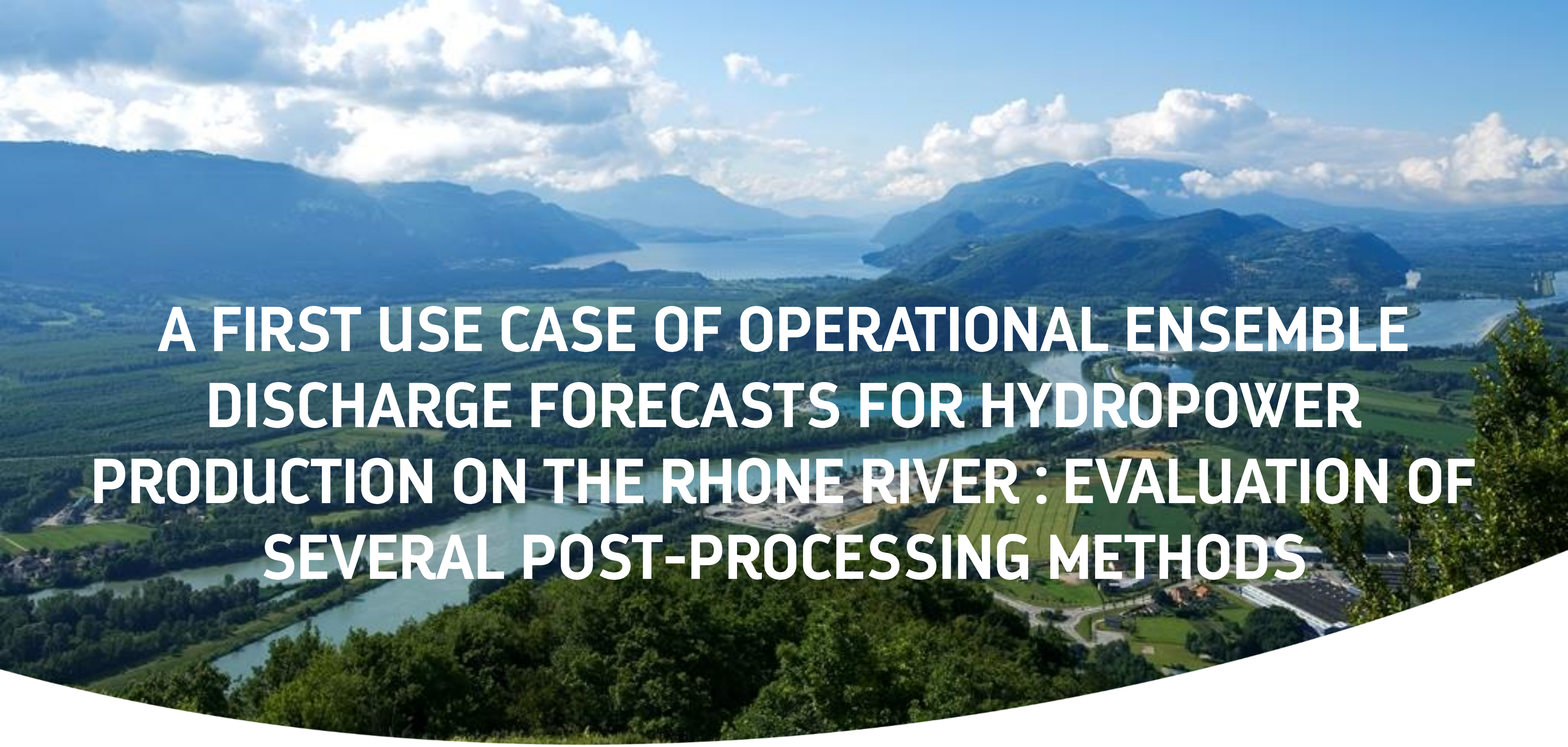

A FIRST USE CASE OF OPERATIONAL ENSEMBLE DISCHARGE FORECASTS FOR HYDROPOWER PRODUCTION ON THE RHONE RIVER : EVALUATION OF SEVERAL POST-PROCESSING METHODS

Olivier Vannier[1], Sabrina Celie[1], Sébastien Legrand[1] and Joseph Bellier[2]

[1] Compagnie Nationale du Rhône, Lyon, France
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2018 HEPEX WORKSHOP
MELBOURNE, 6-8 FEBRUARY, 2018

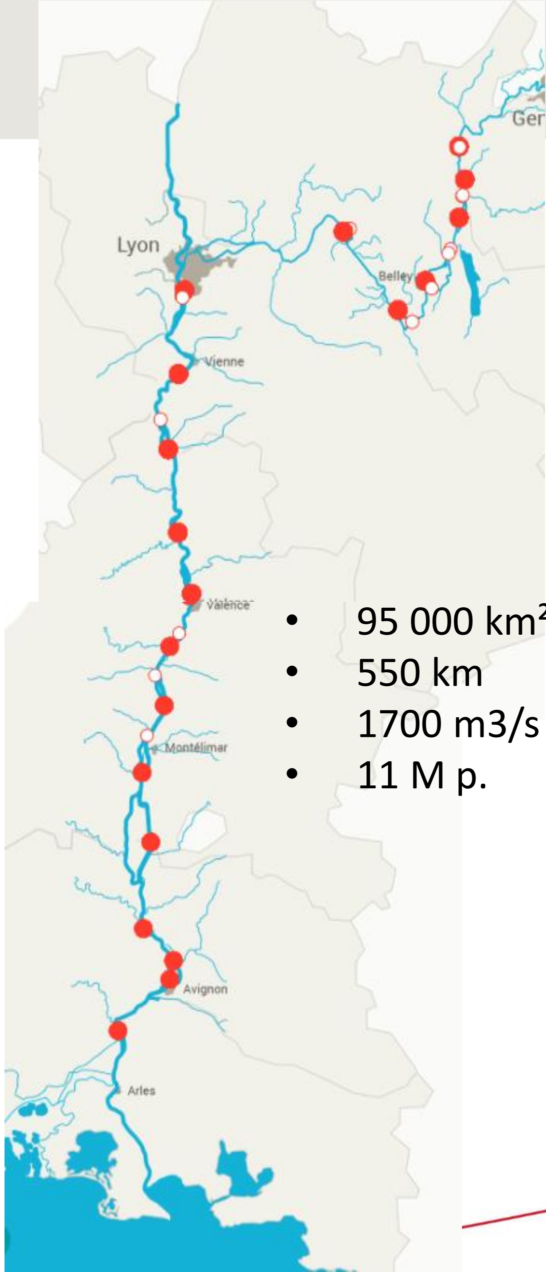
IDENTITY RECORD

Since 1934

- Producing **hydroelectricity**
- Developing inland **navigation**
- Facilitating **irrigation** for agriculture

