
Pagano


Wang


Shrestha


Robertson

Recent Delft-ian

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Ensemble dressing for hydrological applications

Thomas Pagano, presenting, Durga Lal Shrestha, QJ Wang, David Robertson

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Outline

Ensemble dressing concepts
Evaluation methods
Retrospective ensemble datasets
Performance in Australia

Future opportunities

Hawthorne, Pagano, Hapuarachchi, *Pokhrel, Lim*, Ward, S Wang, *QJ Wang, Robertson*, Shrestha

Short and *long-term* forecasting

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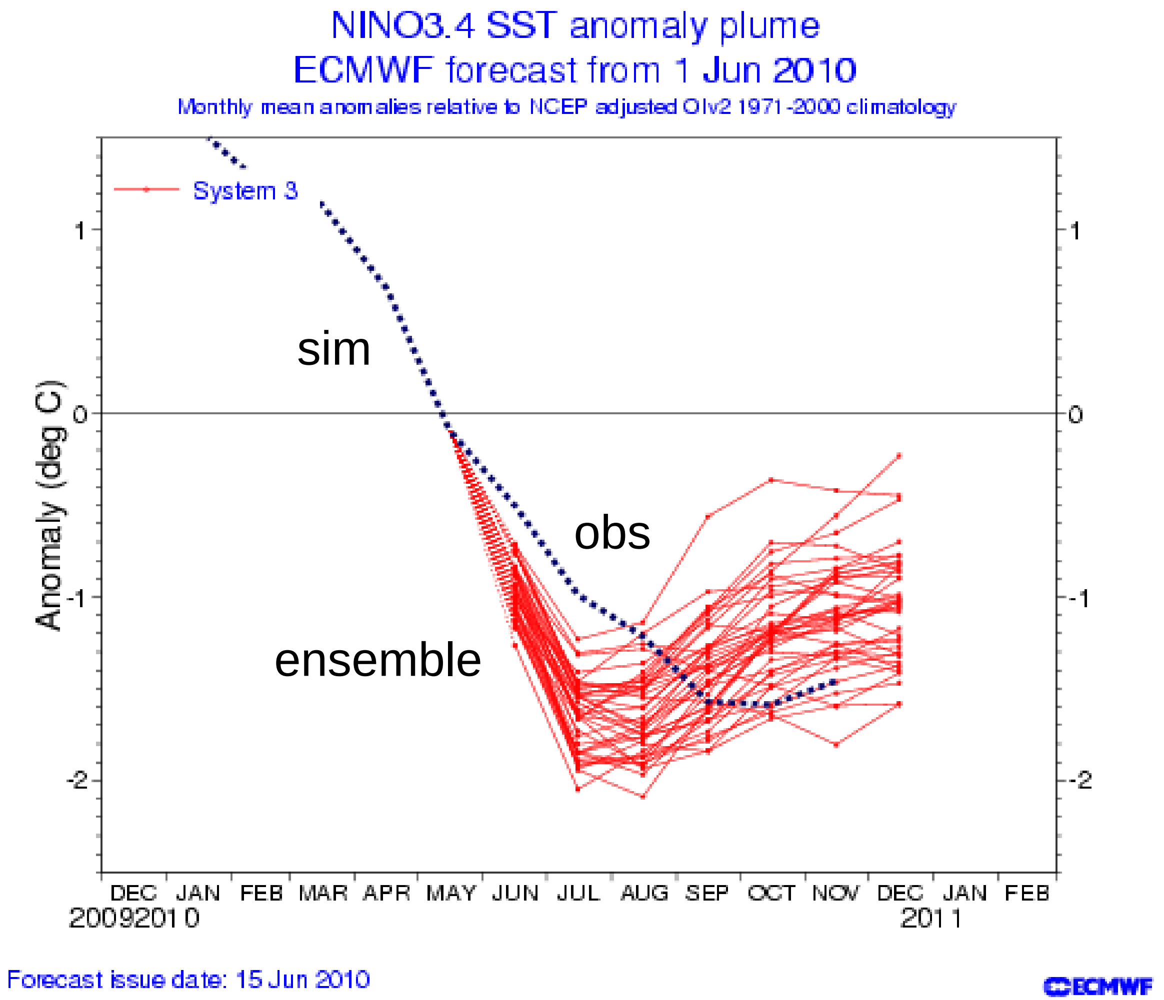
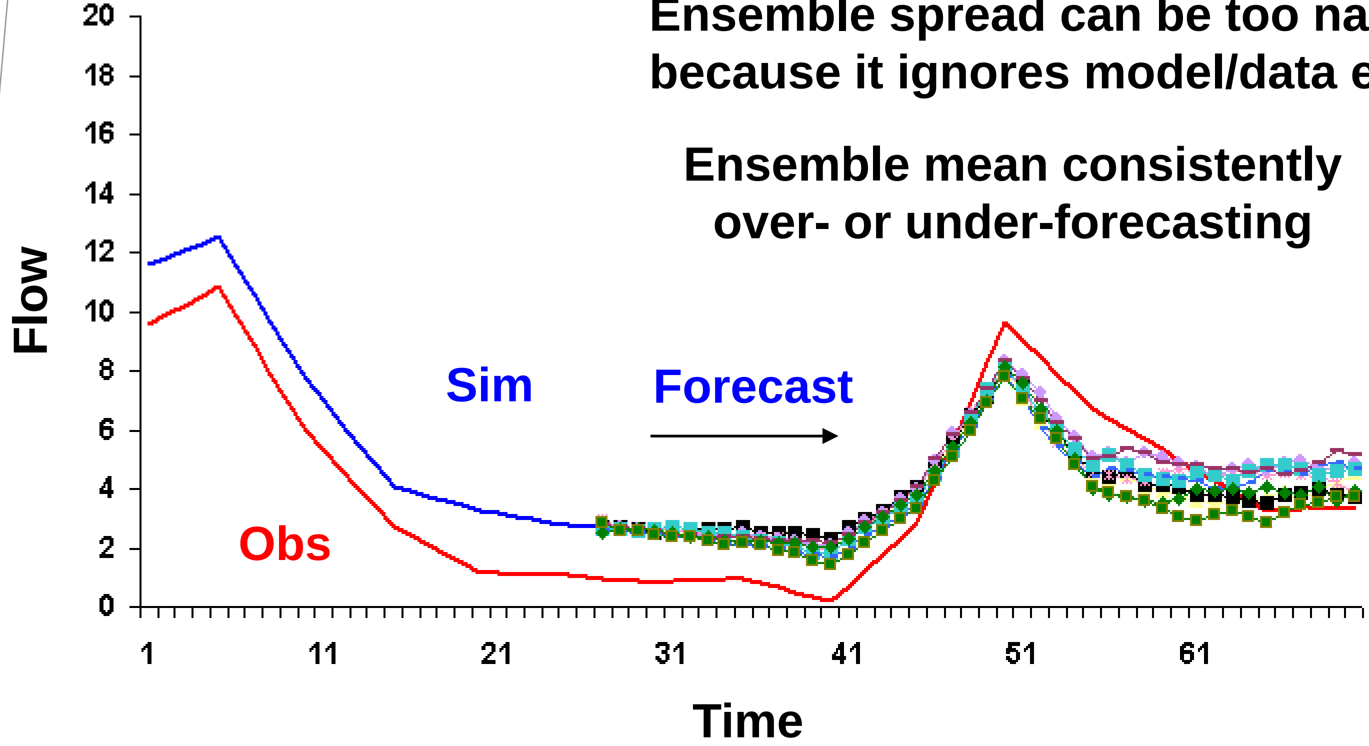
Under-dispersion is common and a problem



Ensemble dressing

Ensemble spread can be too narrow because it ignores model/data error

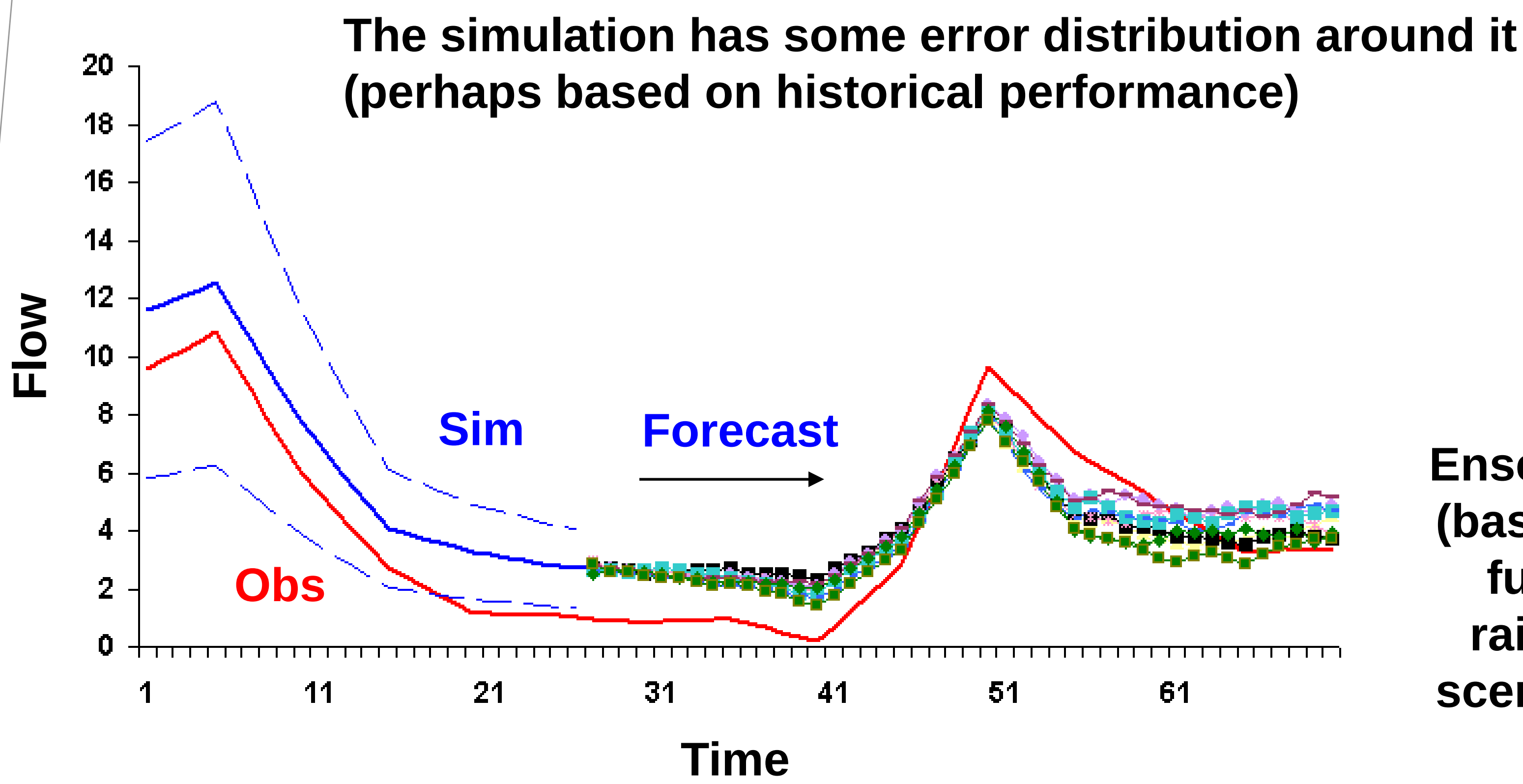
Ensemble mean consistently over- or under-forecasting



Ensembles (based on future rainfall scenarios)

