



Short course on real-time hydrological Forecasting

Jan Verkade (Deltares, Rijkswaterstaat River Forecasting Service)
Marie-Amélie Boucher (Université du Québec à Chicoutimi)



Round of introductions...

Marie-Amélie Boucher

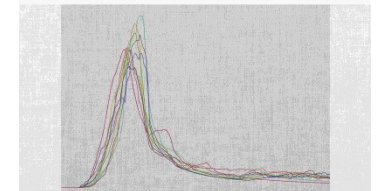
- Hydrologist
- Professor at Université du Québec à Chicoutimi (Canada)
- Research interests: multi-model forecasting, short and long term forecasting, data assimilation, pre and post-processing, assessing the socio-economic value of forecasts.



Round of introductions...

Jan Verkade

- Hydrologist; expert in Real-time hydrological forecasting
- Member of the Rijkswaterstaat River Forecasting Service
- Guest researcher at Delft University of Technology
- Research interests:
 - uncertainty analyses
 - probabilistic forecasting
 - forecast verification
 - forecast use



ESTIMATING
REAL-TIME
PREDICTIVE
HYDROLOGICAL
UNCERTAINTY

JAN VERKADE

Programme

- Introduction
 - Why forecasting?
 - What is realtime hydrological forecasting?
 - How is it different from modeling and simulation?
- Uncertainties and uncertainty estimation
- Techniques for reducing real-time predictive uncertainty
- Techniques for estimating real-time predictive uncertainty
- Verification: how good are my forecasts?
- *Short break*
- Forecasting and decision making
- Using forecasts: some issues, considerations
- Open challenges: a very much non-exhaustive list
- Some resources to go further

Agenda

- 1.
- 2.
- 3.