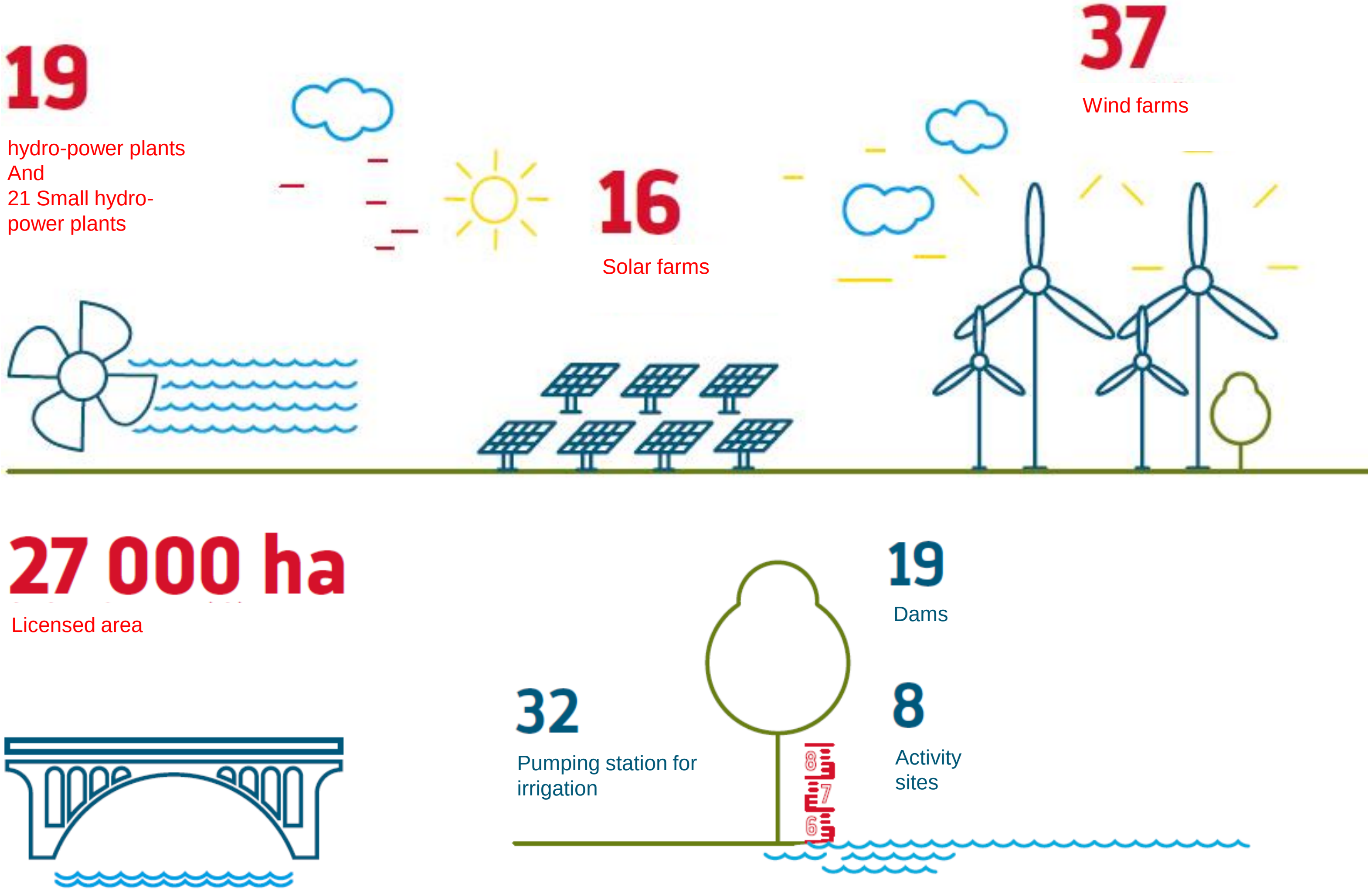
CNR in 2018

- 1st French electricity producer in 100% renewable
- 2nd French electricty producer
- 25% of French hydropower generation
- Optimization of 770 MW from SHEM reservoirs and 52 HPP