Synthetic data for illustration only

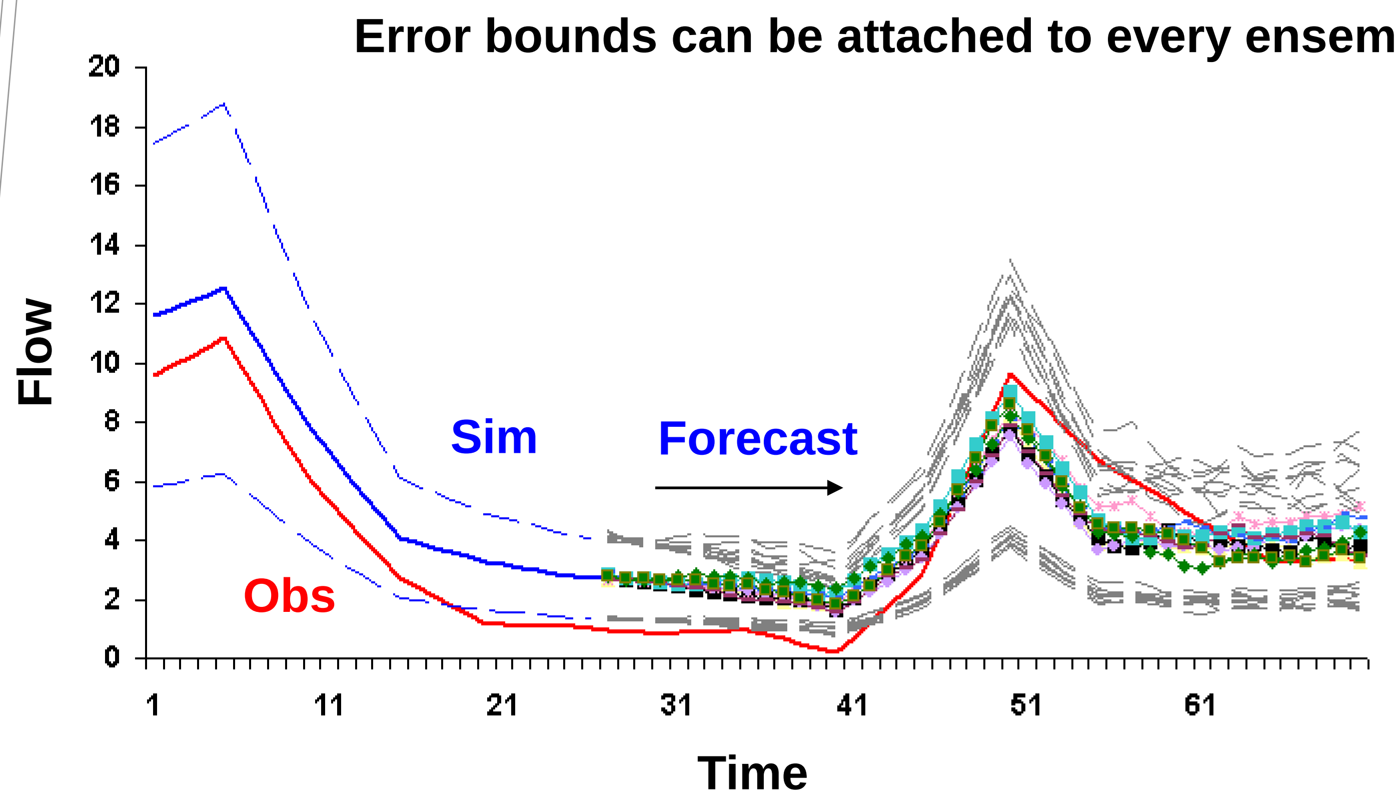
Ensemble dressing



Ensembles (based on future rainfall scenarios)

Synthetic data for illustration only

Ensemble dressing

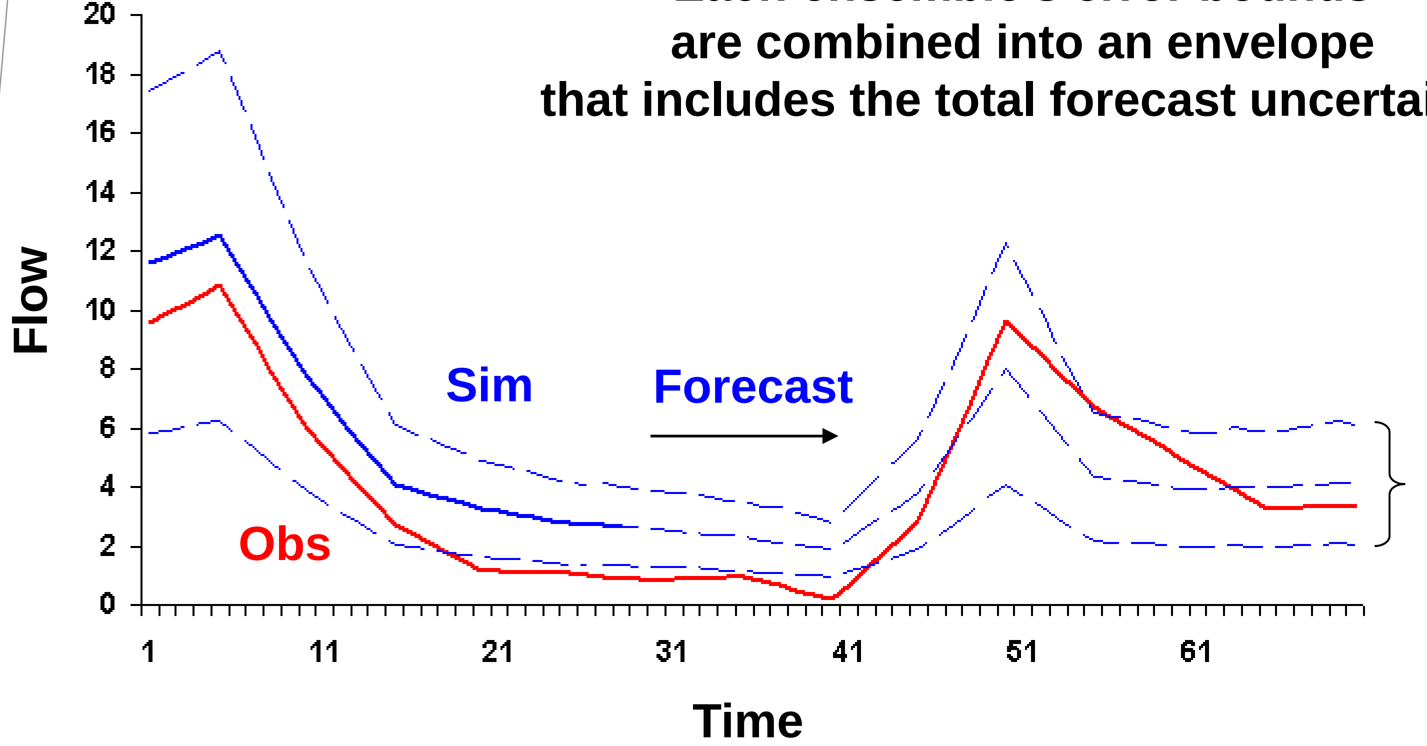


Ensembles (based on future rainfall scenarios)

Synthetic data for illustration only

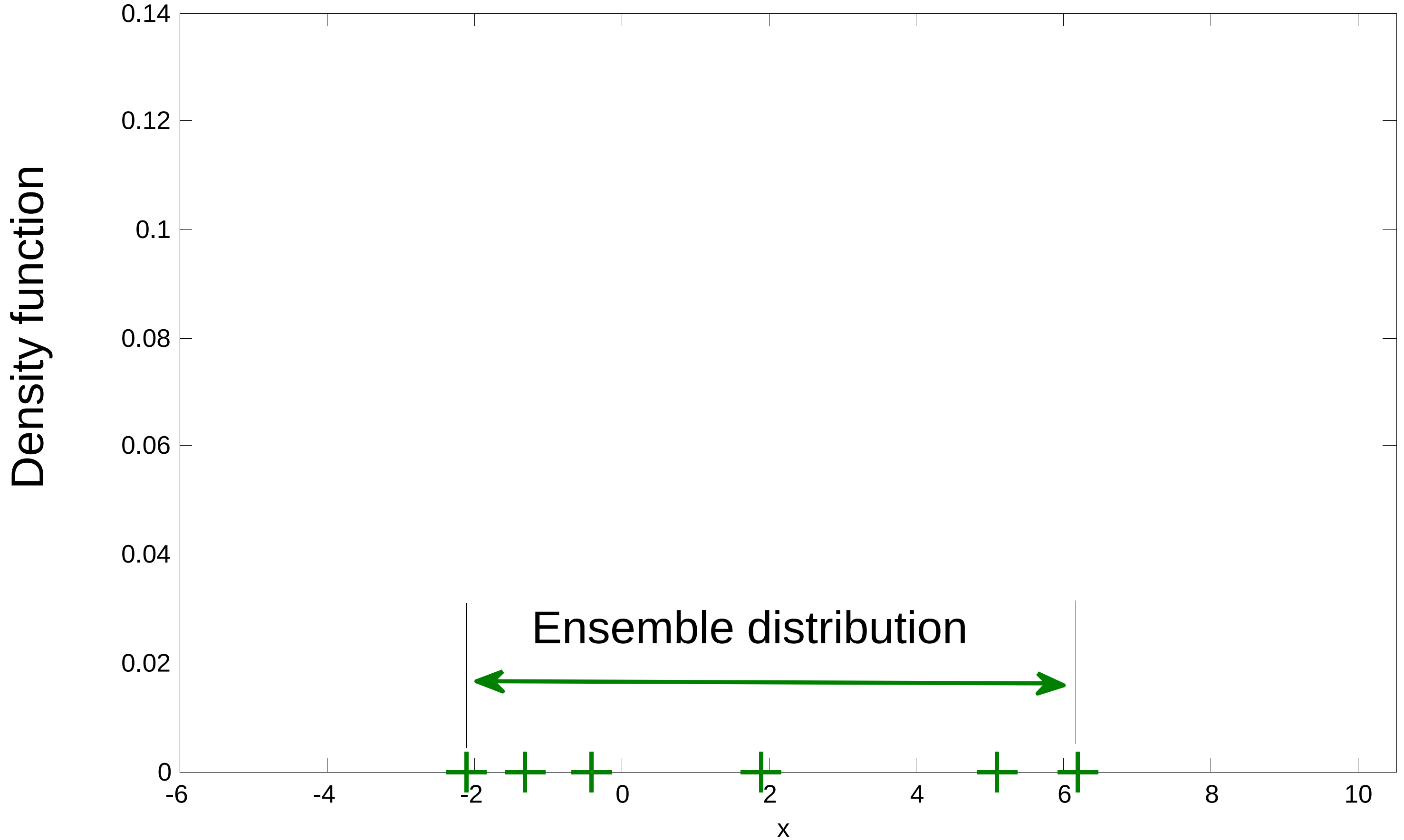
Ensemble dressing

Each ensemble's error bounds are combined into an envelope that includes the total forecast uncertainty.

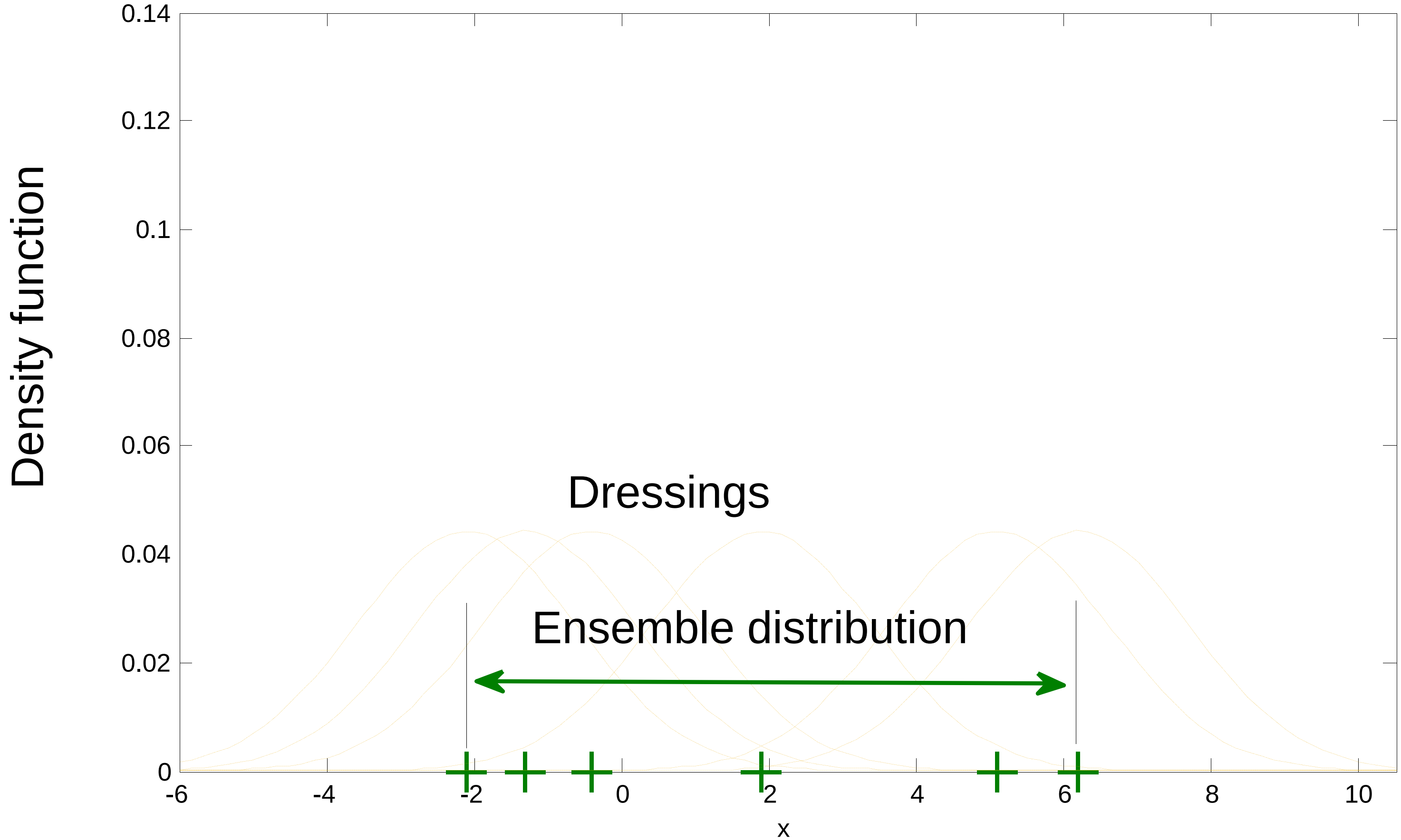


"Dressed" ensemble distribution

Synthetic data for illustration only



Density function
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
-6
-4
-2
0
2
4
6
8
10
x
Ensemble distribution


