km²
  - Designed for safety and optimization of EDF powerplants

- **2 forecasting centers** (~20 forecasters)

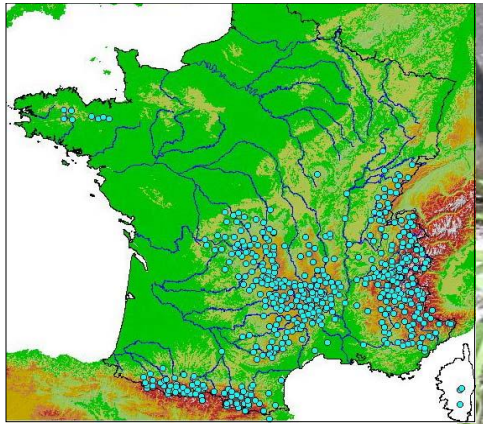
  Grenoble & Toulouse



Hydrometeorological forecasts at EDF

Monitoring

❑ **EDF hydrometeorological network** : ~1200 stations (700 real-time) + partners

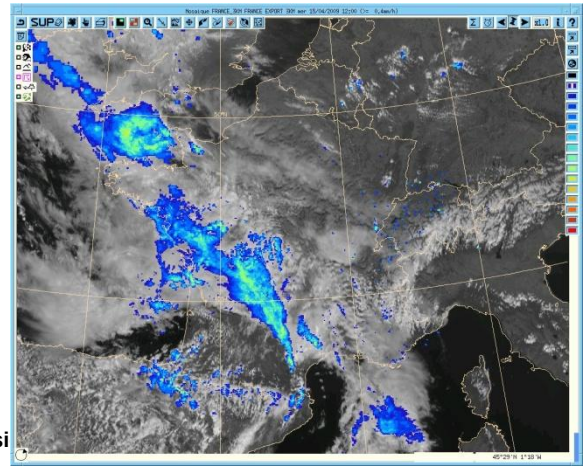


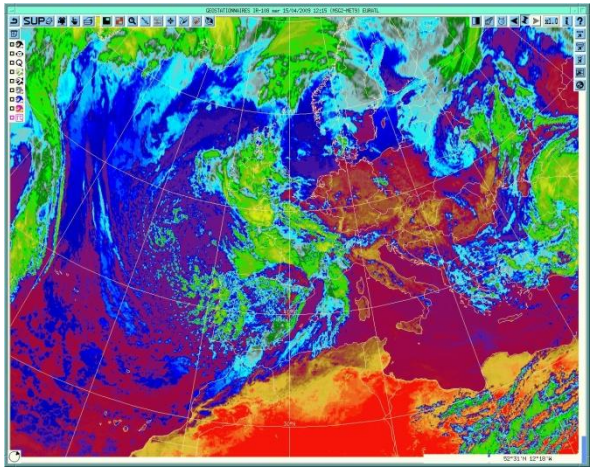
Streamflow

Rainfall & Tair

Snow

❑ **Meteo-France radar and satellite products (+NWP models for forecasts)**





Hydrometeorological forecasts at EDF

Streamflow forecasts

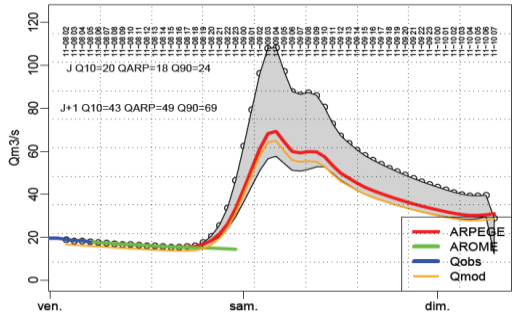
Short-term
Deterministic hourly forecasts
Meteo = High res. NWP models

Dam safety

24 hours

14 days

6 months



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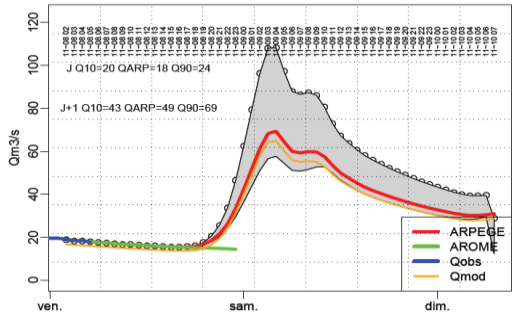
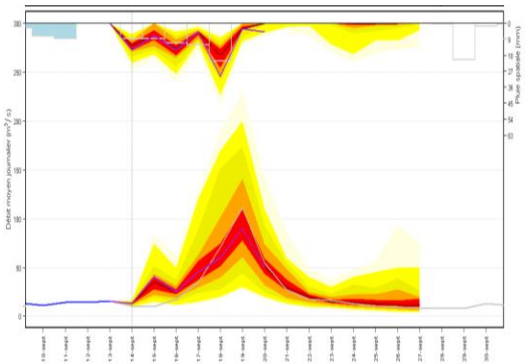


Water management and optimization

Mid-term
7-days deterministic daily forecasts
14-days ensemble daily forecasts
Meteo = NWP models, statistical Analog model, ECMWF ensembles



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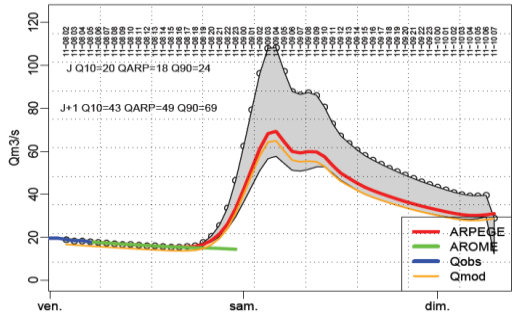

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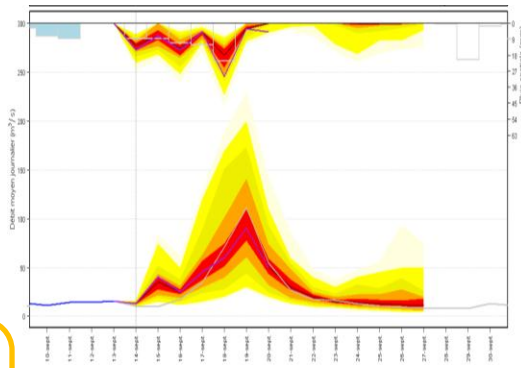
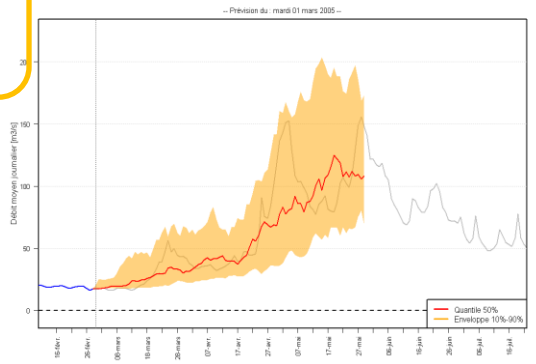


14 days

Long-term
Probabilistic daily forecasts
Meteo = Rainfall and Tair climatology

Dam inflow
Low flows



6 months

Hydrometeorological forecasts at EDF

Streamflow forecasts

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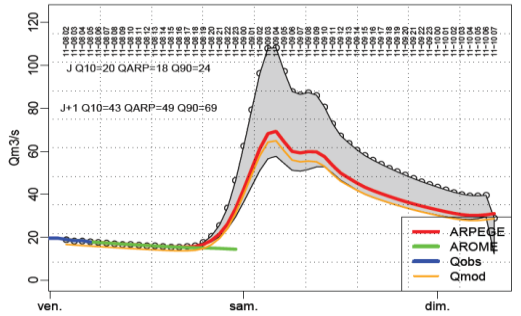

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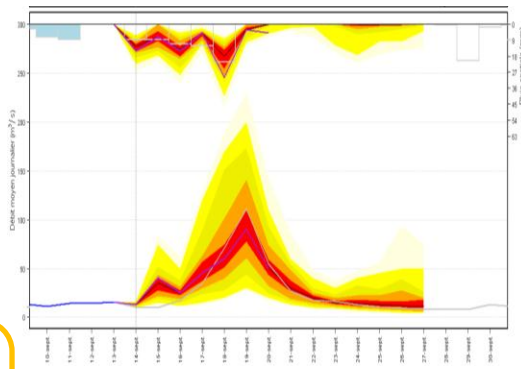

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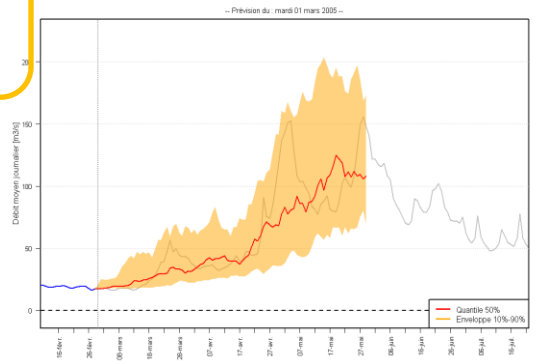