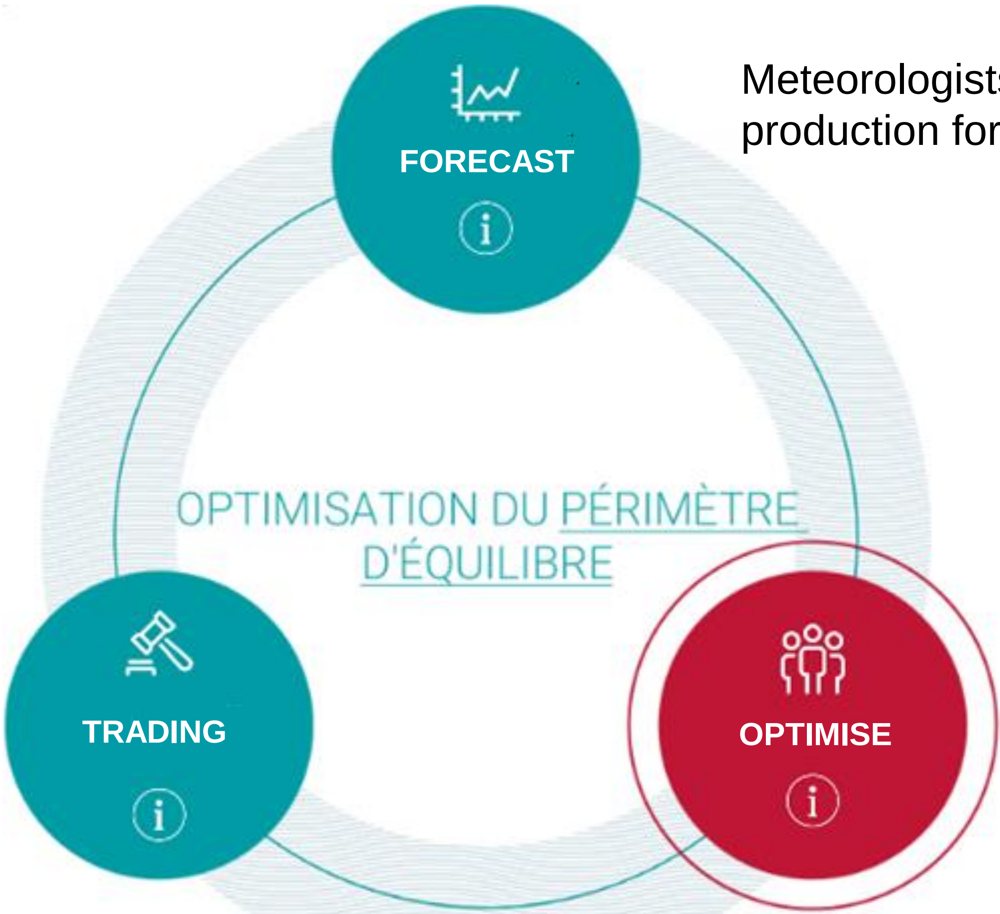
- 95 000 km²
- 550 km
- 1700 m3/s
- 11 M p.

100 % RENEWABLE PRODUCTION



MANAGE AND COMMERCIALIZE ENERGY

The COCPIT (Center for Optimization and Conduct of Intermittent Production): a unique and efficient organization to promote the energy produced by CNR and its customers



Meteorologists make weather and production forecasts.

Market operators sell the energy produced at the best price through direct market access and a high volume of transactions.

Optimizers define the production program according to forecasts, network constraints and prices. Telecontrol operators adjust the production in real time.

ENSEMBLE FORECASTING OF THE RHÔNE RIVER DAILY DISCHARGE

Context

Recent change in European ancillary services market :

- Weekly tenders of control reserve availability organised by RTE (french TSO)
- Tender every Tuesday for next week (W+1)

→ Necessity for CNR to have quantified estimations of hydropower production on week W+1

→Lead times of interest imply to account for uncertainties

Solution

Building of a daily discharge forecasting chain using ensemble meteorological forecasts

ENSEMBLE FORECASTING OF THE RHÔNE RIVER DAILY DISCHARGE

Simplified description of the forecasting chain

Ensemble precipitation and temperature forecasts (ECMWF)

Observed discharge (CNR)

Observed precipitation and temperature (Meteo-France)

10 mountain catchments — CEMANEIGE degree-day snow accumulation and melting model

↓

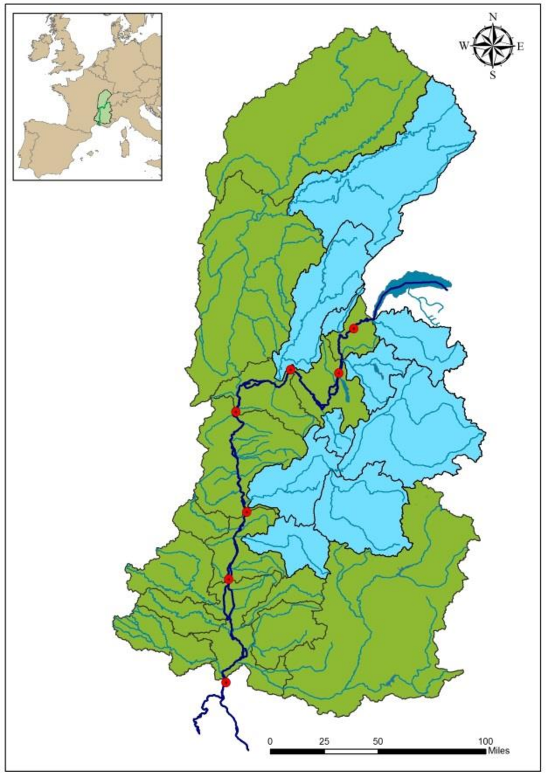
24 catchments — GRP (adapted for daily time-step) rainfall-runoff model

↓

7 gauging stations — Routing module of discharge along the Rhône river

↓

7 gauging stations — Post-processing for bias correction



The Rhône river sub-catchments and gauging stations

ENSEMBLE FORECASTING OF THE RHÔNE RIVER DAILY DISCHARGE

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Post-processing for bias correction

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GRP (ada… rai…

Routing mo… Rhône river

Post-processing for bias correction

Focus on the post-processing step

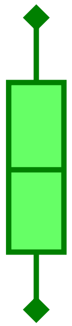
- Necessary step for accurate and reliable forecasts
- Comparison of several post-processing methods
- Verification metrics and operational benefits

CNR

DESCRIPTION OF SEVERAL POST-PROCESSING METHODS

Ensemble Model Output Statistics (EMOS) (Gneiting *et al.*, 2005)

Raw ensemble forecast

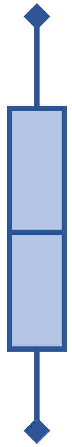


Individual members X_i

Mean of the ensemble $\bar{X}$

Variance S^2

EMOS



EMOS-calibrated ensemble forecast

Gaussian distribution $\mathcal{N}\,(\mu\,;\sigma)$

With $\begin{cases} \mu = a + b\bar{X} \\ \sigma = c + dS^2 \end{cases}$

→ Since discharge distribution is not Gaussian, we first apply a Box-Cox transform

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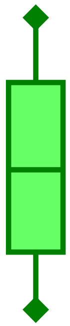