Density function
0.14
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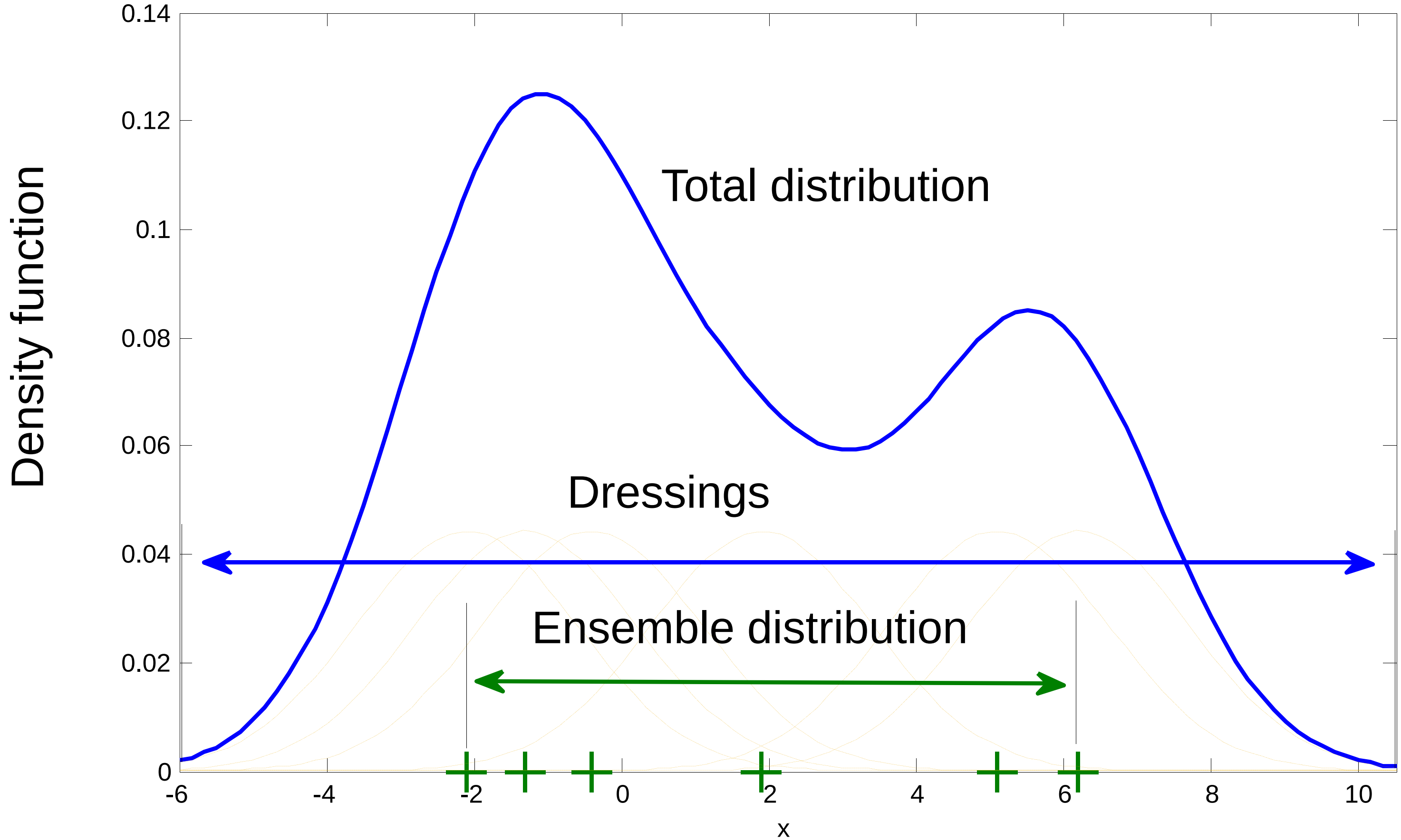
4
6
8
10
x
Dressings
Ensemble distribution



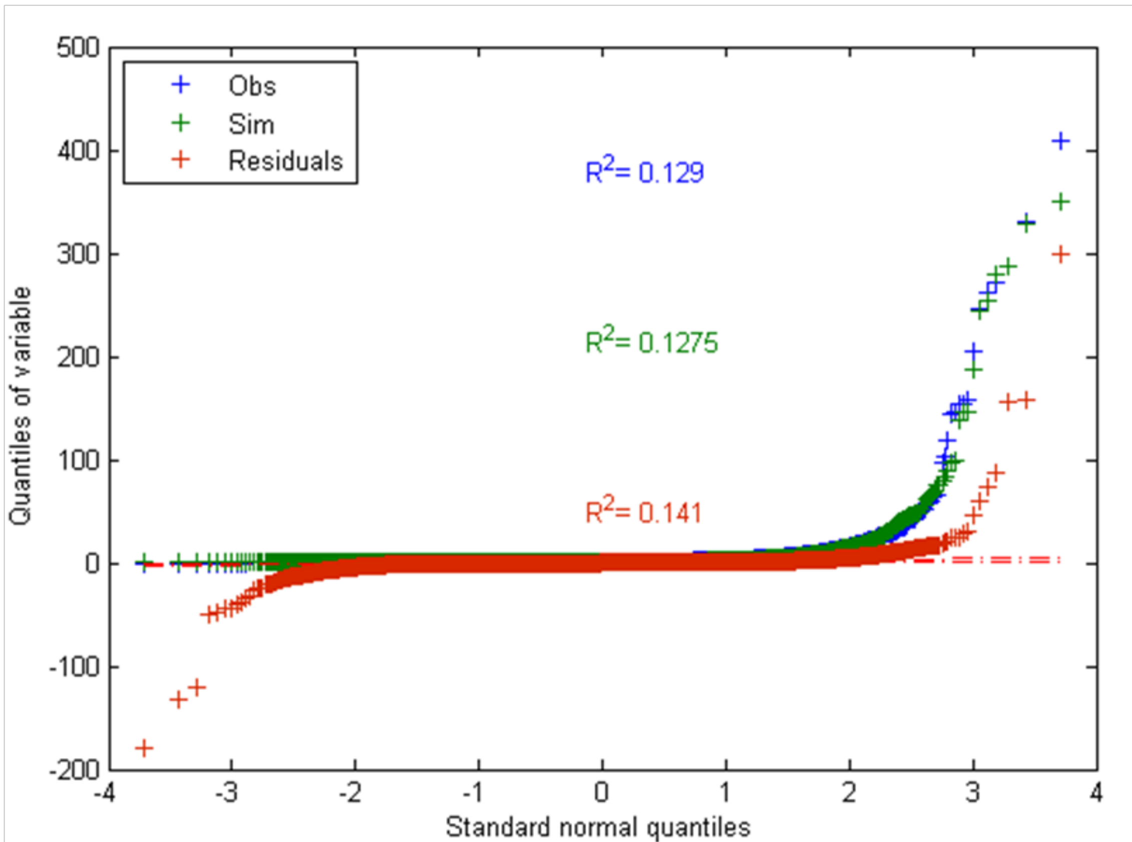
Total distribution
Dressings
Ensemble distribution
Density function
x
0.14
0.12
0.1
0.08
0.06
0.04
0.02
0
-6
-4
-2
0
2
4
6
8
10

But what should this dressing/error distribution be?

Normal (Gaussian) error is ideal, but hydrologic timeseries are often:

Heteroschedastic | Autocorrelated

Non-Normal skew/kurtosis | Non-stationary?



Simulated, Observed and Residuals all highly non-Normally distributed

Log-sinh data transformation

Logsinh transformation[1]

z = 1/b log(sinh(a+by))

A and B are parameters that control strength/shape of transformation

Parameter estimation

MLE estimation

z = logsinh(y)

zsim = logsinh(ysim)

p(z) ≅ $N(\mu + zsim, \sigma)$

P(y) = J_{zy} p(z)

= dz/dy p(z)

Likelihood function

$$L(a,b,\mu,\sigma) = \prod_{i=1}^{n} p(y_i) = \prod_{i=1}^{n} \frac{dz}{dy} p(z)\Big|_i$$

Jzy = coth(a+by)

Raw ensembles

↓ Transform

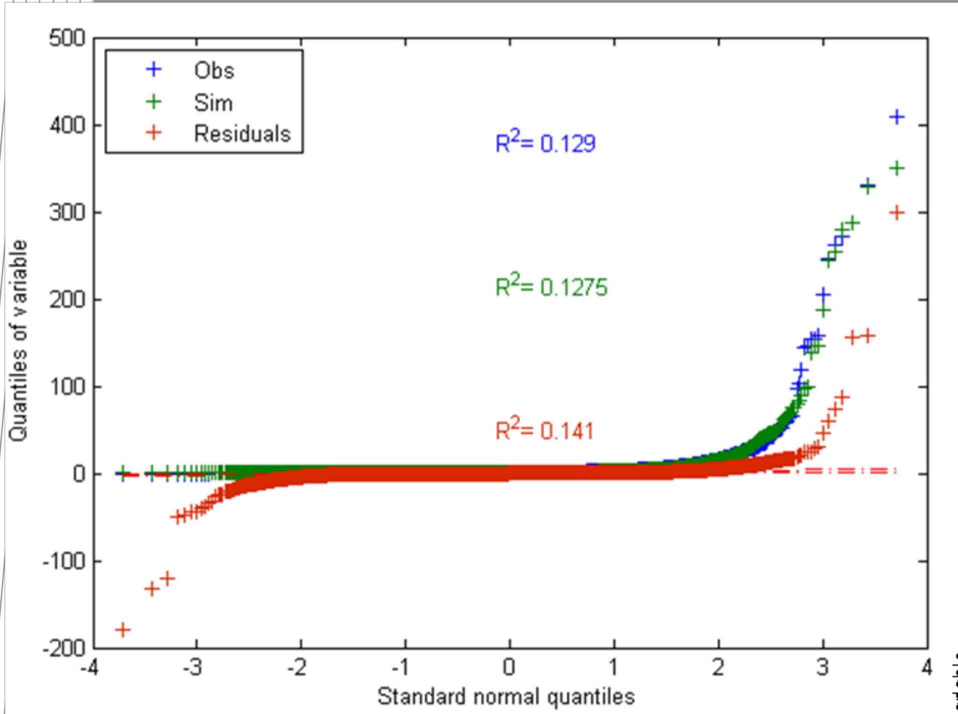
Calculate residuals

Attach uncertainty

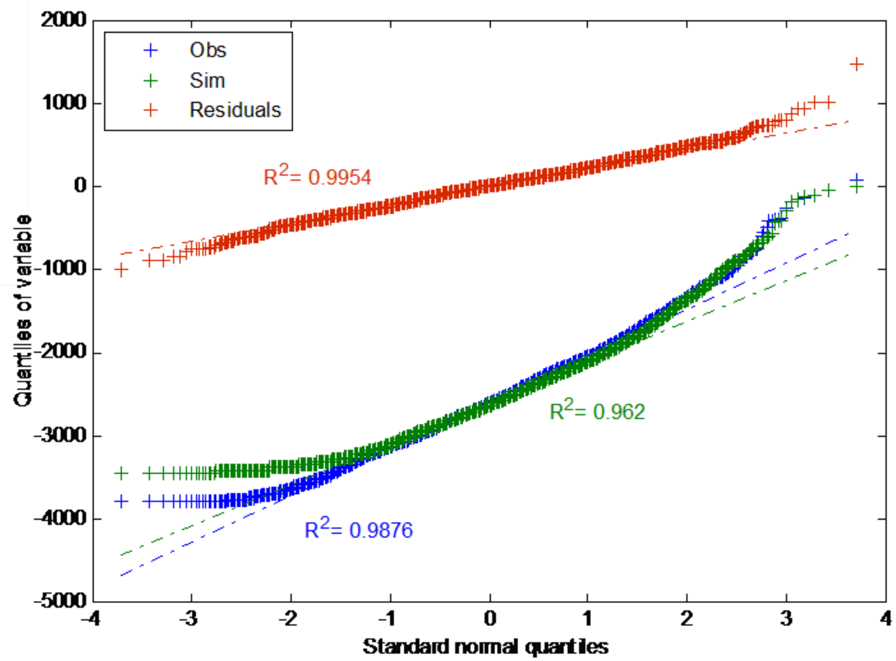
↓ Un-transform

1Wang, QJ, Shrestha, DL, Robertson, DE, Pokhrel, P. A log-sinh transformation for data normalisation and variance stabilisation, (in preparation)

QQ plot



Simulated, Observed and Residuals all highly non-Normally distributed



Transformed variables non-Normal, but the residuals are.