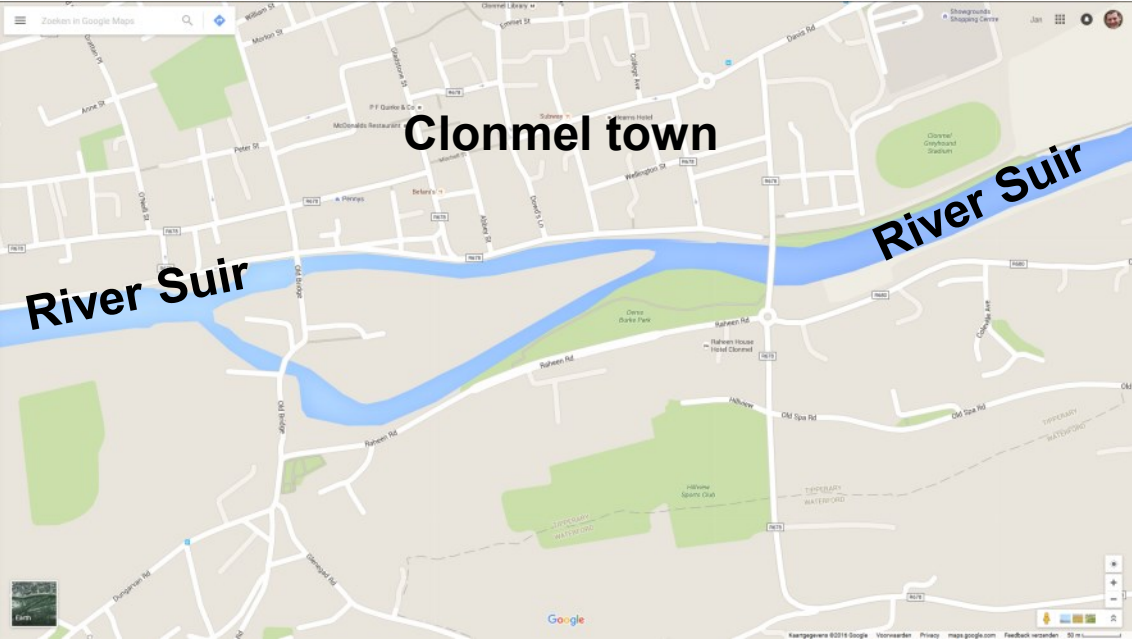
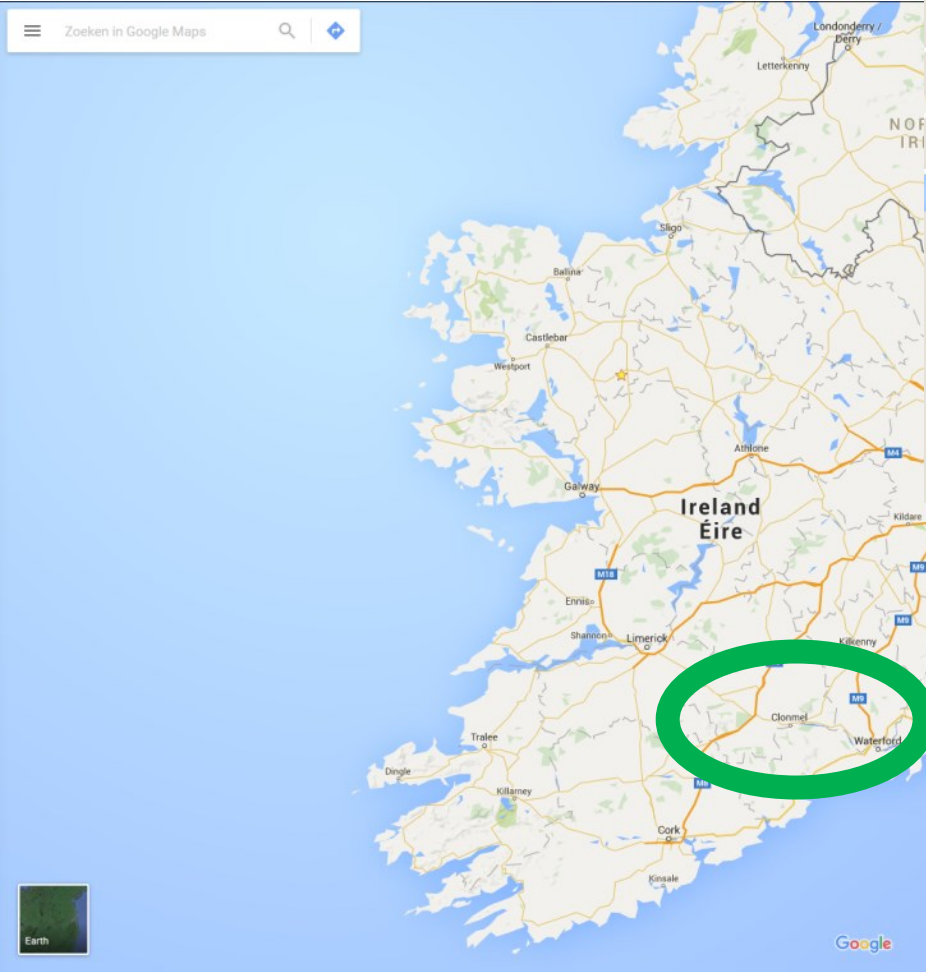




Why forecasting?