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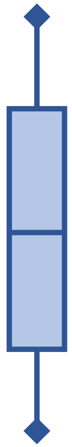

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EMOS performed by flow range

❖ Same as EMOS, with distinction between 4 different groups of discharge values

❖ We separate discharge in 4 equal groups defined by quantiles:

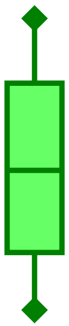
- Min-Q25%,
- Q25%-Q50%
- Q50%-Q75%
- Q75%-Max

DESCRIPTION OF SEVERAL POST-PROCESSING METHODS

Quantile Regression Forests (QRF) (Meinshausen, 2006)

Raw ensemble forecast

Describers of the raw distribution:



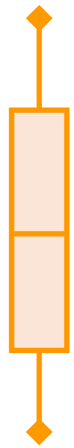
- Mean
- Median
- Standard deviation
- Min
- Max
- Interquartile range
- Skewness
- Kurtosis
- Date of forecast
- …

Predictors

Random Forests learning algorithm

Link with past observed values

QRF post-processed ensemble forecast



Empirical distribution composed of past observed values (used as quantiles)

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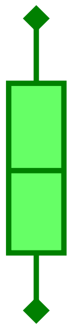

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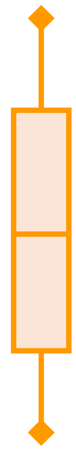


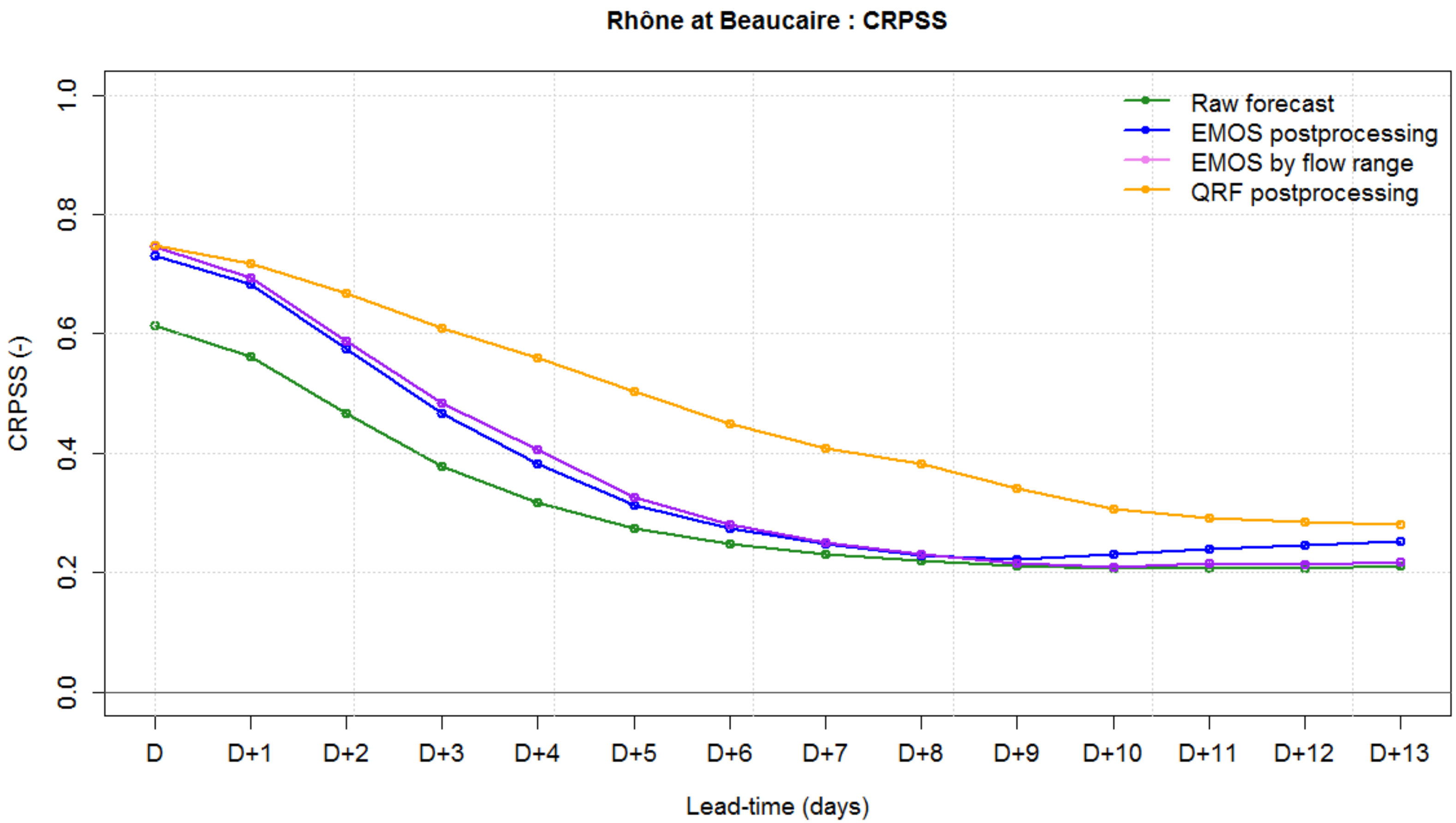
Empirical distribution composed of past observed values (used as quantiles)

Evaluation strategy for the 3 compared post-processing methods

- 5 years of observed values and raw forecasts (2011-2015)
- 3 years used for calibration and learning (2011-2013)
- 2 years for evaluation of performances (2014-2015)

EVALUATION OF POST-PROCESSING METHODS

Continuous Ranked Probability Skill Score (CRPSS)