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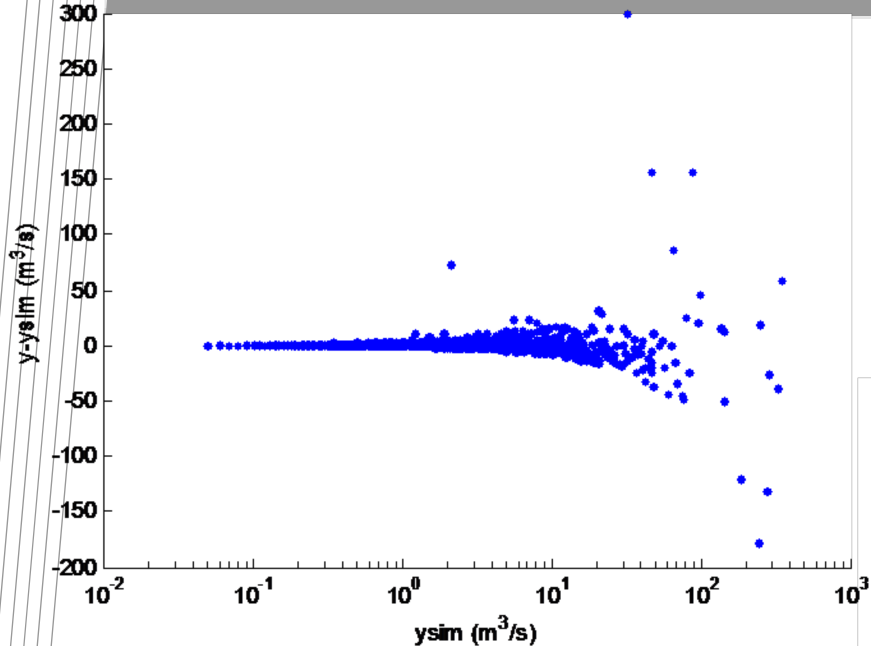
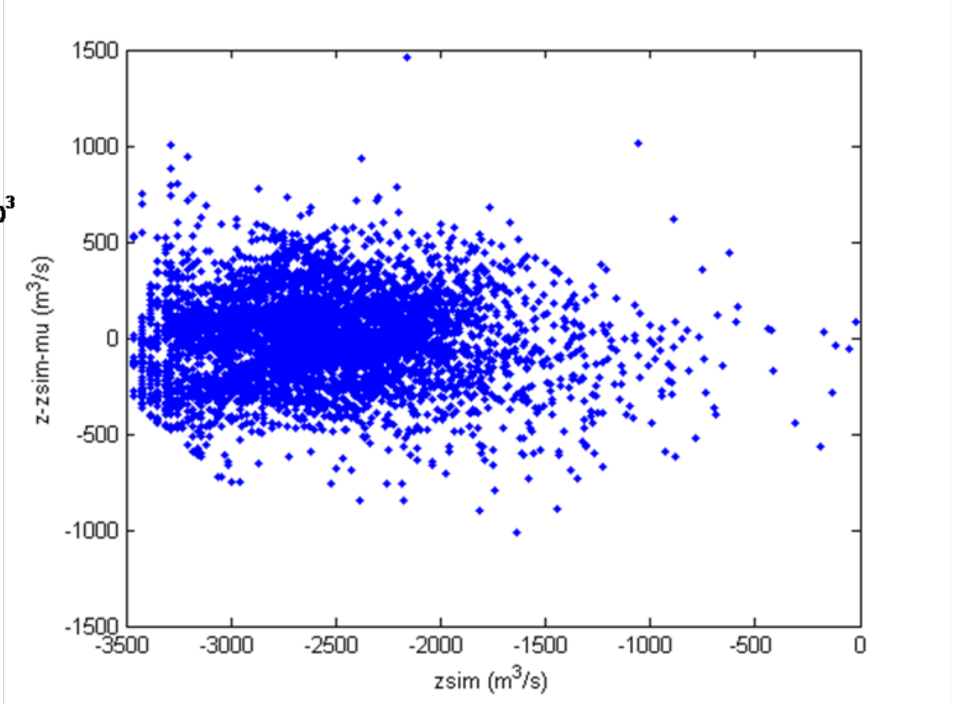
Residual plot



Raw residuals' variance depends on forecast magnitude

Transformed residuals' variance roughly constant



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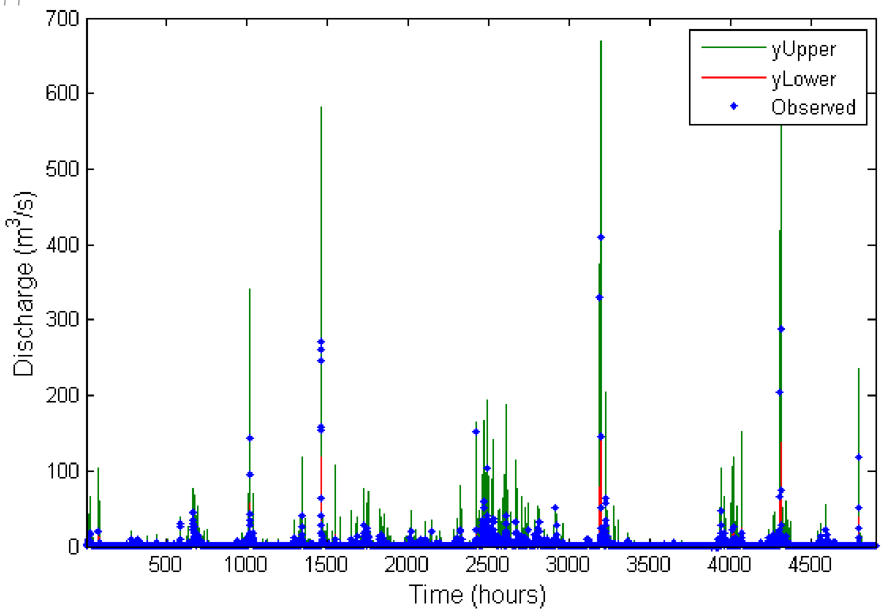
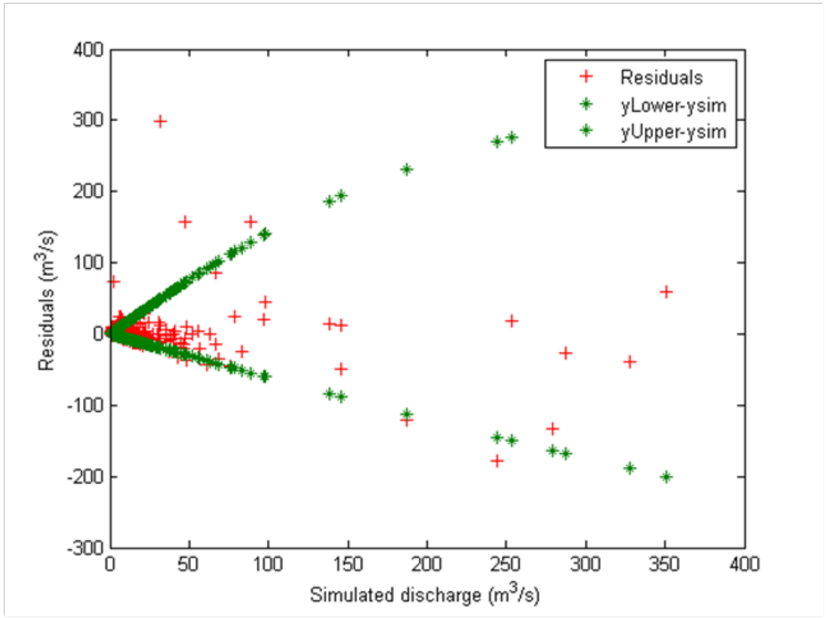
Uncertainty estimation

- $y_L(\alpha) = \text{logsinh}^{-1}(\mathcal{N}^{-1}((1-\alpha)/2, \mu+\text{zsim}, \sigma))$
- $y_U(\alpha) = \text{logsinh}^{-1}(\mathcal{N}^{-1}((1+\alpha)/2, \mu+\text{zsim}, \sigma))$
- $y_m = \text{logsinh}^{-1}(\mathcal{N}^{-1}(0.5, \mu+\text{zsim}, \sigma))$





Error distribution width asymptotes with forecast size (which is good).

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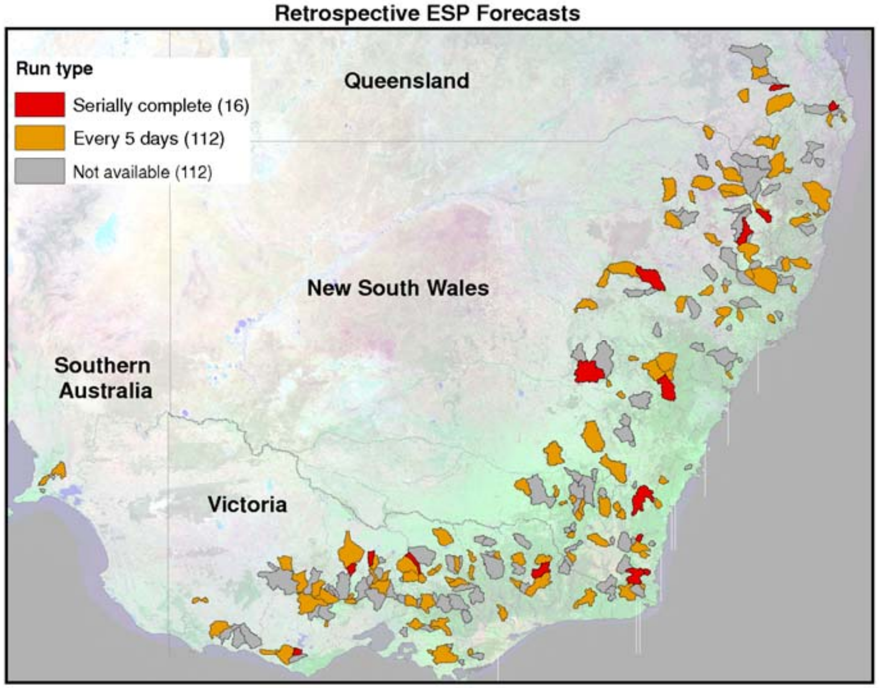
Application

- 16 Australian catchments with a serially complete set of retrospective daily ensemble forecasts (starting from 1979-2006).

  10,197 forecasts per catchment, each with 33 members.
- Additional 112 catchments to have forecast issue dates staggered every 5 days (2,043 start dates/site)
- GR4J model
- Ensemble forecasts using ESP

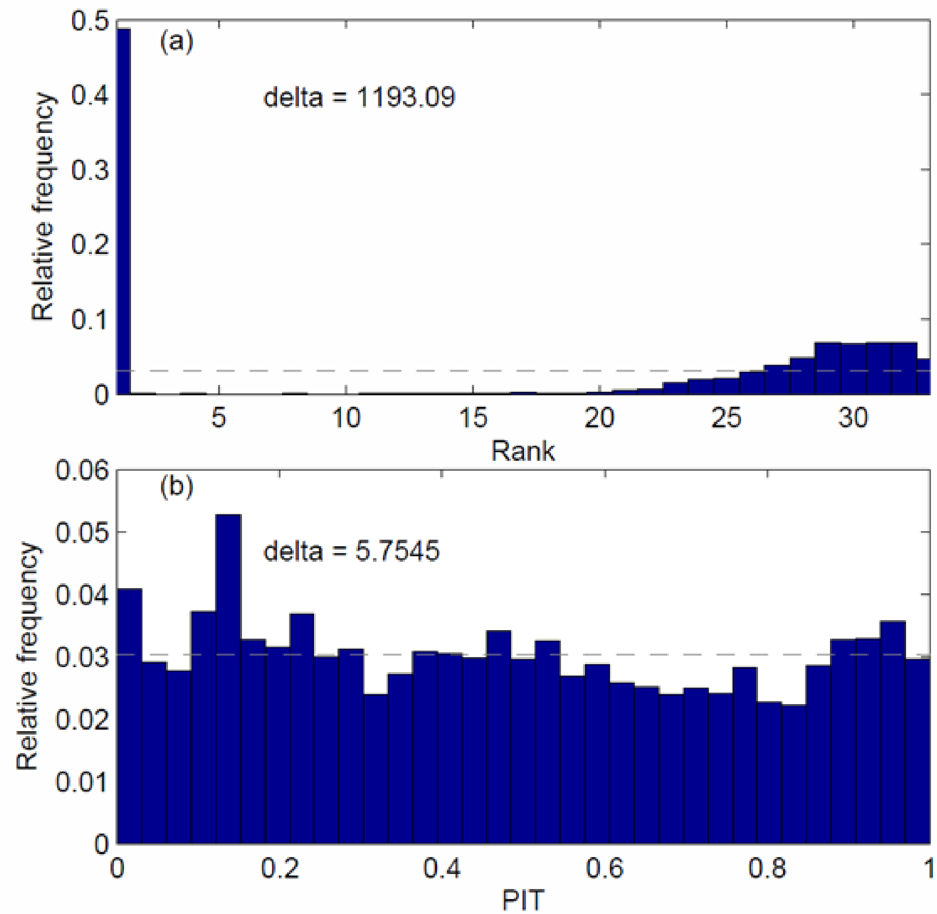
Half of record for calibration of GR4J and ensemble dressing parameters. Half for validation.