Dam inflow
Low flows

6 months

EDF Ensemble forecasting chain

Context

- **Our experience showed that:**
  - Communication of uncertainties to end-users is critical
  - Estimation of these uncertainties must be objectified to avoid underdispersion and forecaster dependance (complex industrial issues)
  - Forecasters expertise is usefull and should be maintained

EDF Ensemble forecasting chain

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  - Estimation of these uncertainties must be objectified to avoid underdispersion and forecaster dependance (complex industrial issues)
  - Forecasters expertise is usefull and should be maintained

→ Hence, we developped a semi-automatic ensemble forecasting chain to improve forecasters estimation & communication of uncertainties

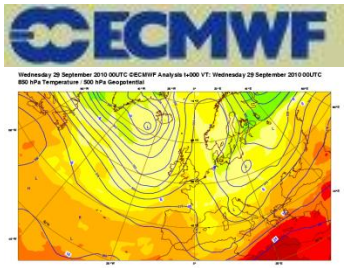
This System (EDF-EPS) was designed to:

- take into account the **full range of uncertaintites** (meteorological and hydrological)
- ensure forecasts with **good statistical properties**
- allow a **human expertise** of meteorological and hydrological forecasts

Houdant [2004] – Garçon et al. [2008] - Mathevet et al. [2010,2012] - Ramos et al. [2010] – Le Lay et al. [2011]

EDF Ensemble forecasting chain

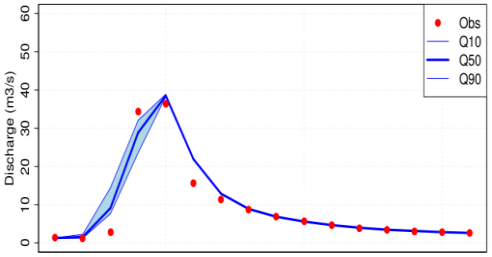
Description



50 scenarios of rainfall & temperature

RR model

Altier@LaGoulette



50 scenarios of streamflow

EDF Ensemble forecasting chain

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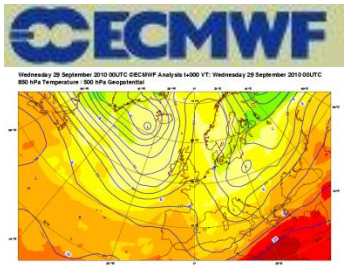

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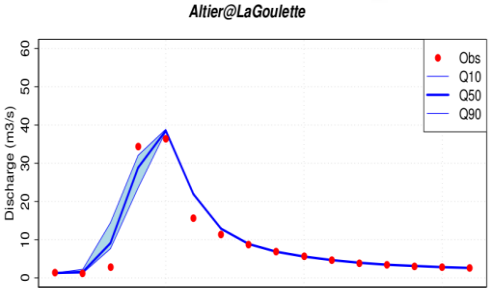


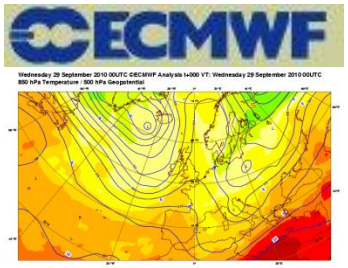
50 scenarios of streamflow

• **Raw ensemble forecasts generally suffer from bias & underdispersion**, both precipitation/temperature and streamflow (need to correct and spread the forecasts)

→ Ensemble forecasts **dressing/post-processing** is necessary to ensure a good reliability (e.g. a good statistical calibration of the system)

EDF Ensemble forecasting chain

Description



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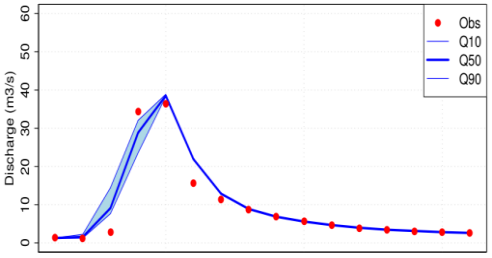

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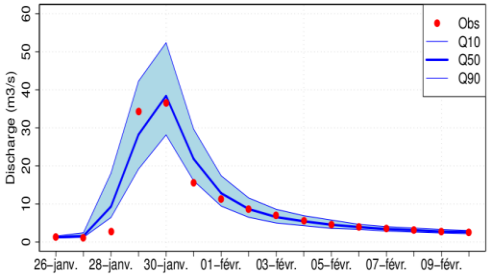


Ensemble post-processing :

1 Analog approach (Z700-Z1000)

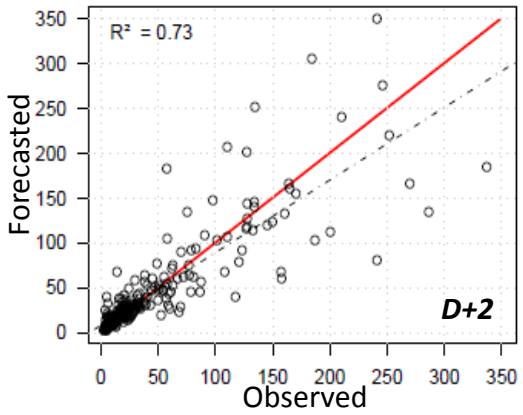
2 RR model forecast uncertainties

EDF Ensemble forecasting chain

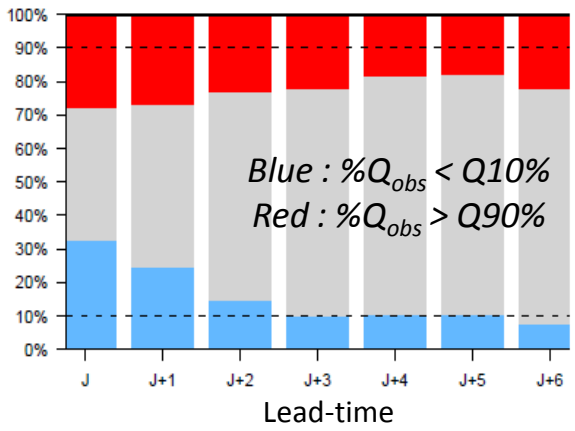
Ensemble verification

- **Statistical properties:** We want our forecasts to be : unbiased , reliable and sharper than climatological forecasts (forecasts from historical data)

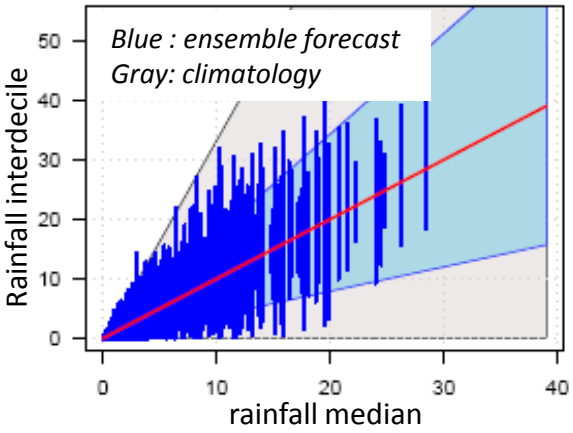
Deterministic skill



Reliability



Sharpness



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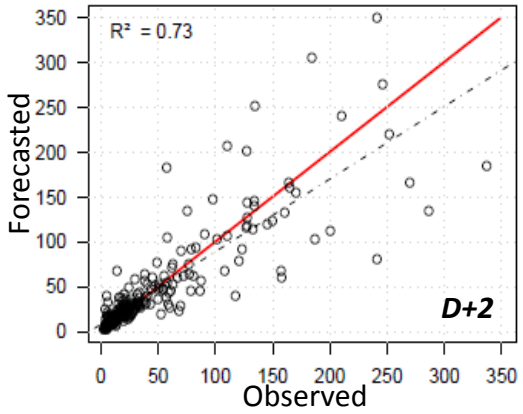

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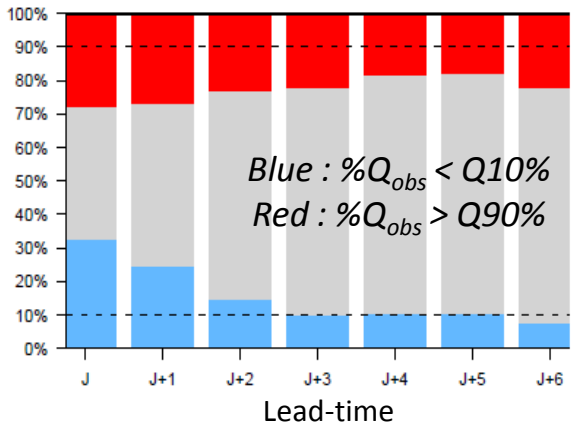

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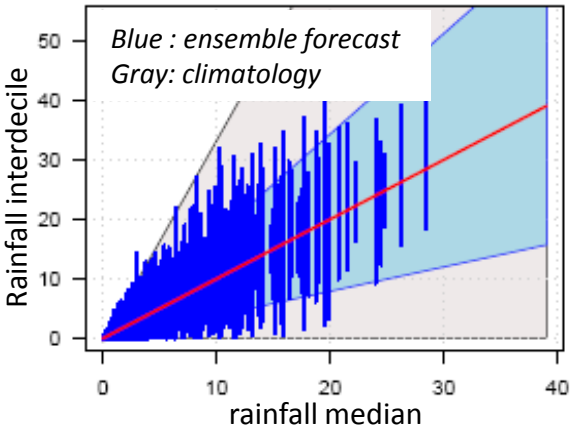