Main features

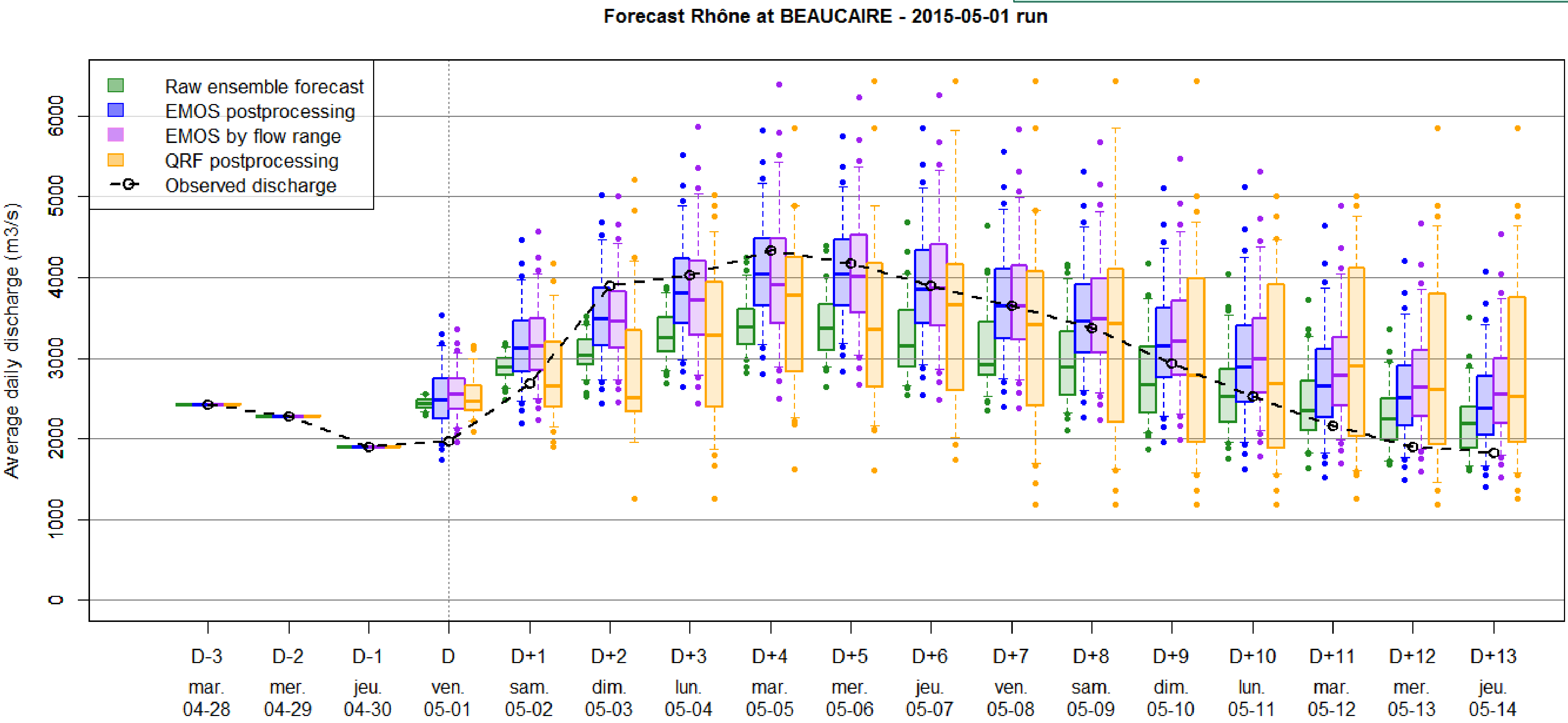
- All 3 post-processing methods improve general performances
- Differentiating EMOS by flow range does not enhance performances
- Quantile Regression Forests (QRF) appears as the most performing method