Run using Condor Cluster

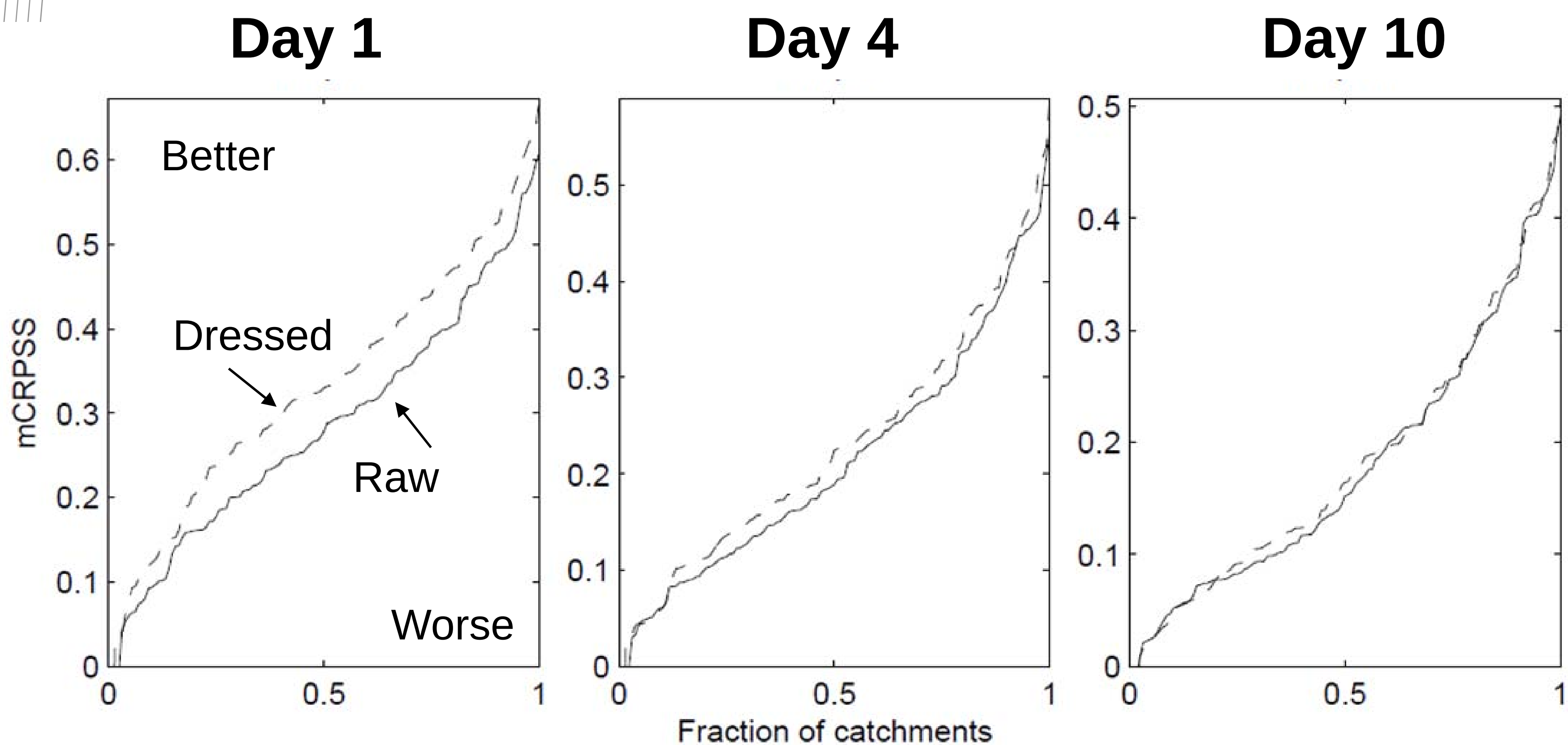


Verification

- Root mean squared error of ensemble mean (not shown)
- Continuous ranked probability skill score
- Delta score (flatness of ranked histogram, Wilson et al 2007)

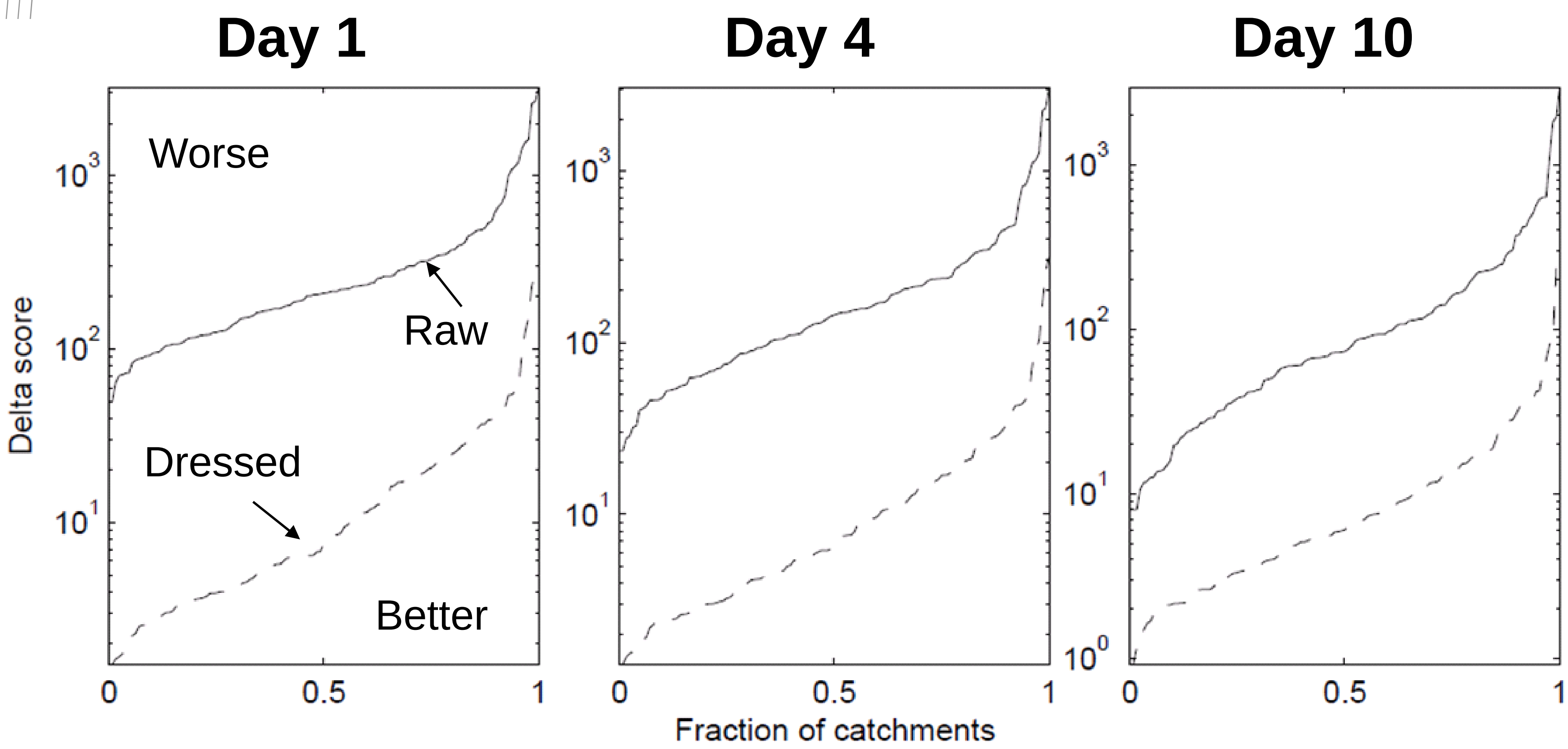


Cont. Ranked Prob Skill Score vs leadtime



Most benefits at short leadtimes when climate uncertainty is small

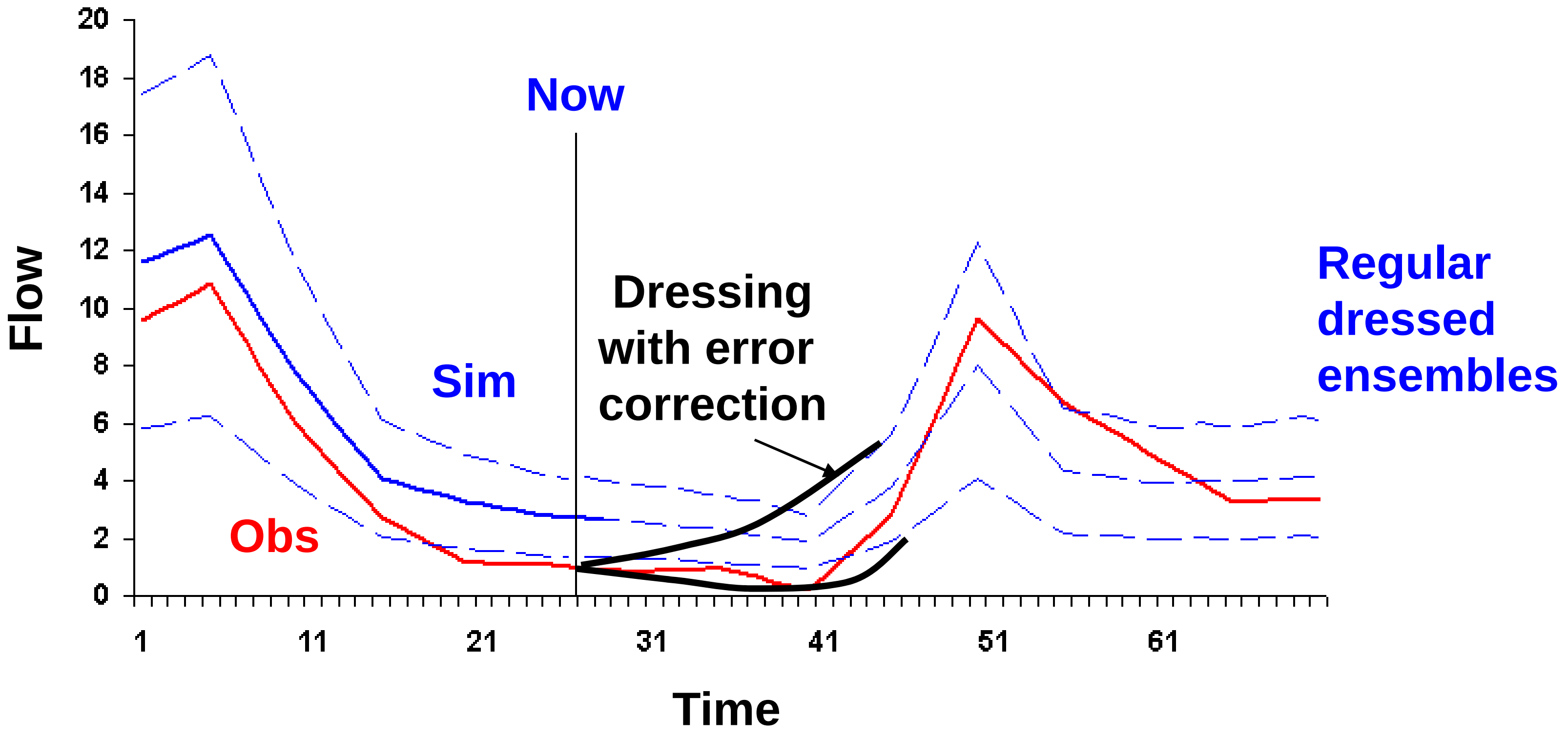
Delta score (rank histogram flatness) vs leadtime



Raw ESP rank histograms very non-flat. Dressing helps a lot.

Possible formal expansions

Consider error autocorrelation, blend with error correction.



Limitations of what we did

Model error is only based on magnitude, not timing or regime.

Does not quantify chance of zero flow.

Ensemble spaghetti is lost (forever?).

This all may have a different name elsewhere.

This is the least possible effort to try and achieve our objectives.

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This is the least possible effort to try and achieve our objectives.

HEPEX runs we performed

Ensemble post-processing

GFS and Climatology

Both catchments

Calibration options 1 – 4

2,5,10,15 and 30 day targets

No data assimilation

My future

Travelling for a year (Aug 2011-12) to meet other researchers and forecasters. I am hoping to write a book for the public about the human side of river forecasting. I also aim to meet strange rivers, hydrologic oddities and impressive structures.

Contact me if you

have suggestions!