Short course on real-time hydrological forecasting

Clonmel, Co Tipperary, Ireland



Clonmel, Co Tipperary, Ireland, early September 2015



Clonmel, Co Tipperary, Ireland, October 2011

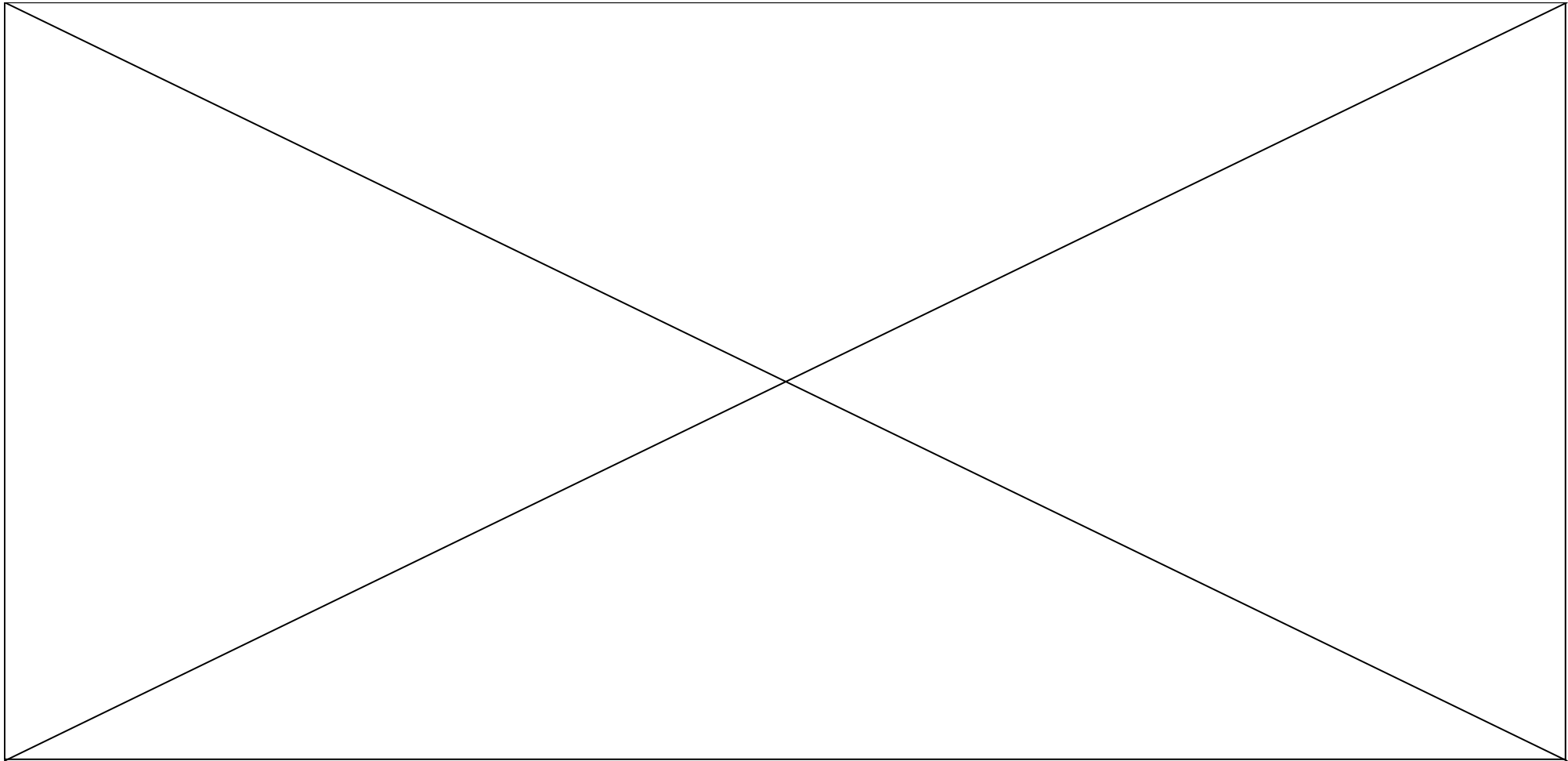


Clonmel, Co Tipperary, Ireland, late December 2015



Photo credit: Joseph O'Dwyer, Tipperary Co Council

... these were required to protect the town from flooding



Video by [EOS productions](#)