EVALUATION OF POST-PROCESSING METHODS

Examples of actual use cases: flood

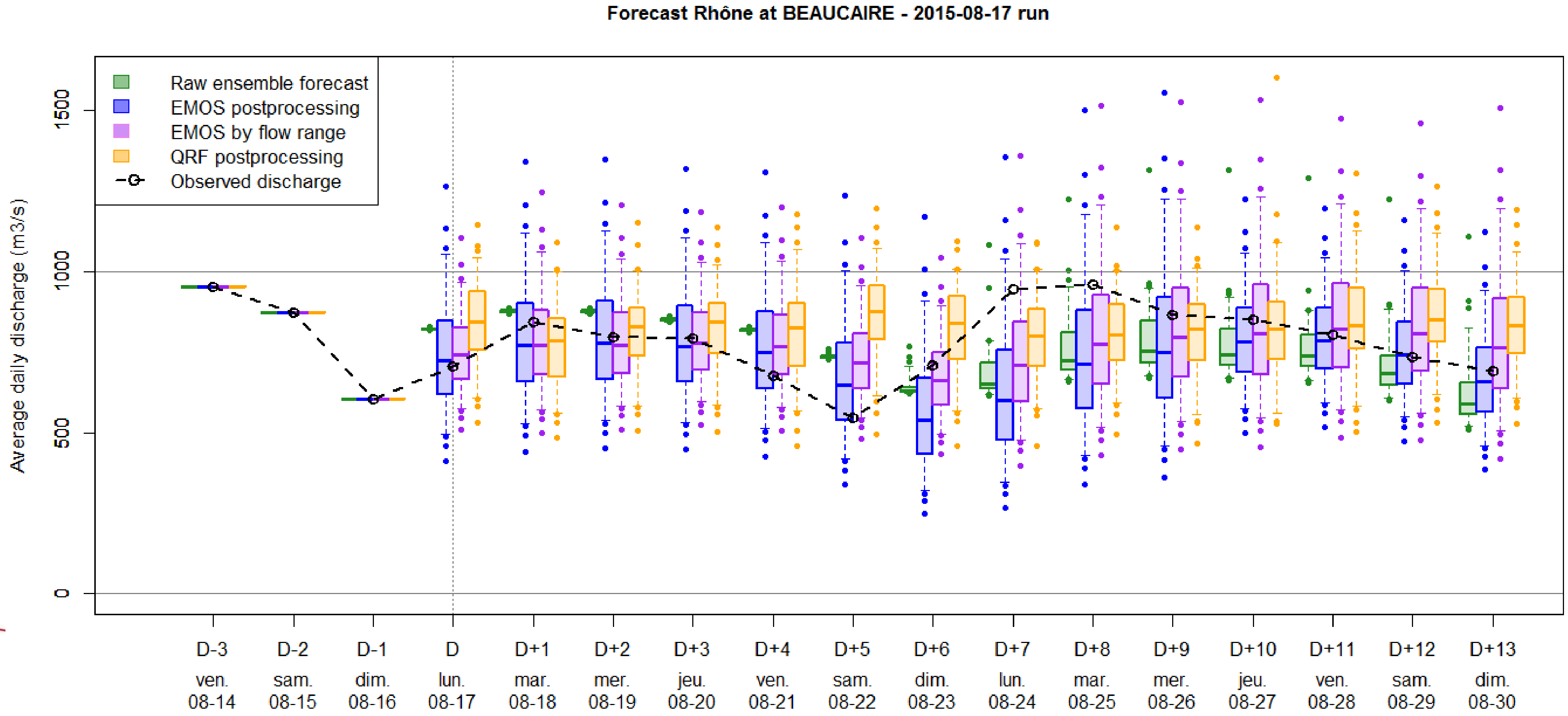
Flood situation

- EMOS fixes the tendency of raw forecasts to underestimate discharges
- QRF seems to present over-dispertion



EVALUATION OF POST-PROCESSING METHODS

Examples of actual use cases: low flows



EVALUATION OF POST-PROCESSING METHODS

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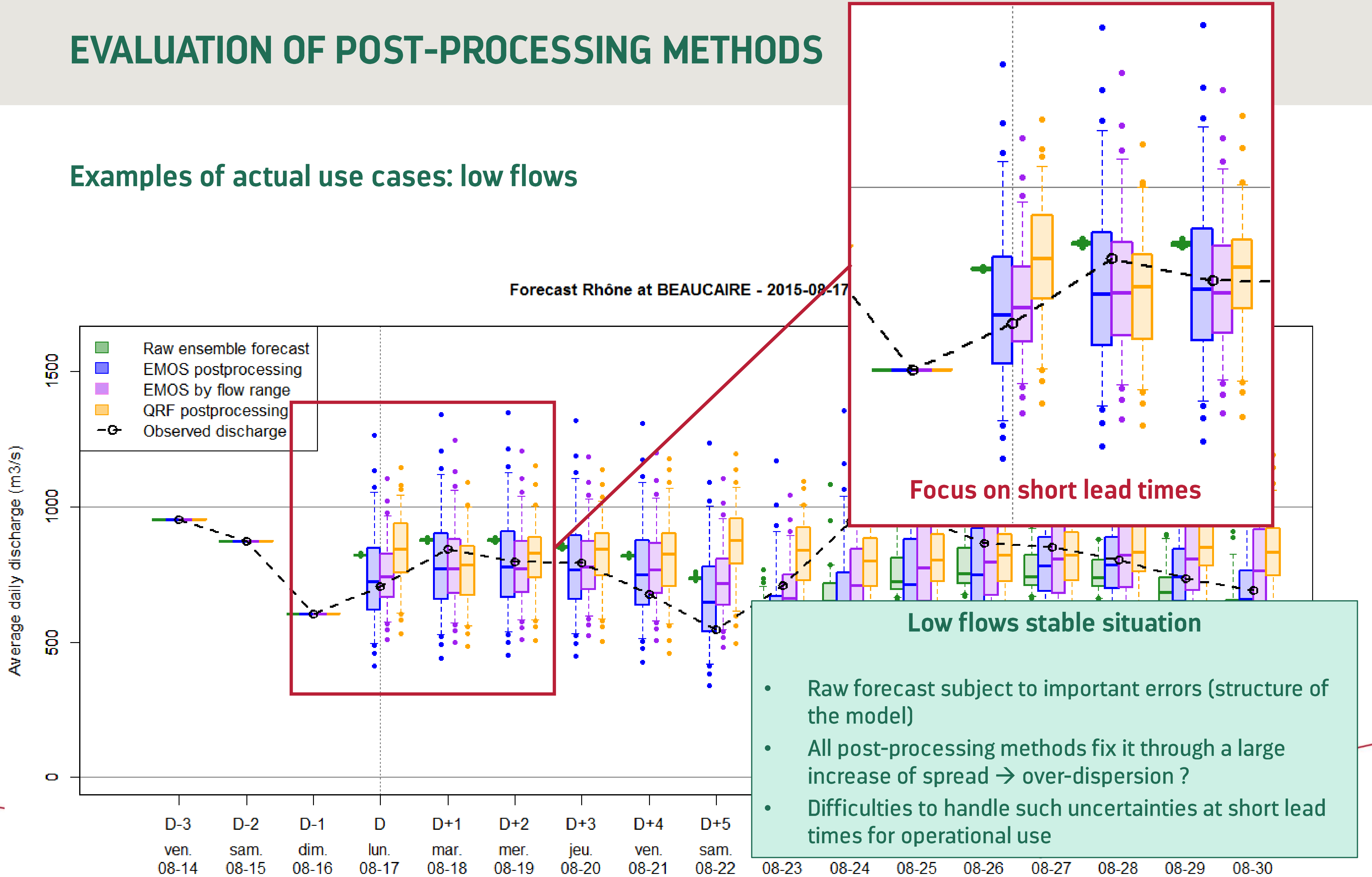
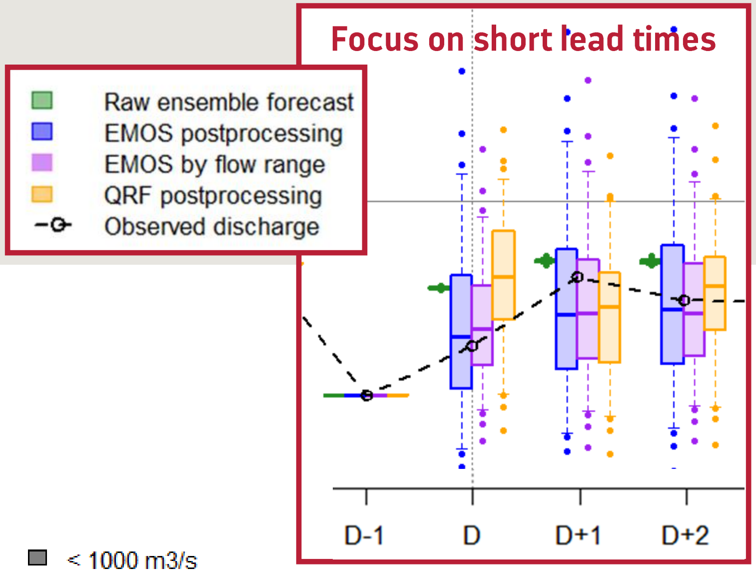