→ **Resumed in a probabilistic score: Continous Ranked Probability Score** *[Brown, 1974]*

- Raw score: $$CRPS = \frac{1}{N}\sum_{i=1}^{N}\int_{-\infty}^{+\infty}\left(F^{prev}(x_i) - H(x_i)\right)^2 dx_i$$

$$H(x < x_{obs}) = 0$$
$$H(x > x_{obs}) = 1$$

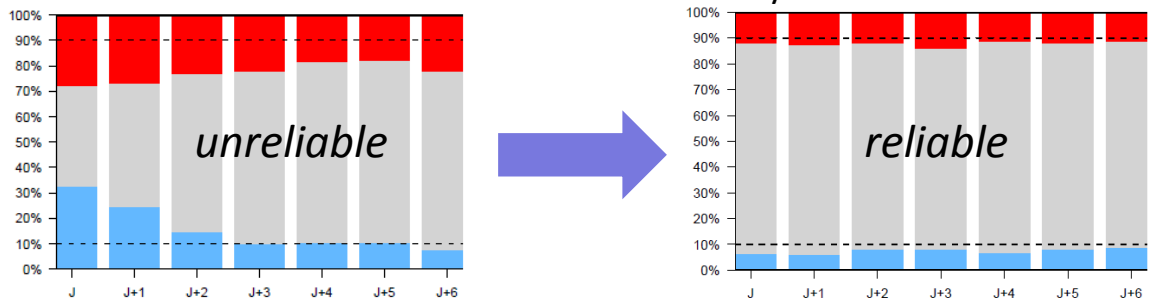
- Skill score (vs climatology): $$CRPSS = \frac{CRPS_{clim} - CRPS_{fc}}{CRPS_{clim}} > 0$$

EDF Ensemble forecasting chain

Ensemble post-processing and expertise

- **Dressing the meteorological scenarios:** ECMWF EPS & Analog rainfall forecast mixing

Rainfall forecast reliability



Blue : $\%P_{obs} < Q10\%$
Red : $\%P_{obs} > Q90\%$

EDF Ensemble forecasting chain

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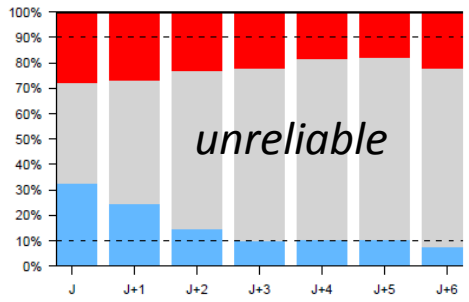

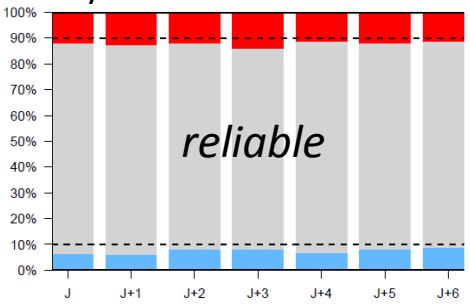

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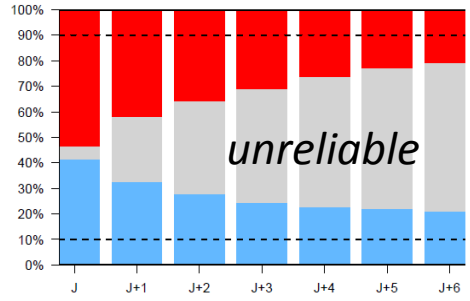
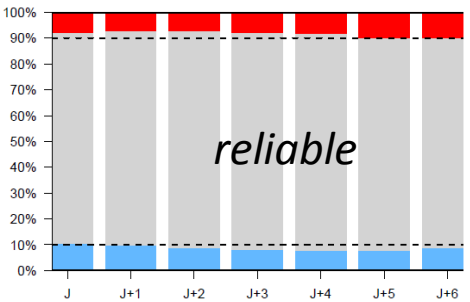
- **Dressing the hydrological scenarios:** statistical modelisation of RR model uncertainty *(Chardon et al. 2013)*

Streamflow forecast reliability





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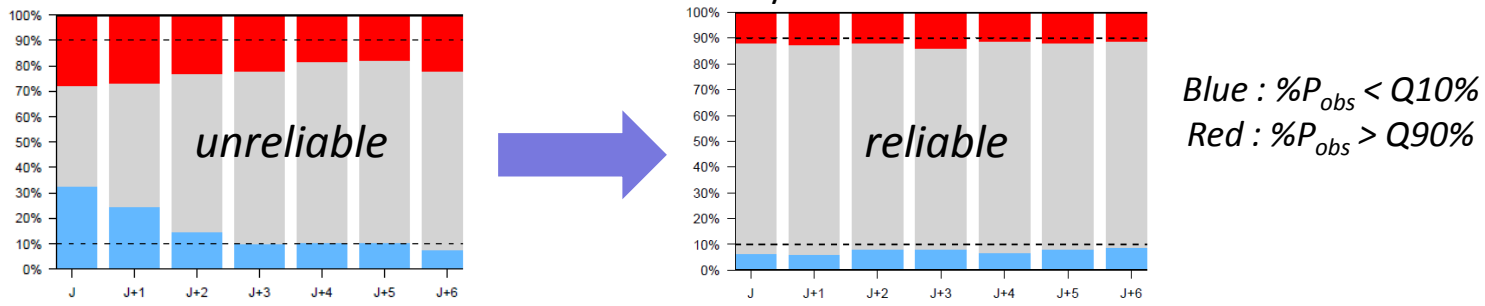

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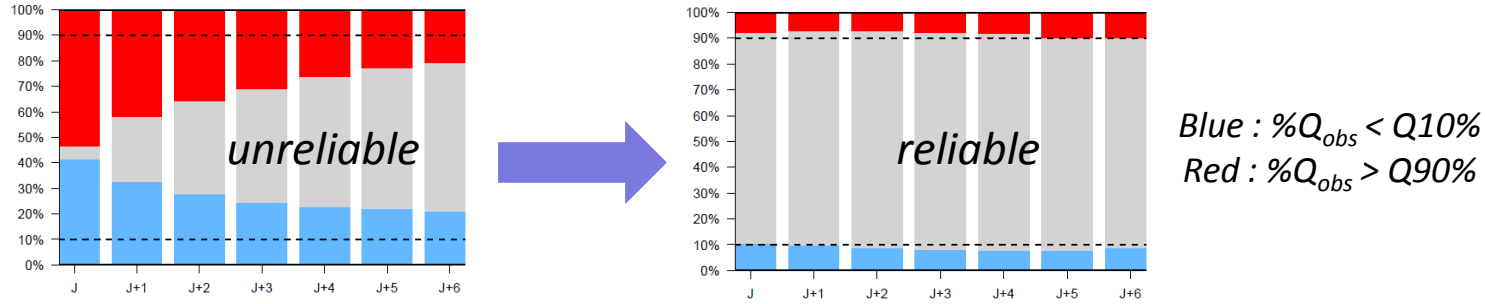

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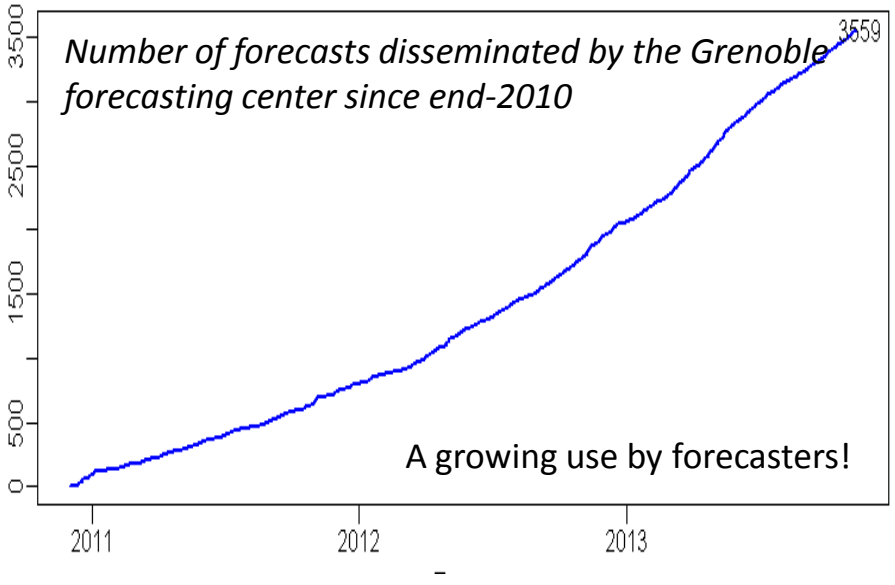
- **Expertise:** forecasters can modify rainfall, temperature and discharge scenarios according to other informations (High res. NWP models, radar or satellite monitoring, hydrological errors, …)

What do we learn from 3 years of operational forecasts ?