UQAC

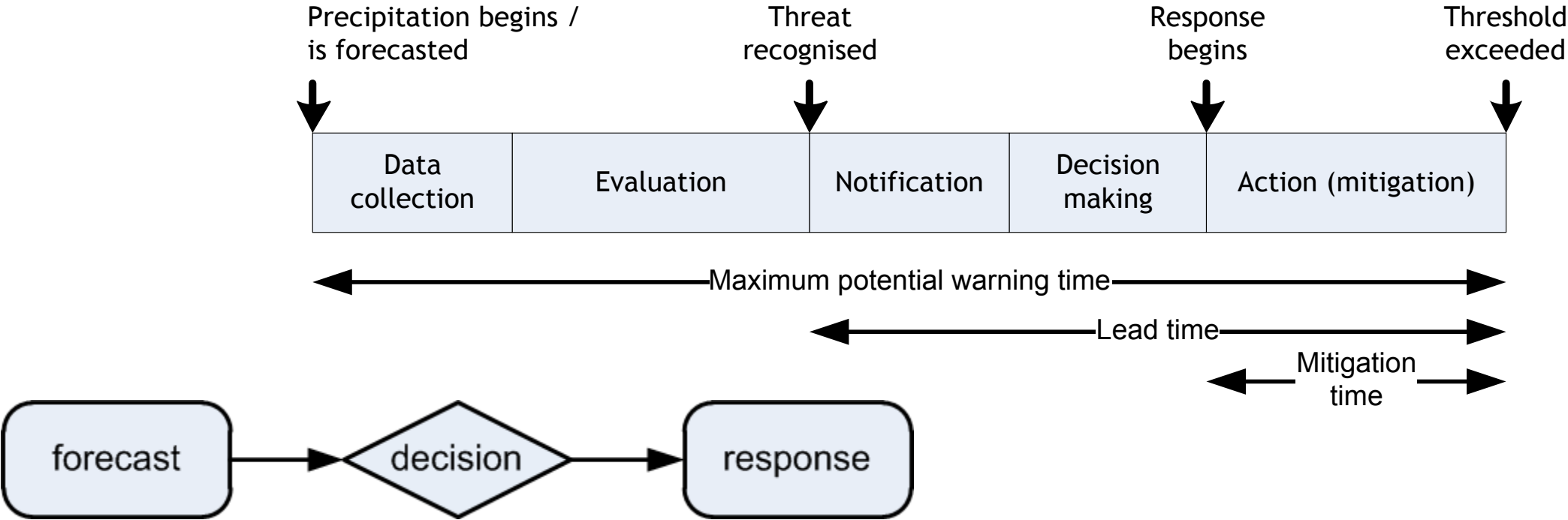
Deltares

... but they take some time to be mounted



Photo credit: Joseph O'Dwyer, Tipperary Co Council

Forecast – warning – response chain



Source: Verkade, J. S.: On the value of flood warning systems, Master of Science dissertation, Delft University of Technology, Delft, The Netherlands, 2008. (modified from Carsell, K. M., Pingel, N. D. and Ford, D. T.: Quantifying the benefit of a flood warning system, Natural Hazards Review, 5, 131, 2004.)



Floods

Flood induced landslide on « du Danube » boulevard, near Bécancour in Quebec. April 10, 2017



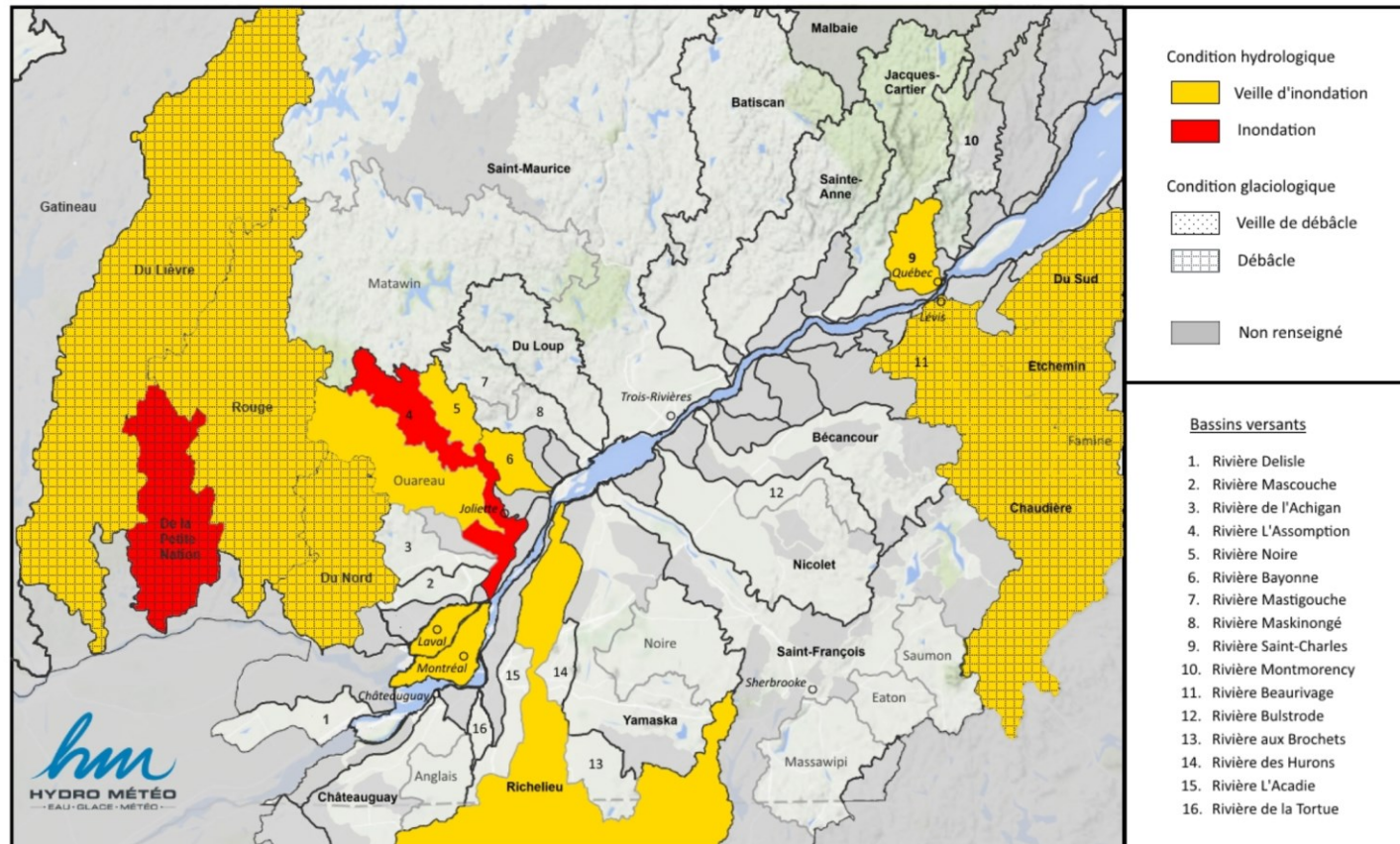
<http://ici.radio-canada.ca/nouvelle/1027347/inondation-crue-printaniere-fleuve-st-laurent-lac-st-pierre>