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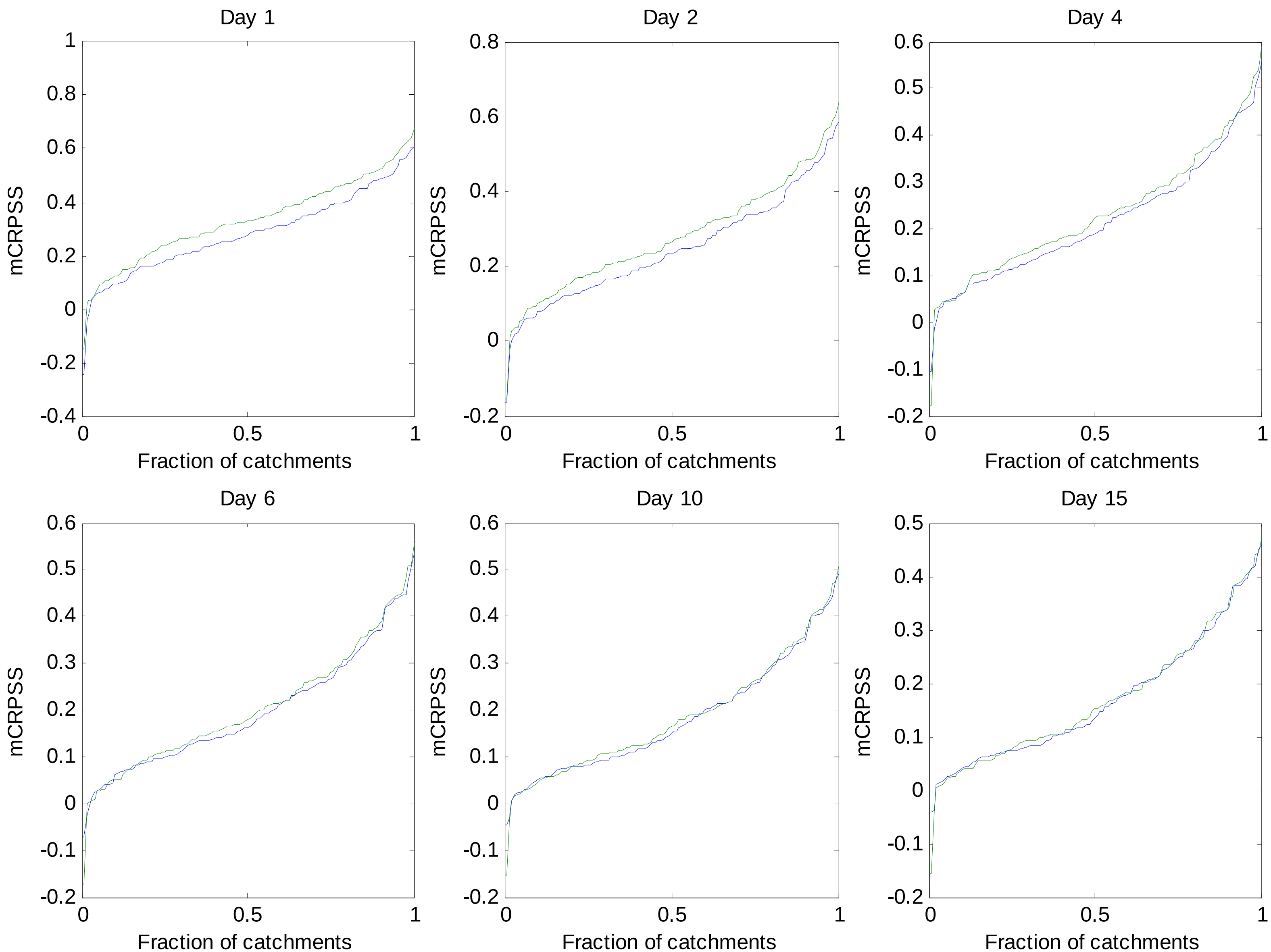
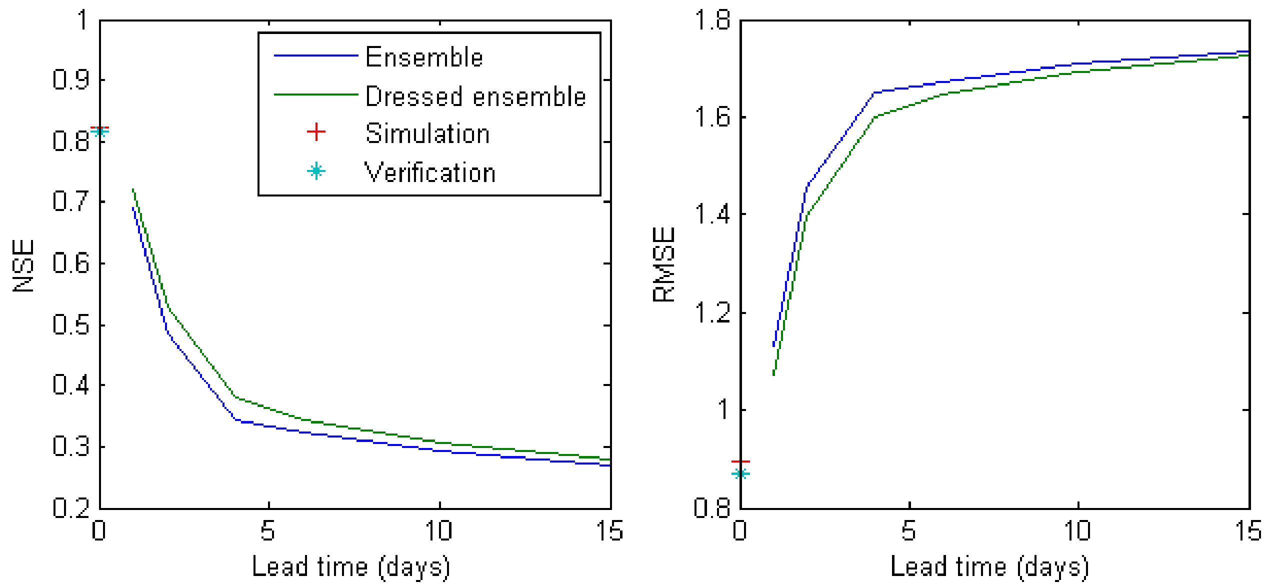
END

Cont. Rank. Prob Skill Score - 128 catchments



Verification

- Ensemble average skill scores
  - NSE, RMSE



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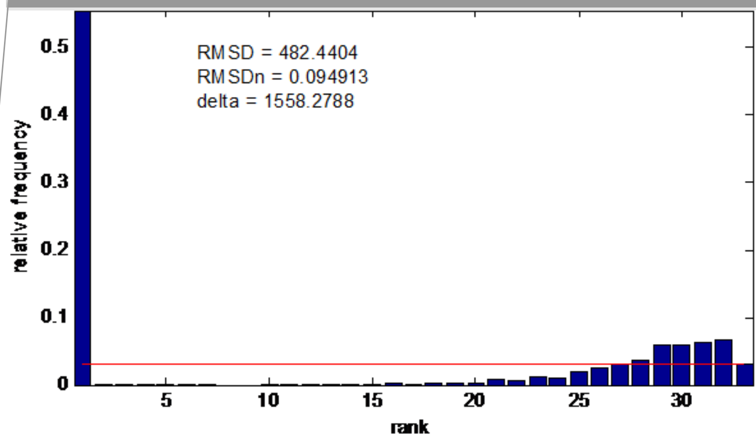
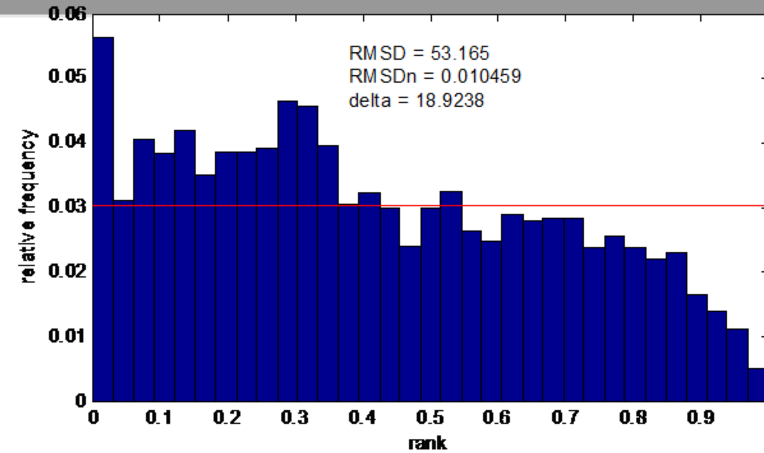
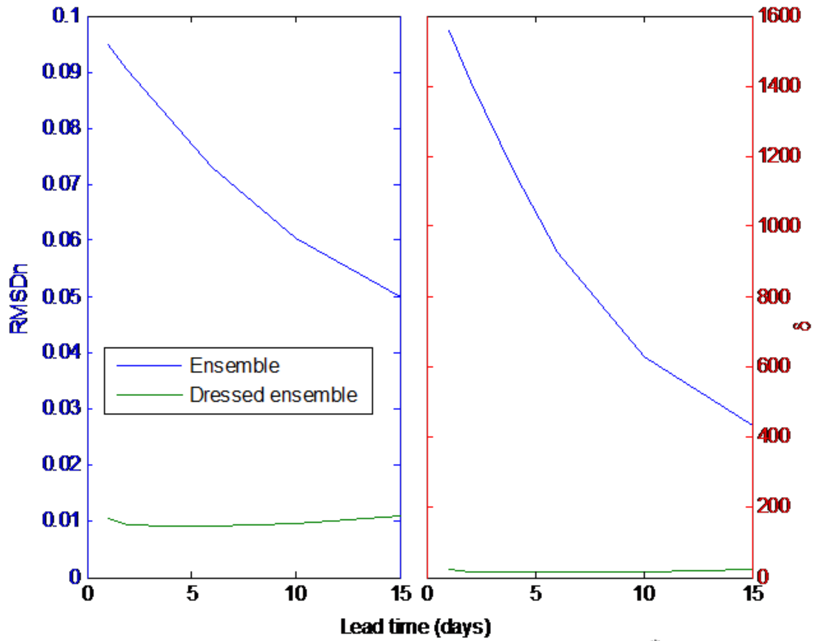
Rank histogram based skill scores