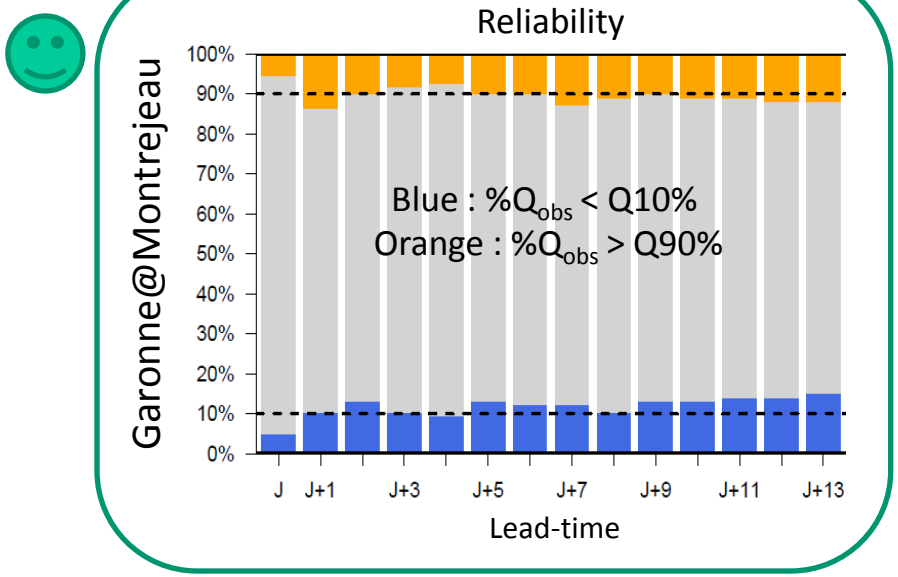
- EDF-EPS is operational since **December 2010**
- In October 2013:
  - EDF-EPS is operated on **50 watersheds** (from ~50 to 35500 km²)
  - **~6000 expertised forecasts** have been disseminated to 200 end-users
  - Raw ensemble forecasts, dressed ensemble forecasts and expertised forecasts have been archived for statistical analyses

→ A interesting dataset!



What do we learn... on forecasts reliability?

- A **good reliability** on ~2/3rd of the watersheds, thanks to:
  - A good post-processing calibration
  - A good forecasters expertise



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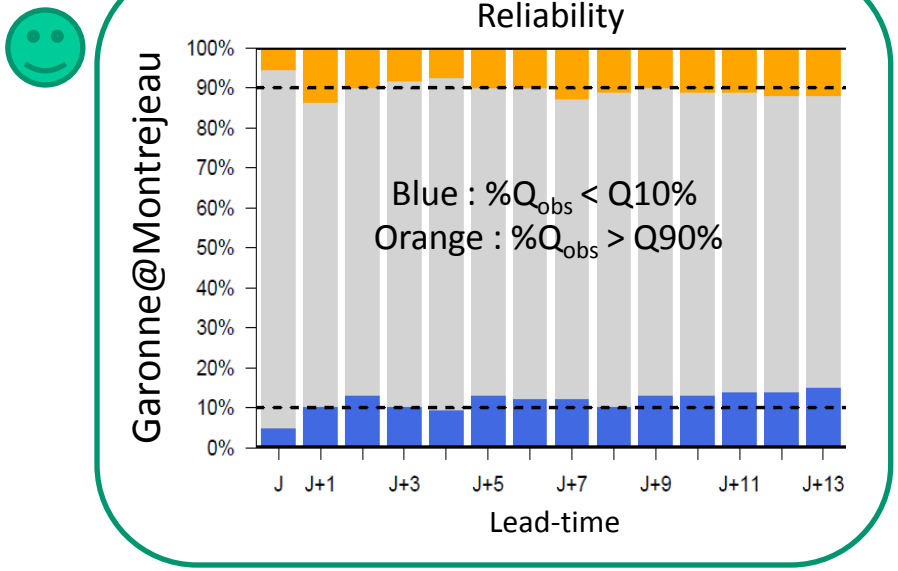
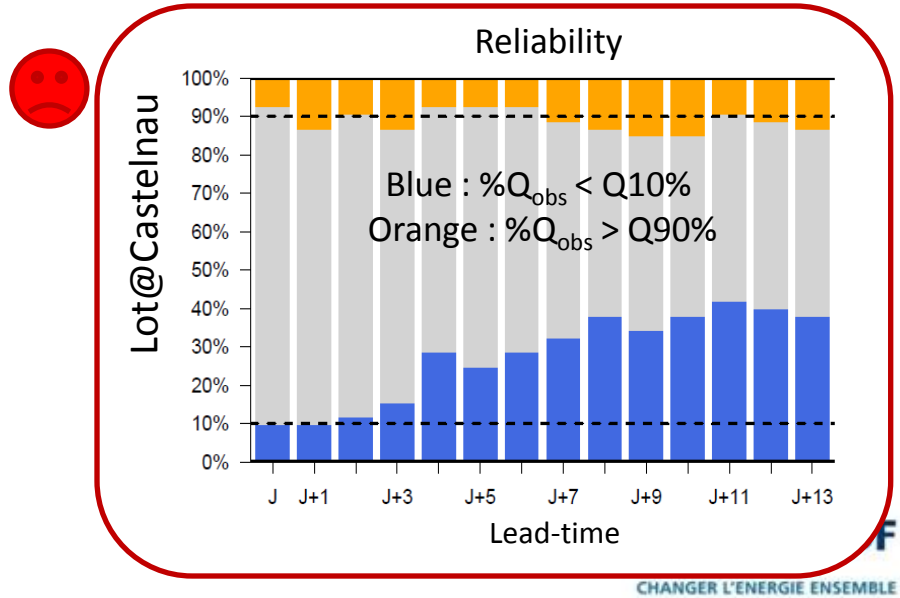
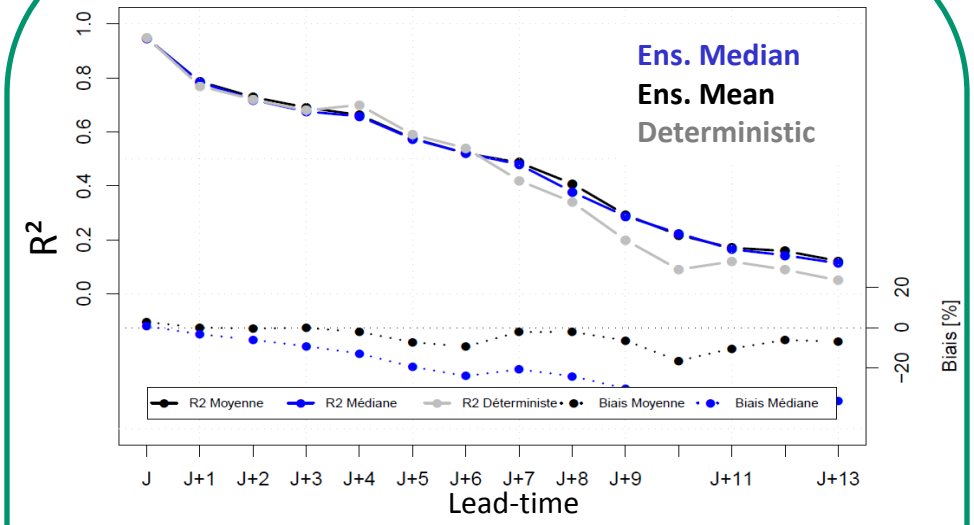


- A **bad reliability** on ~1/3rd of the watersheds (under-dispersion & bias) , due to:
  - Poor RR model performances
  - Mis-calibration of the meteorological and hydrological post-processing
  - Highly uncertain & influenced streamflows

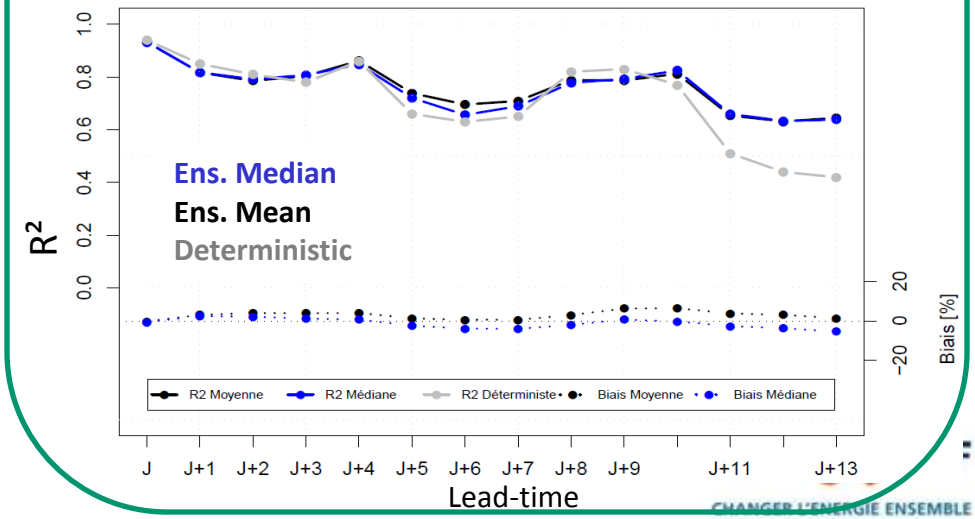


What do we learn... on forecasts skill?