Floods

HYDRO MÉTÉO INC.

CONDITIONS HYDRO-GLACIOLOGIQUES DES BASSINS

Pour plus de détails, vous pouvez consulter le bulletin hydrométéorologique en cours.



On April 14th 2017

<http://hydrometeo.net/index.php/info-riviere>

Cette carte est fournie à titre indicatif seulement. L'information y est de portée générale et ne tient pas compte des cas particuliers. Cette carte ne doit en aucun cas être utilisée comme outil à la prise de décision sans l'expertise des consultants d'Hydro-Météo.

Cette carte exclue les inondations reliées aux refoulements d'égouts, aux embâcles de débris ou d'arbres et causées par un mauvais drainage urbain ou naturel. Valable pour les rivières seulement.

Des changements peuvent être apportés à ces prévisions à tout moment et ce, sans préavis.

Les inondations peuvent être causées par la formation d'embâcle de glace.



Hydropower



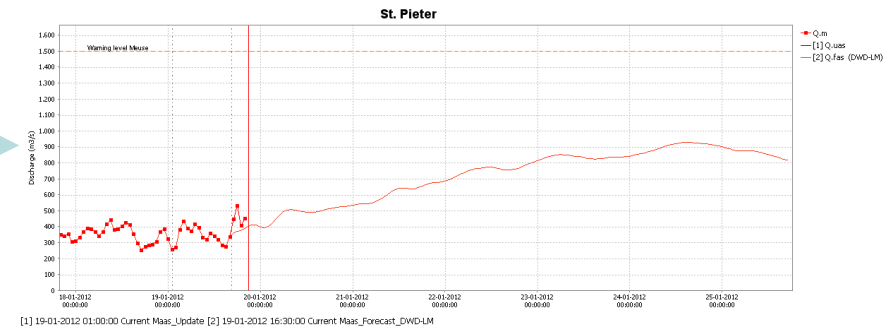
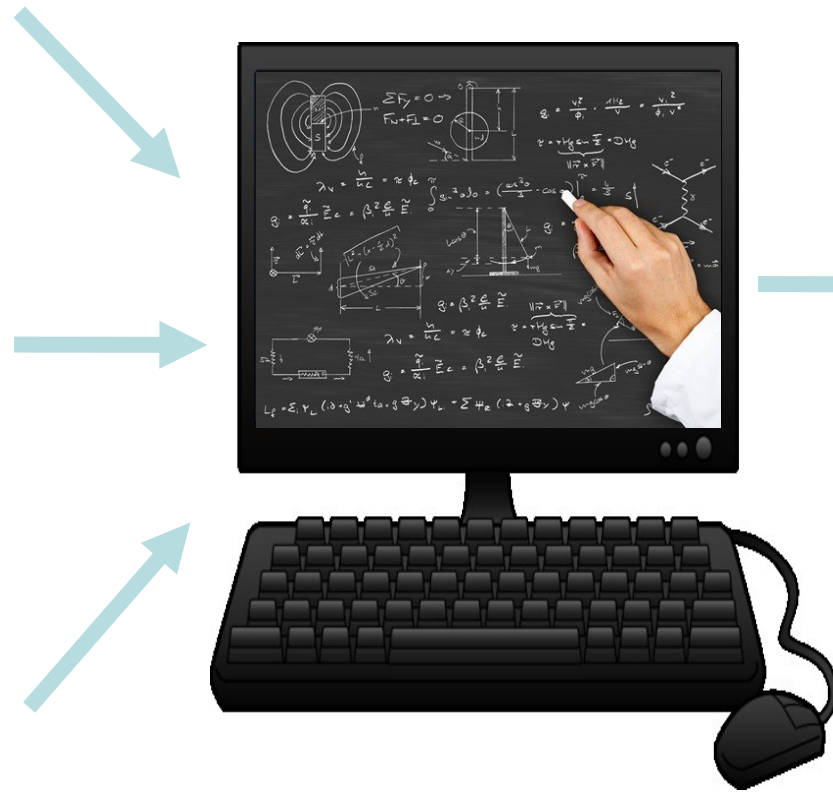