$$\Delta = \sum_{k=1}^{N+1}\left(s_k - \frac{M}{N+1}\right)^2$$

$$\Delta_n = \sum_{k=1}^{N+1}\left(\frac{s_k}{M} - \frac{1}{N+1}\right)^2$$

$$\mathrm{RMSD} = \sqrt{\frac{1}{N+1}\Delta}$$

$$\mathrm{RMSD}_n = \sqrt{\frac{1}{N+1}\Delta_n}$$

$$\Delta_0 = \frac{MN}{N+1}$$

$$\delta = \Delta / \Delta_0$$

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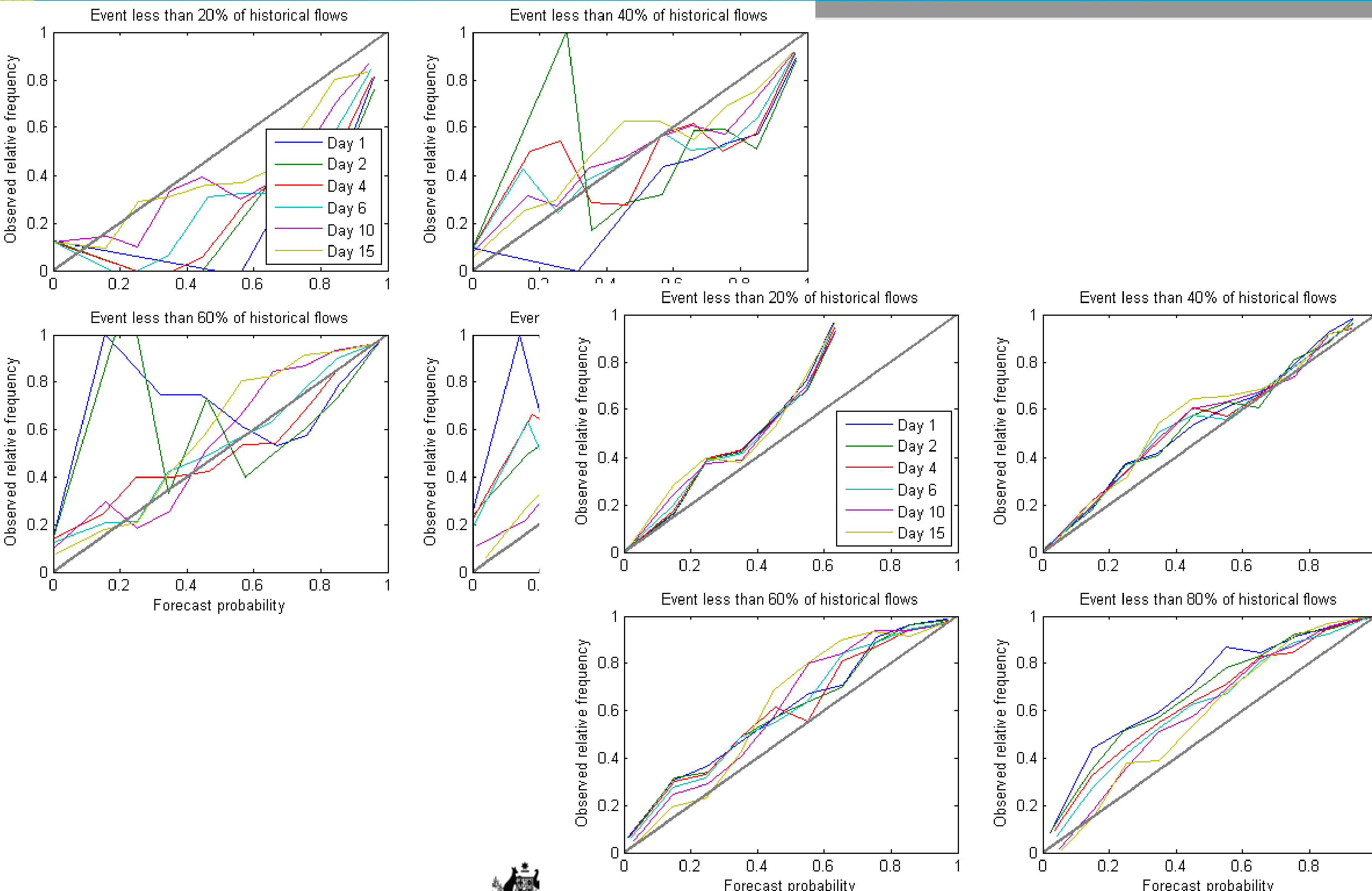
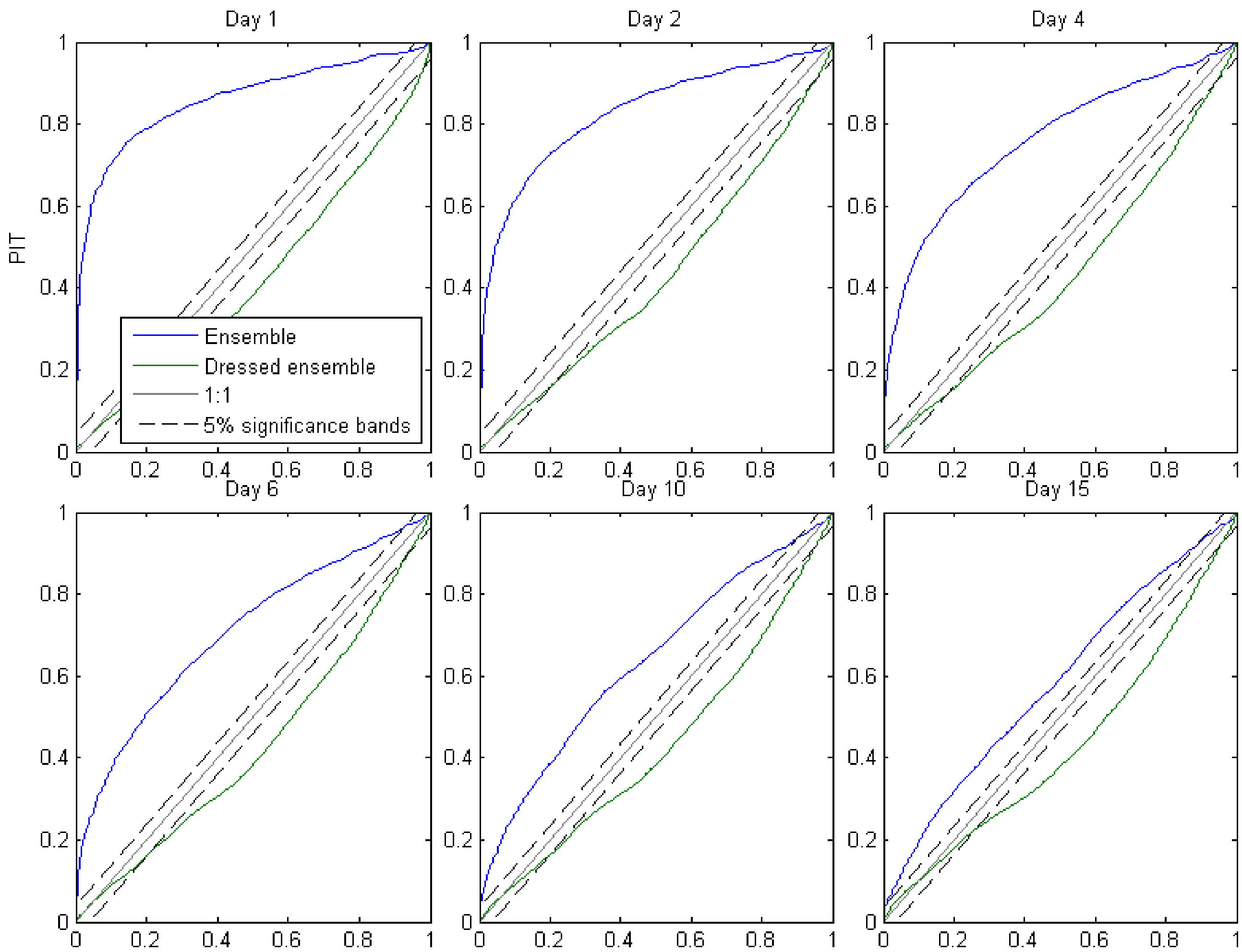
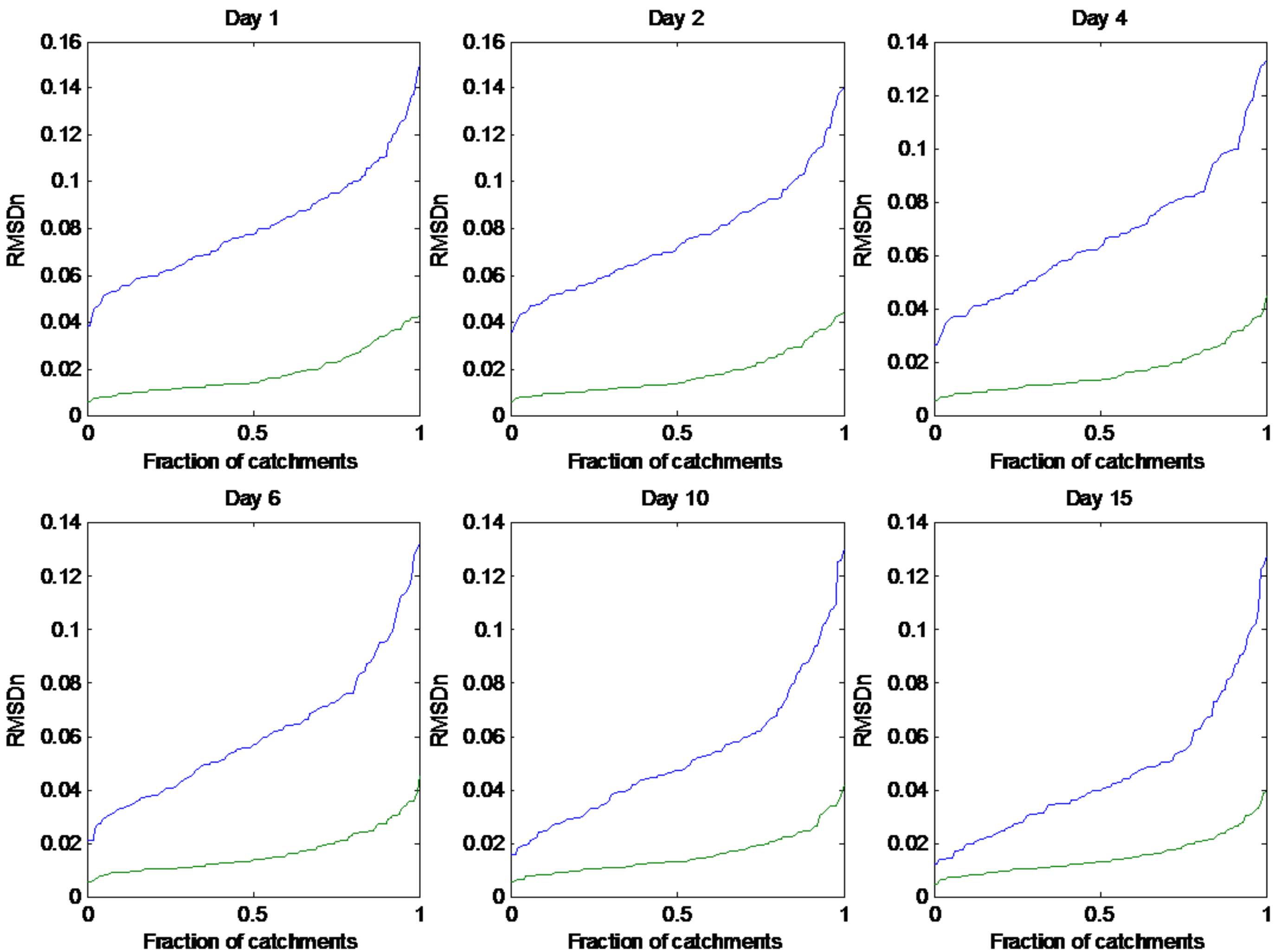
Reliability diagrams



PIT Plots


Day 1
Day 2
Day 4
Day 6
Day 10
Day 15
PIT
Ensemble
Dressed ensemble
1:1
5% significance bands
0
0.2
0.4
0.6
0.8
1

Flatness of rank histogram – 128 catchments



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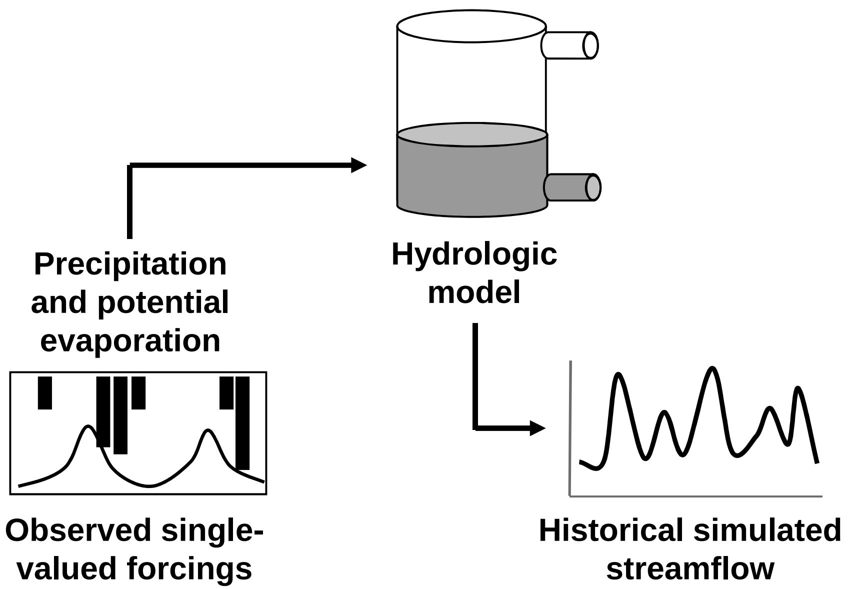
Conclusions

- The ensemble dressed forecasts are verified with various ensemble verification metrics, such as the continuous ranked probability score, rank histograms and attributes diagrams.
- The results demonstrate that ensemble dressed forecasts are more skilful and reliable than the undressed ensembles.
- This technique fills a gap by proposing an ensemble post-processing technique that considers multiple sources of uncertainty while requiring only minimal computational resources.
- This method would be well suited for operational forecasting