Ain@Vouglans [2011-2012]



Durance@SerrePonçon [2011-2012]

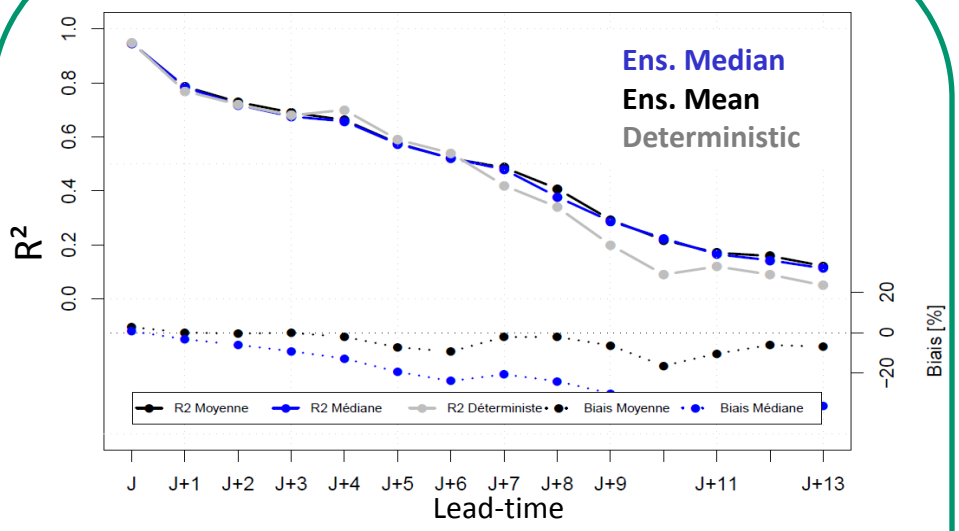


What do we learn... on forecasts skill?

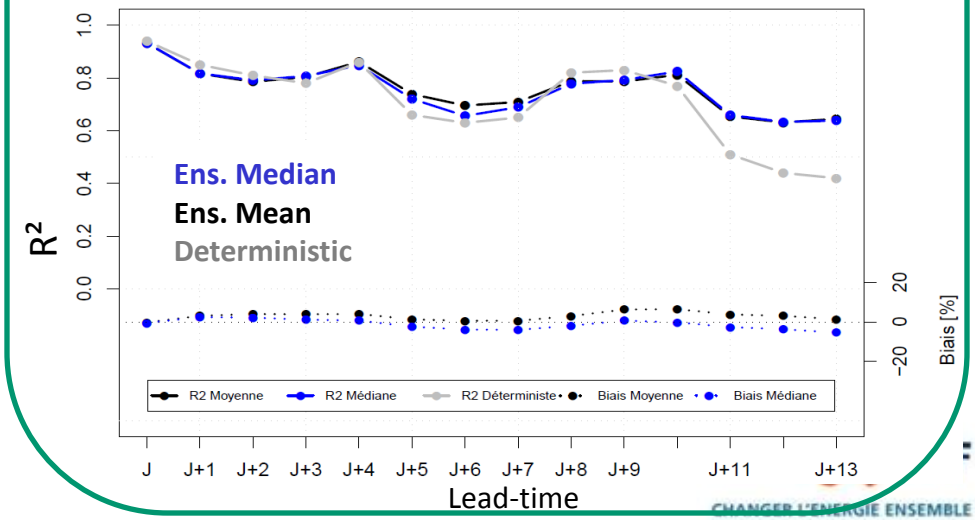
- A **good deterministic skill** on ensemble mean or median :
  - R^2 ranging from ~1 (D+0) to 0.4/0.8 (D+6)
  - A limited bias, less than +/- 15% (D+6)
  - A lower bias with ensemble mean

- Ensemble mean skill equal or better than **deterministic forecasts** issued by the former forecasting system (deterministic D+7 +persistance model).

Ain@Vouglans [2011-2012]

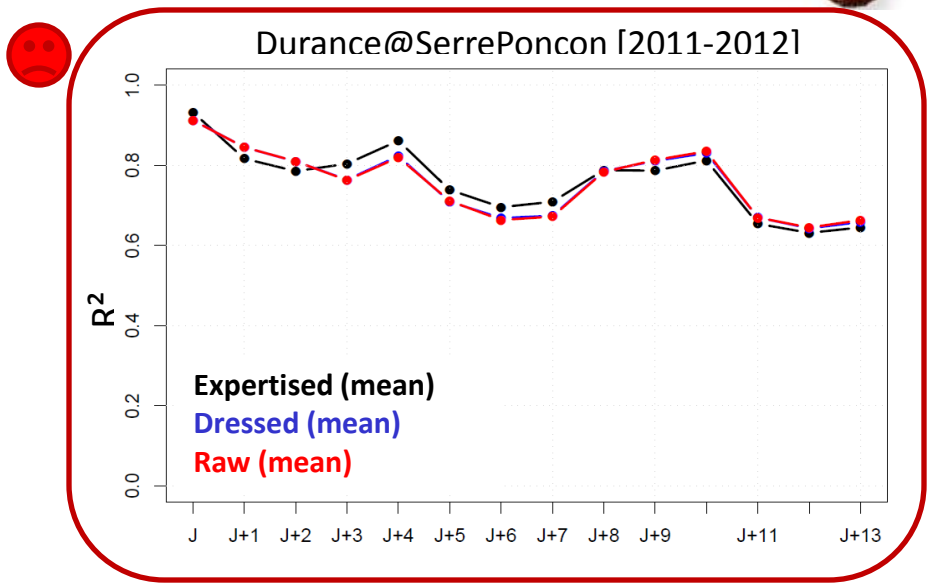


Durance@SerrePonçon [2011-2012]



What do we learn... on human expertise?

- On most of the watersheds, **human expertise** have a **limited impact** on forecasts skill (from a **deterministic point of view**).



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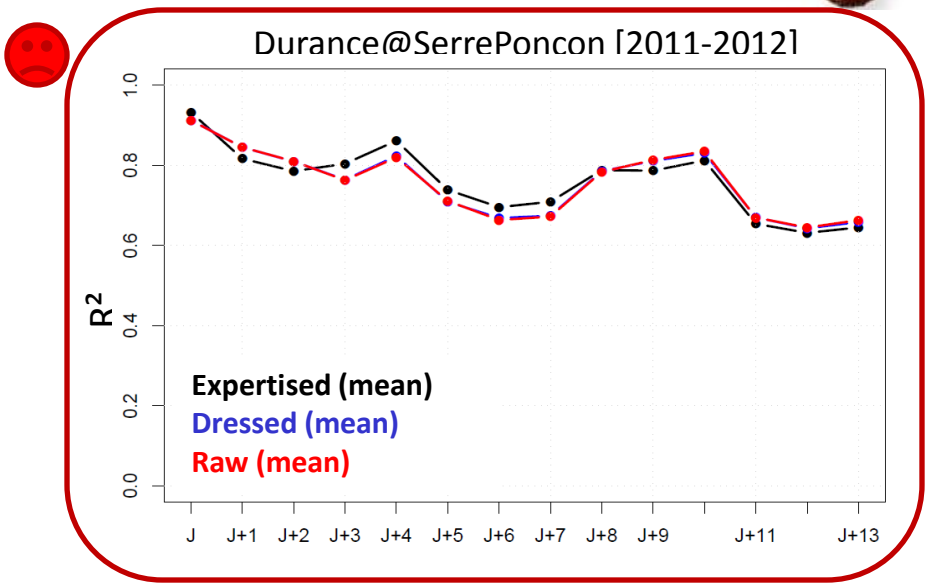
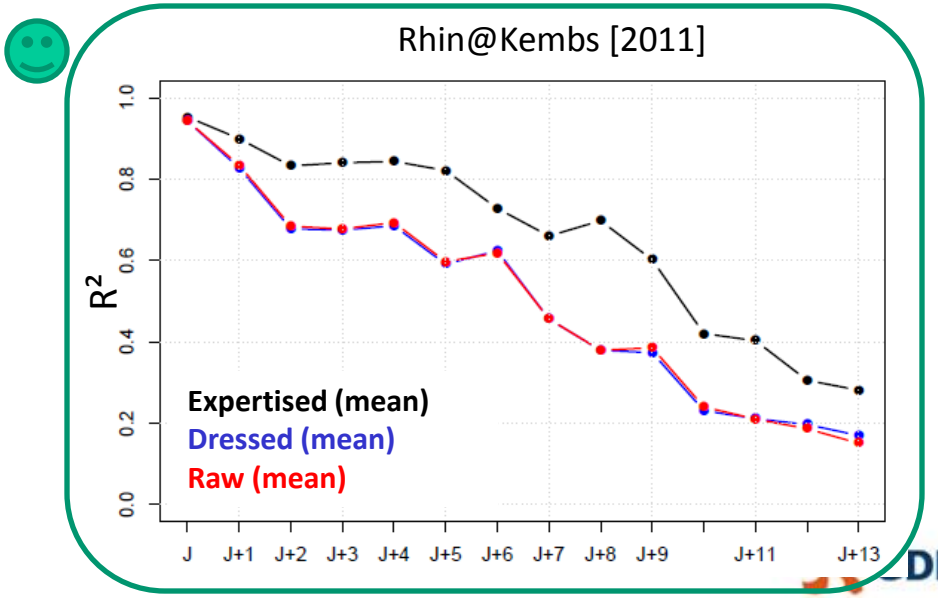


- Rhine at Kembs watershed is the exception! **Human expertise strongly improve forecasts skill**, with 2 day lead-time increase. On this watershed, expertise is made thanks to a **distributed RR model**, better than the global model used in the EPS-EDF.