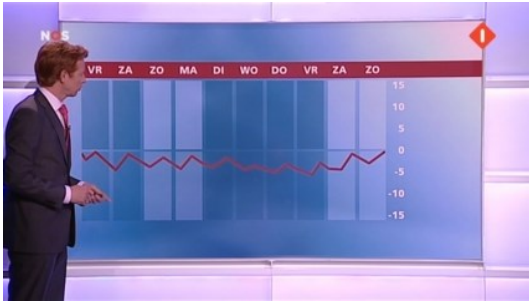
Daniel-Johnson Dam. Source: Hydro-Québec (hydroquebec.com) autorisation for non-commercial reuse



What is real-time forecasting? How is it different from modeling and simulation?

Short course on real-time hydrological forecasting

How is a hydrological forecast produced?



Forecasting v “offline” simulation

- Time available to produce a result is limited
 - Models need to run reasonably quickly (in relation to the required lead time)
 - Less time available to prepare and quality-assess input data record
- Nature of boundary conditions
 - (near) realtime telemetry data → allows for data assimilation
 - Numerical Weather Prediction products --> forcings pertaining to a yet unknown future



What's unique to real-time forecasting?

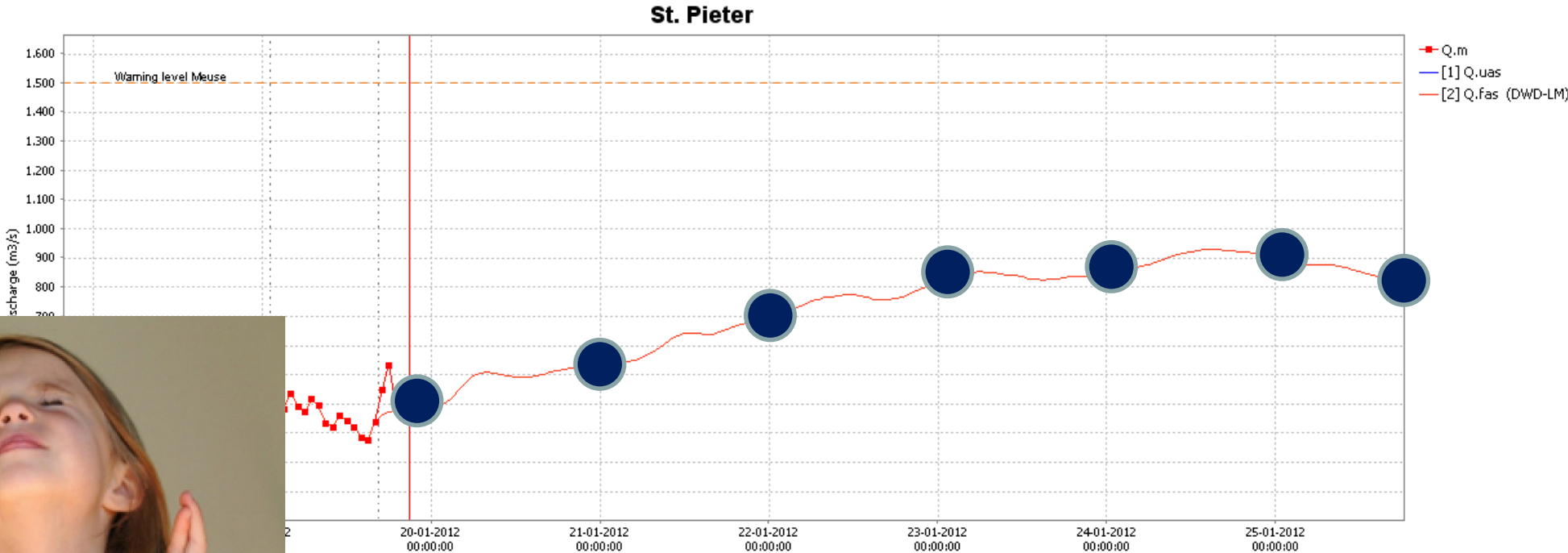
- Availability of (near) realtime data
 - Option to use data-assimilation
- Management of initial conditions