Low flows stable situation

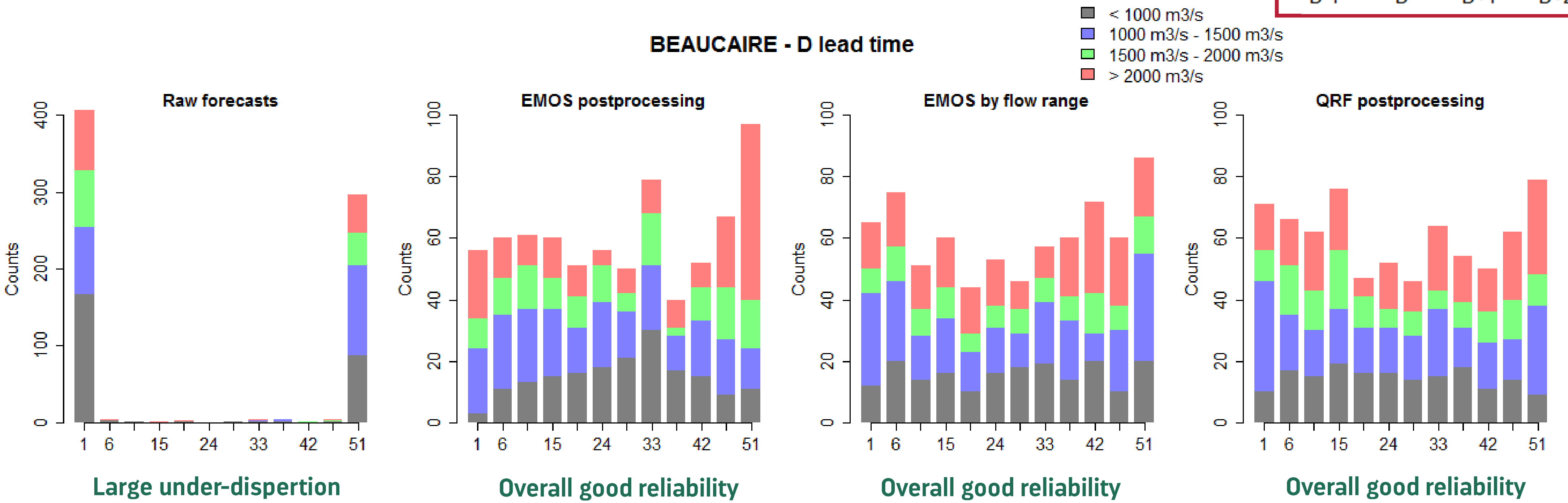
- Raw forecast subject to important errors (structure of the model)
- All post-processing methods fix it through a large increase of spread → over-dispersion ?
- Difficulties to handle such uncertainties at short lead times for operational use

EVALUATION OF POST-PROCESSING METHODS



Examples of actual use cases: low flows

Reliability (rank) histograms for D day lead time :



EVALUATION OF POST-PROCESSING METHODS

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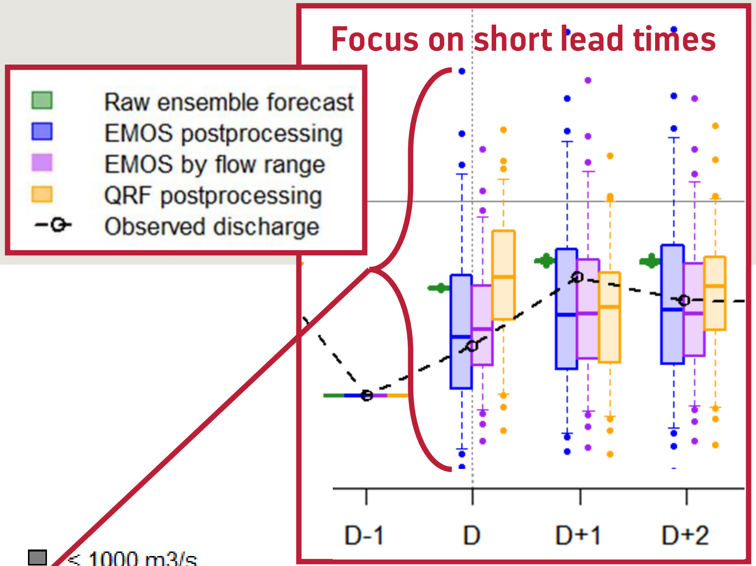

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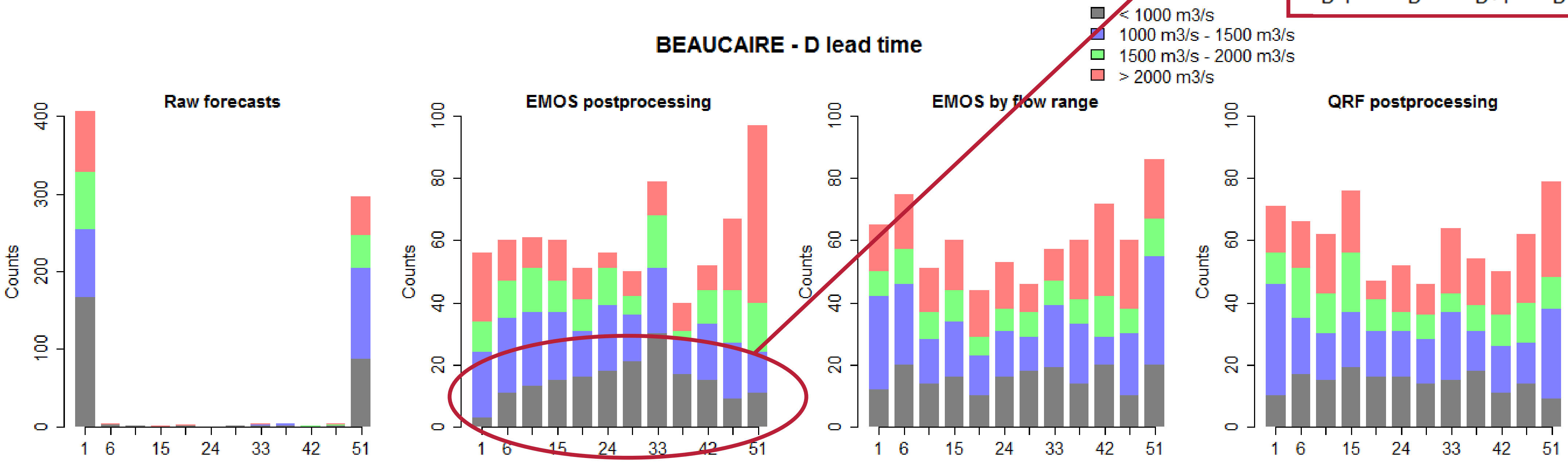