The total system



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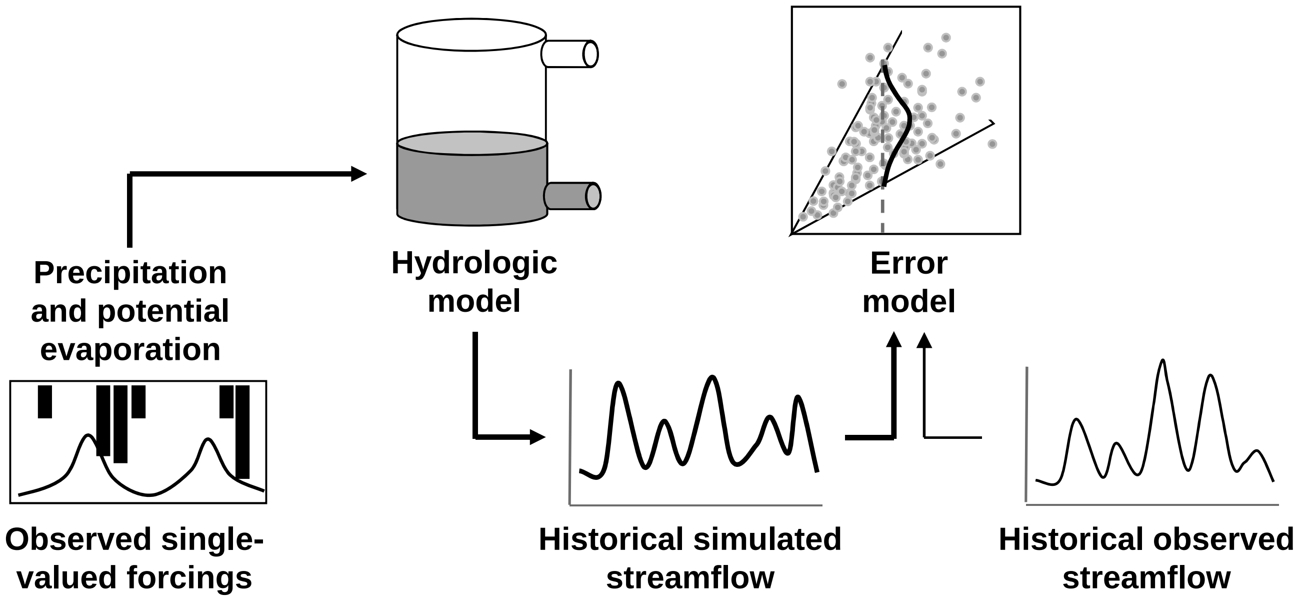

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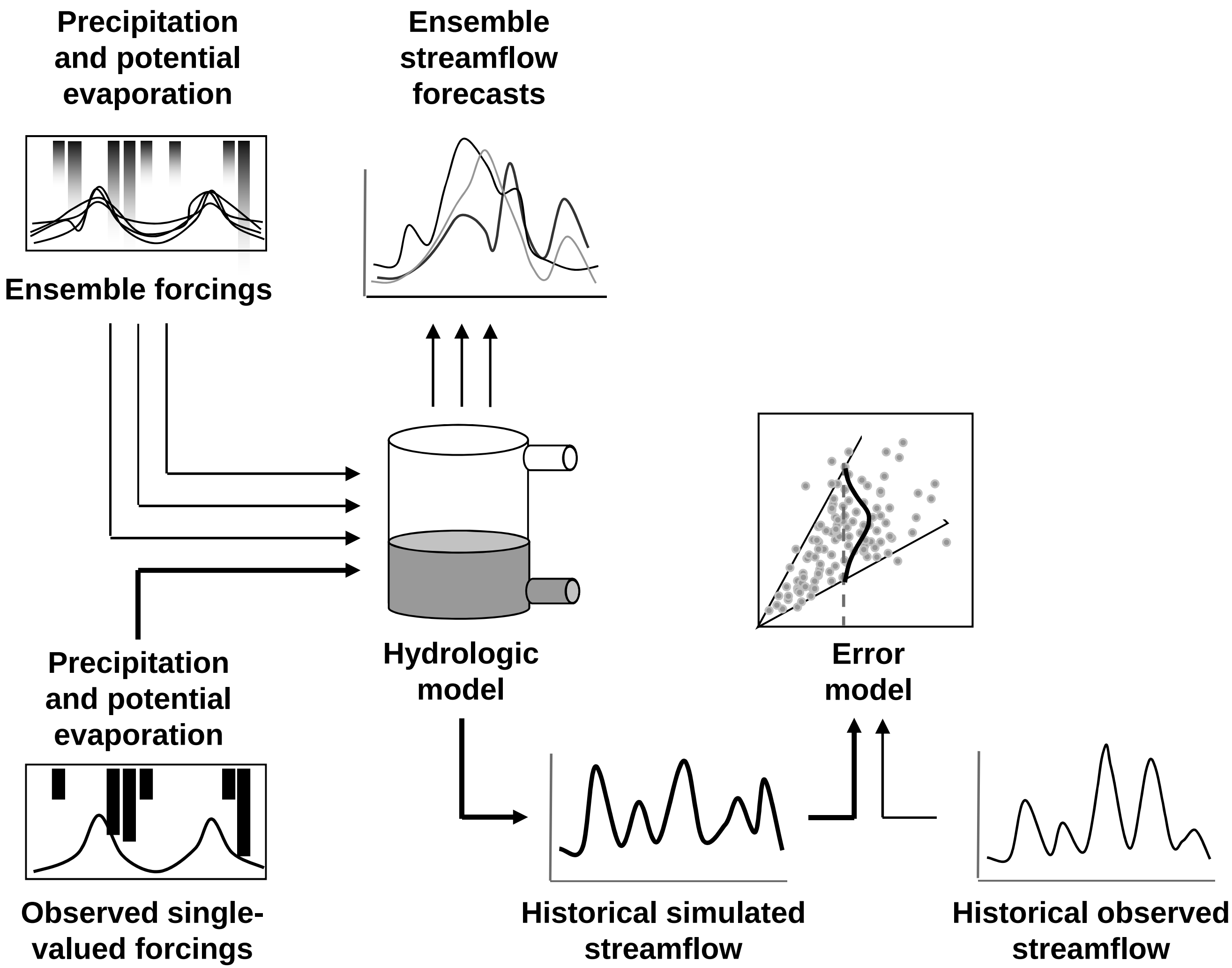
The total system



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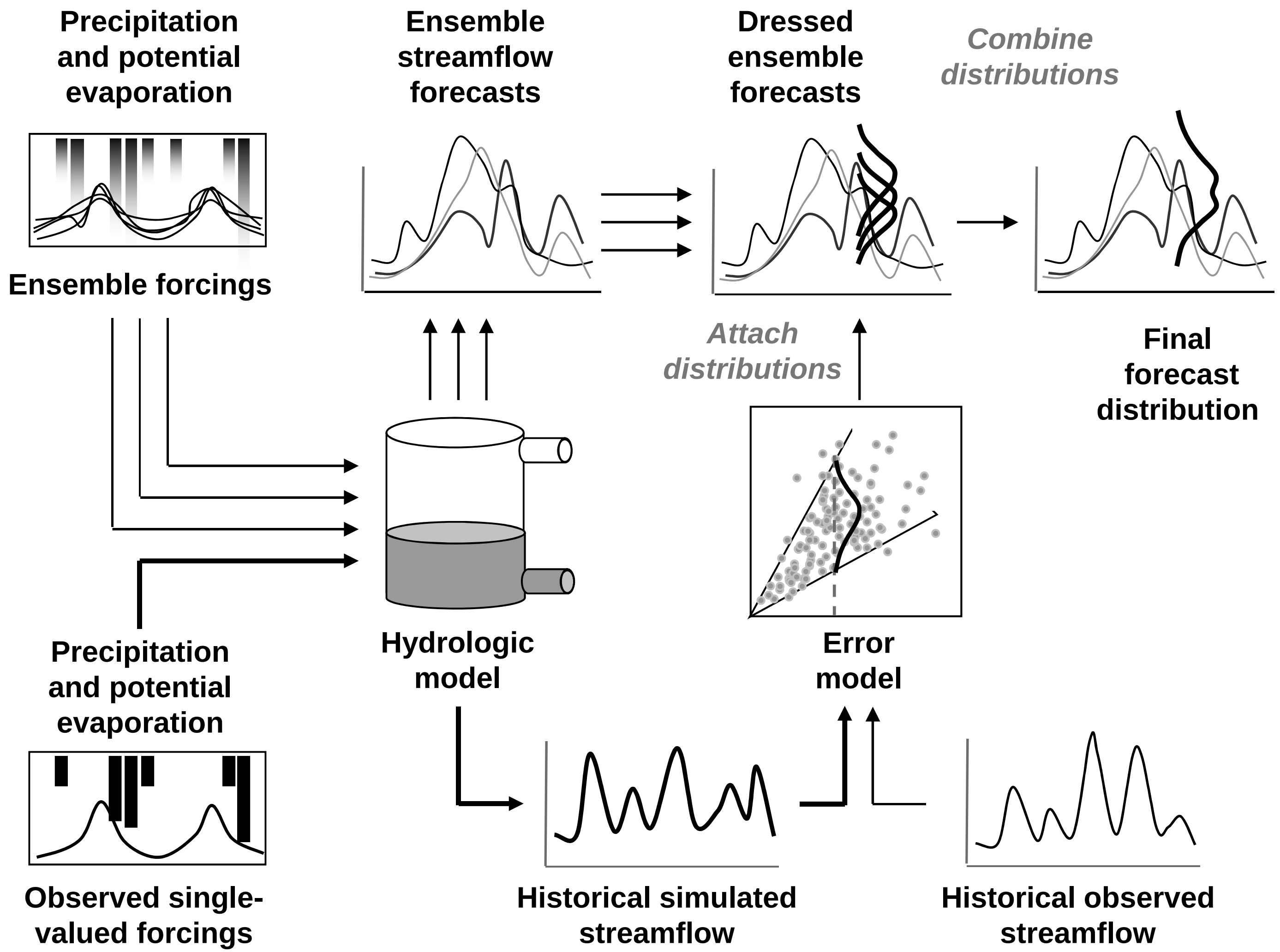
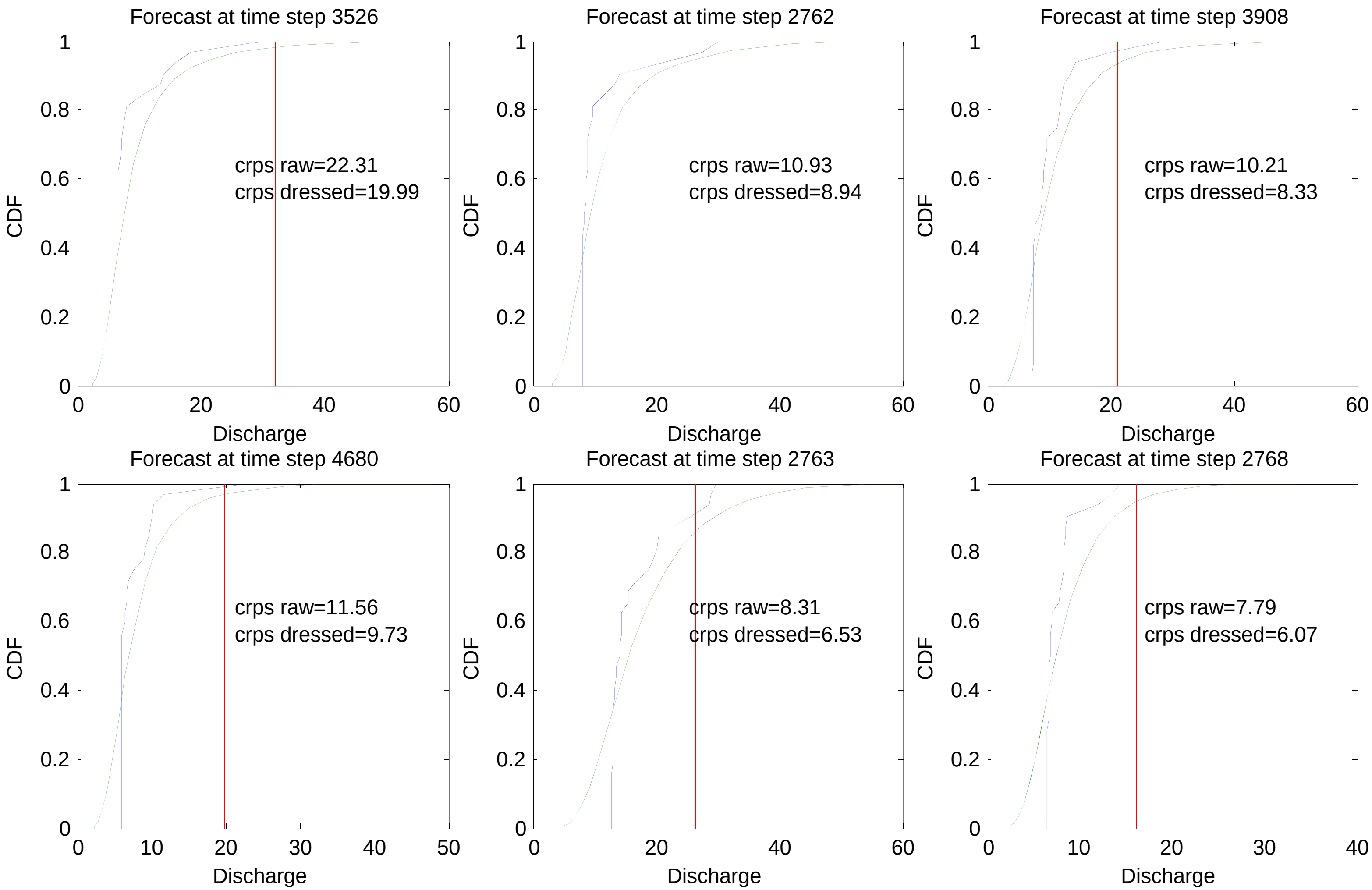


Examples of dressed ensemble forecasts



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