What do we learn... on previsibility?

Previsibility is analysed as the lead-time until which the forecast performance overpass the performance of climatological system (forecast using historical ensembles) [CRPSS]

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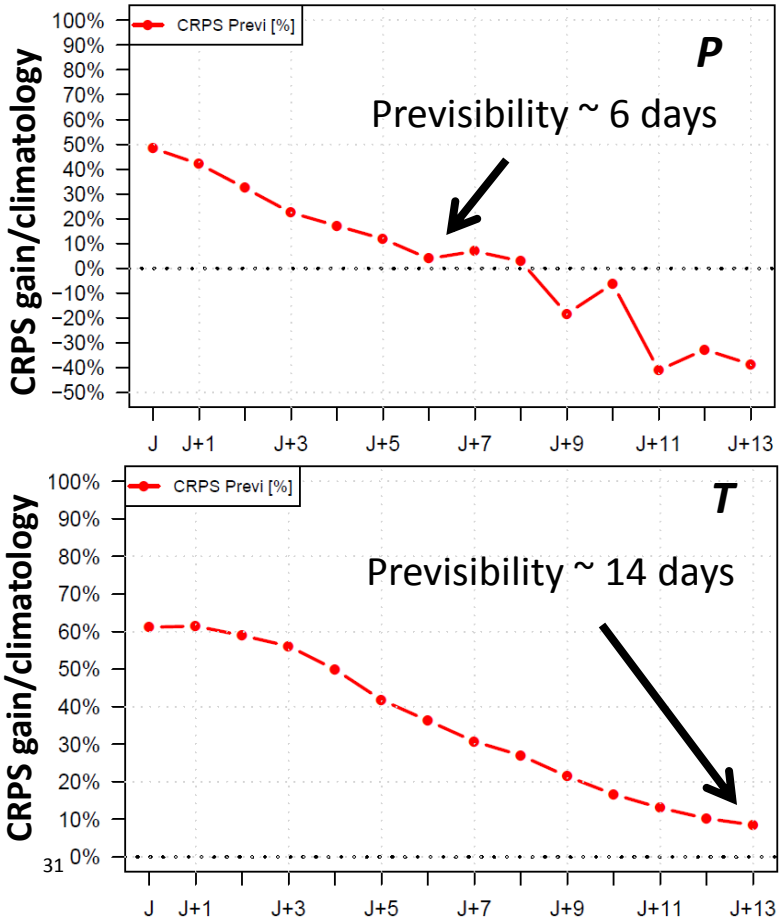
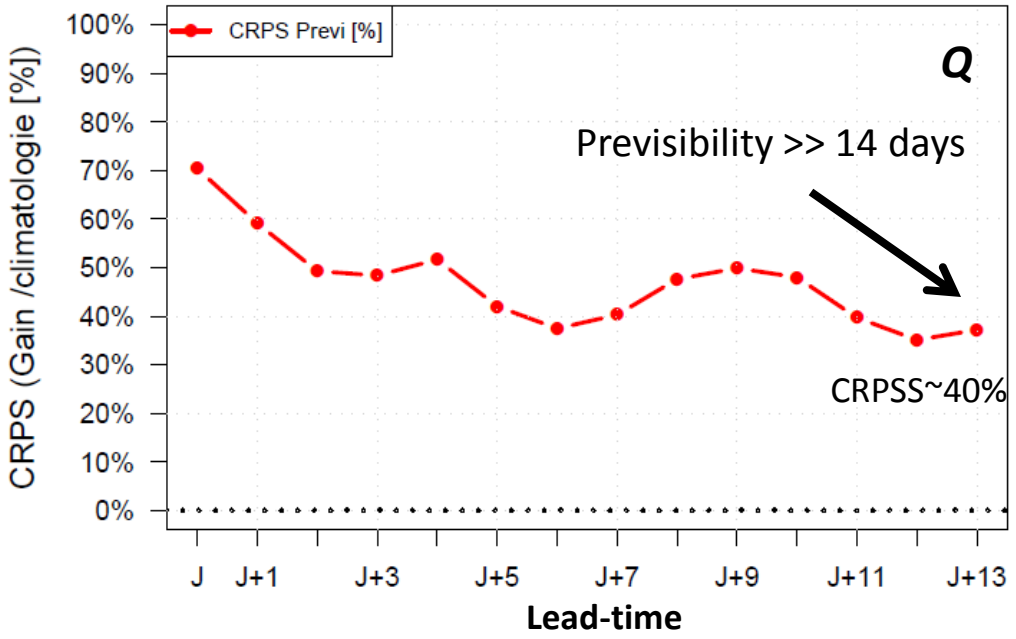
[Durance@SerrePonçon - 2011-2012]





Each watershed has its own hydrological previsibility, defined as the sum of the meteorological previsibility and its own hydrological inertia

CHANGER L'ENERGIE ENSEMBLE

What do we learn... from end-users?

Rhin@Kembs [35500 km²]

2011/10/10 flood event

End-user issue:
The hydroelectric chain (1500MW) is saturated above 1400m3/s → this threshold have to be anticipated

A 3-forecasts sequence

I let you find which forecast the end-users prefered…

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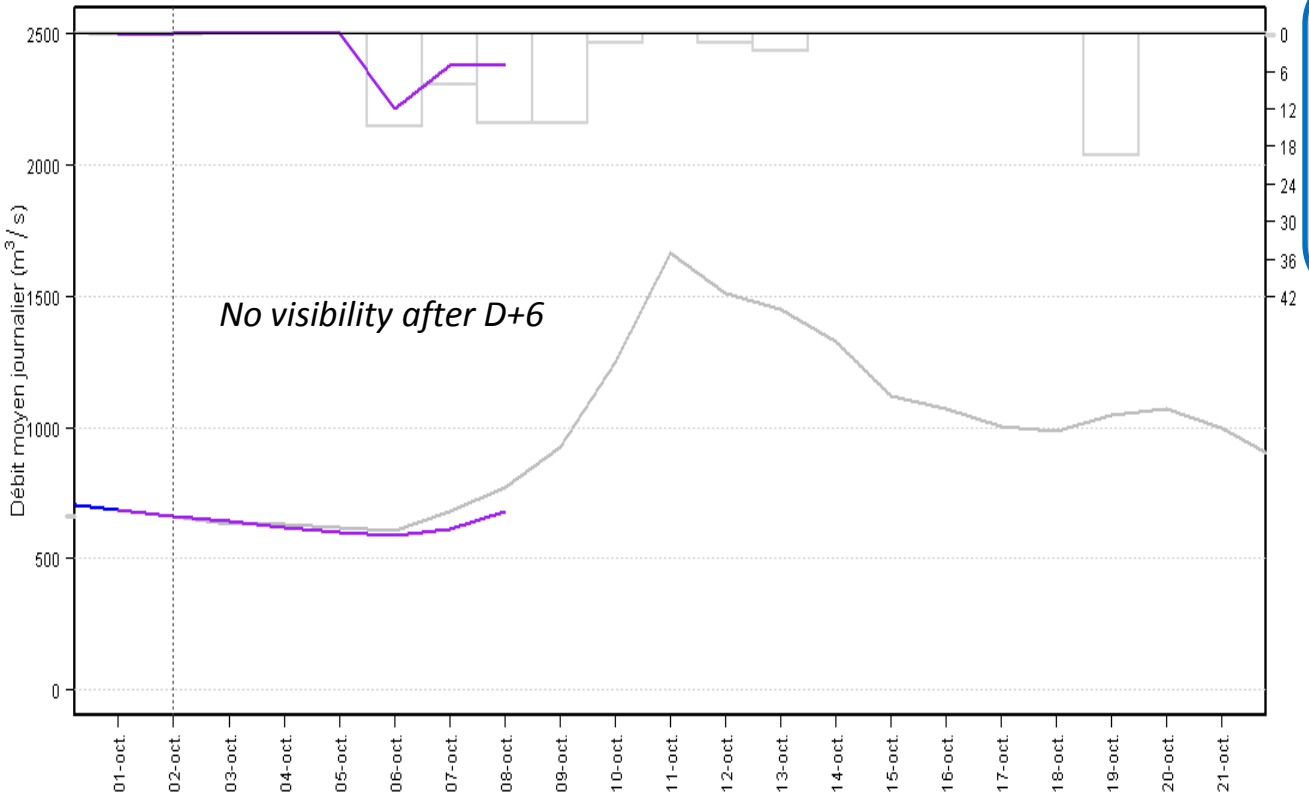