Large under-dispertion

Overall good reliability

… but over-dispertion at low flows

Overall good reliability

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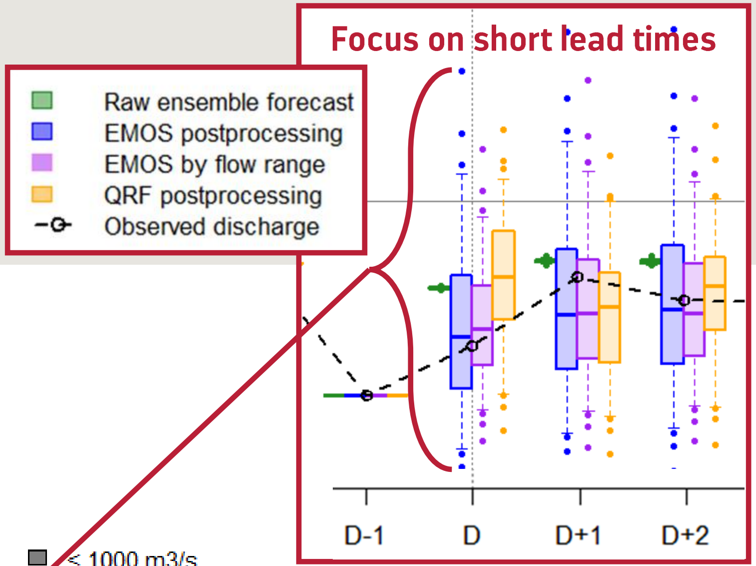

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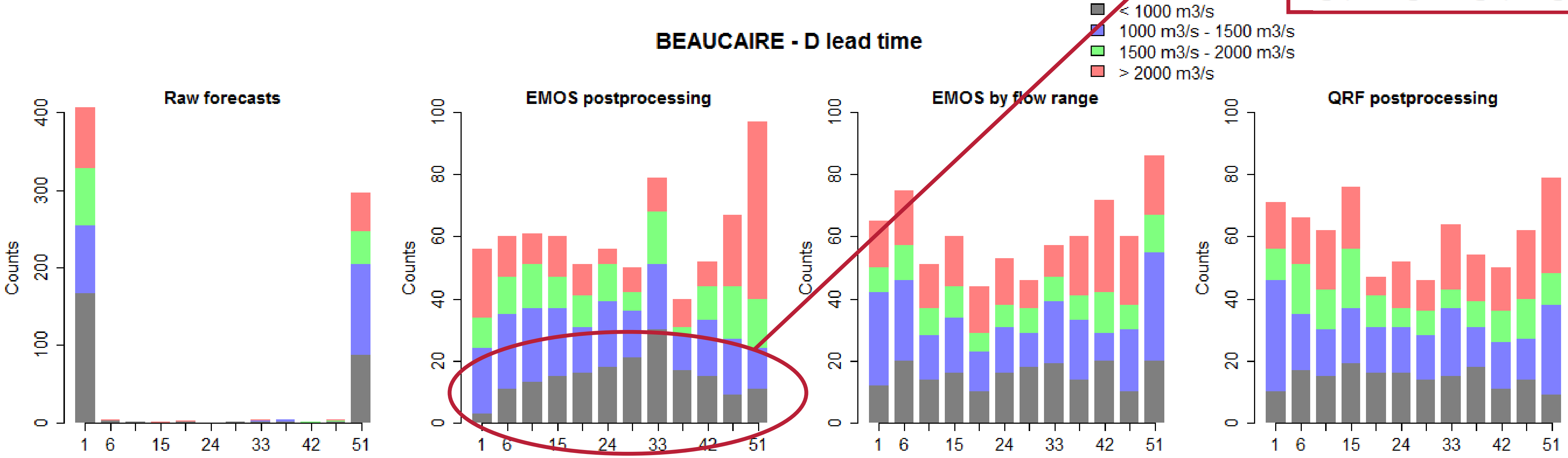

Large under-dispertion

Overall good reliability

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Overall good reliability

Overall good reliability

Low flows stable situation

- EMOS calibrated by flow range and QRF better than EMOS for reliable low flows forecasts at short lead times
- Still an unrealistic large spread for short lead times → post-processing methods can not totally fix structural errors of the model

CONCLUSIONS / PERSPECTIVES

Key findings

- First implementation of an ensemble forecasting chain for operational purpose at CNR
- Several post-processing methods have been compared
- Quantile Regression Forests (QRF) appears to give better results than EMOS
- Satisfying behaviour of the model in flood conditions
- Difficulties to predict low-flow situations: unrealistic over-dispersion of the forecasts
  - → Inherent to structural errors (hydrological + routing modules)
  - → Post-processing methods <u>can not totally fix structural errors</u>

Perspectives

- Improvement of the hydrological and routing steps of the model
- Design of a more complex and ambitious operational ensemble forecasting tool working at 6 hours timestep and dedicated to flood predictions

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