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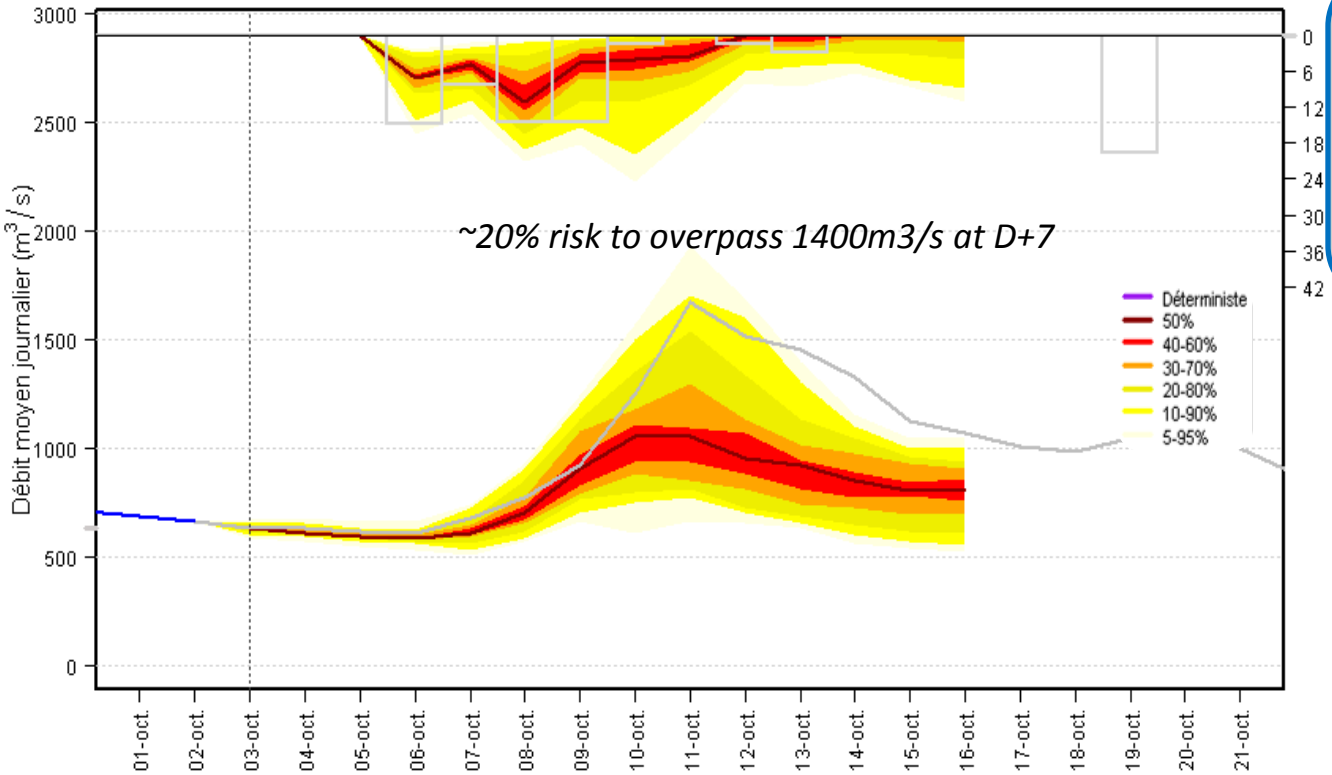

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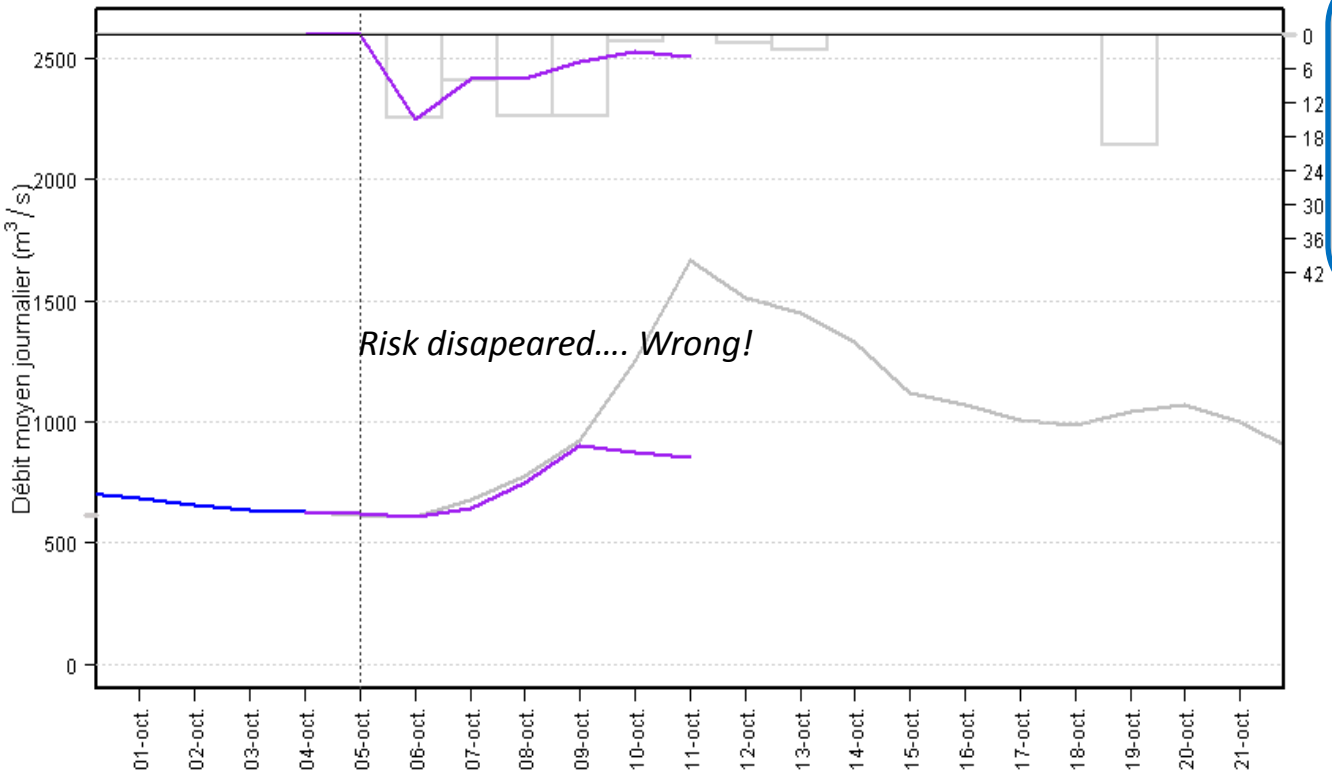

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When we have large uncertainties , these uncertainties have to be communicated!

What do we learn... from end-users?

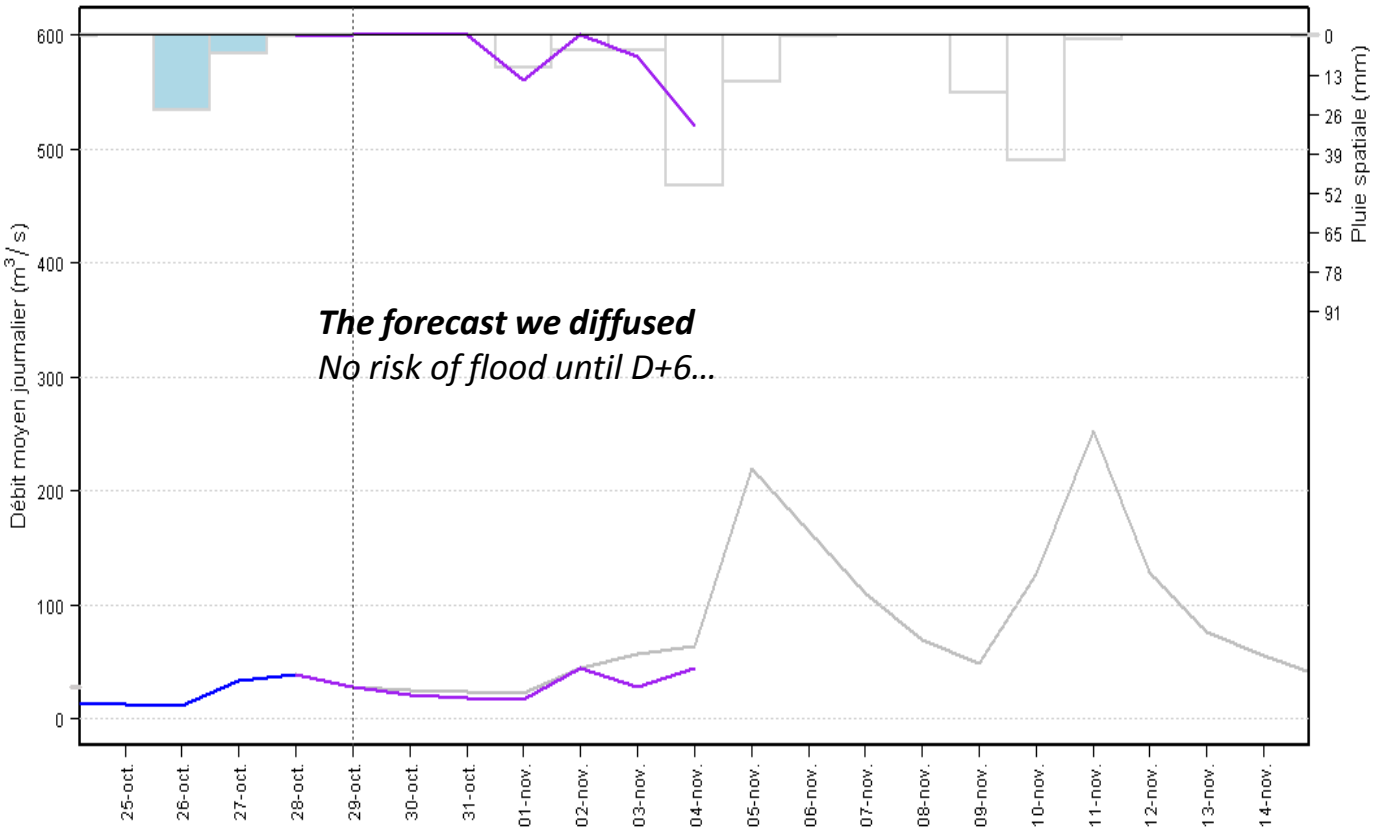
Ain@Vouglans [1000 km²]
2012/11/4 flood event

A big reservoir (for french…) with many constraints and a strong need of anticipation

What do we learn... from end-users?

Ain@Vouglans [1000 km²]

2012/11/4 flood event



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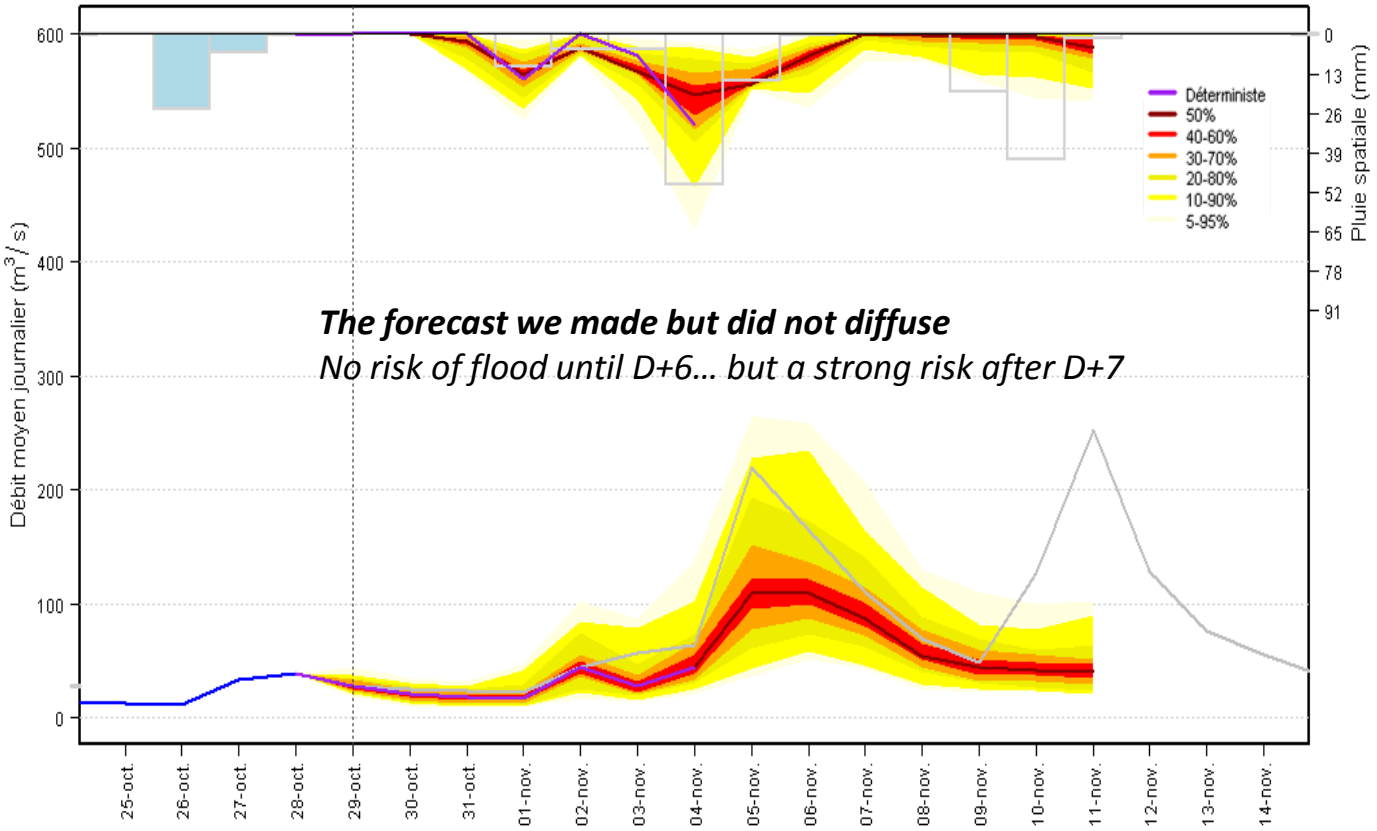

Probabilistic forecasts allow an earlier warning

Conclusions

- EDF-Ensemble Prediction System was developped to better estimate and communicate the forecasting incertainties to end-users
- A particular attention was paid to achieve a good statistical calibration of hydrological ensembles
- Experience showed that use of EPS allowed us to:
  - increase the forecasts lead-time (14-days lead-time irrealistic in a deterministic way)
  - properly quantify and communicate forecasts uncertainties
  - improve water management (use of different quantiles depending on end-users issues)
- The EDF-EPS follows a continuous development since its first operational use

Thanks for your attention!

What do we learn... From end-users?

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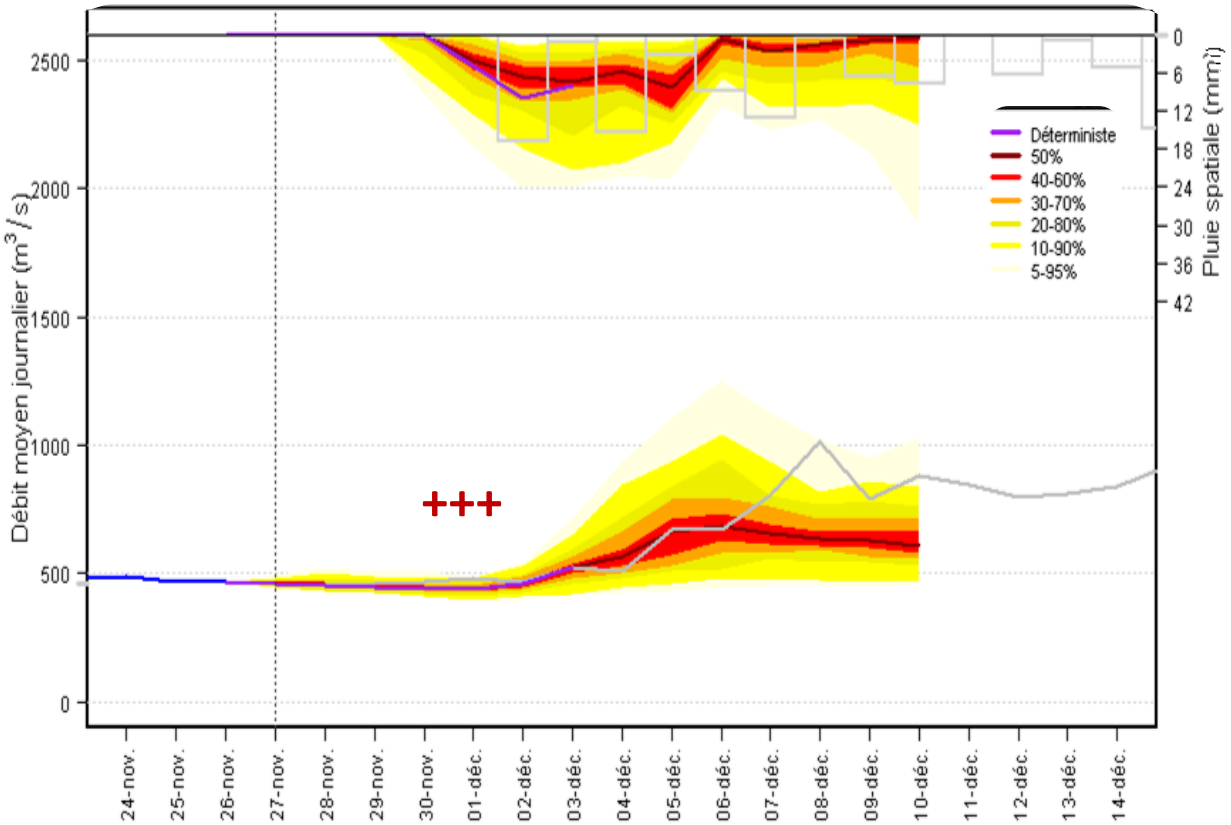
2011/12/ 5 to 10 event



27th November forecast

« the increase of the forecast length allow a very good anticipation of the end of automn low-flows, compared to the persistance model used to increase deterministic forecasts length»