Uncertainties and uncertainty estimation

Short course on real-time hydrological forecasting

How is a hydrological forecast produced?

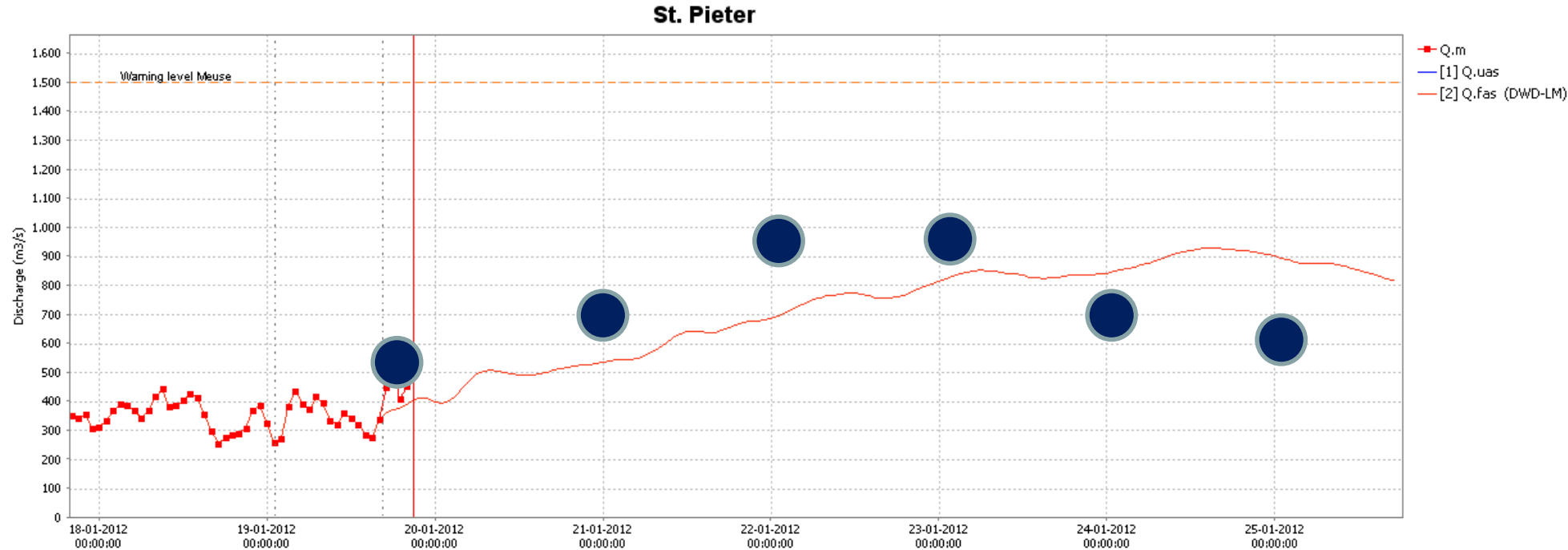


Update [2] 19-01-2012 16:30:00 Current Maas_Forecast_DWD-LM

● Observation



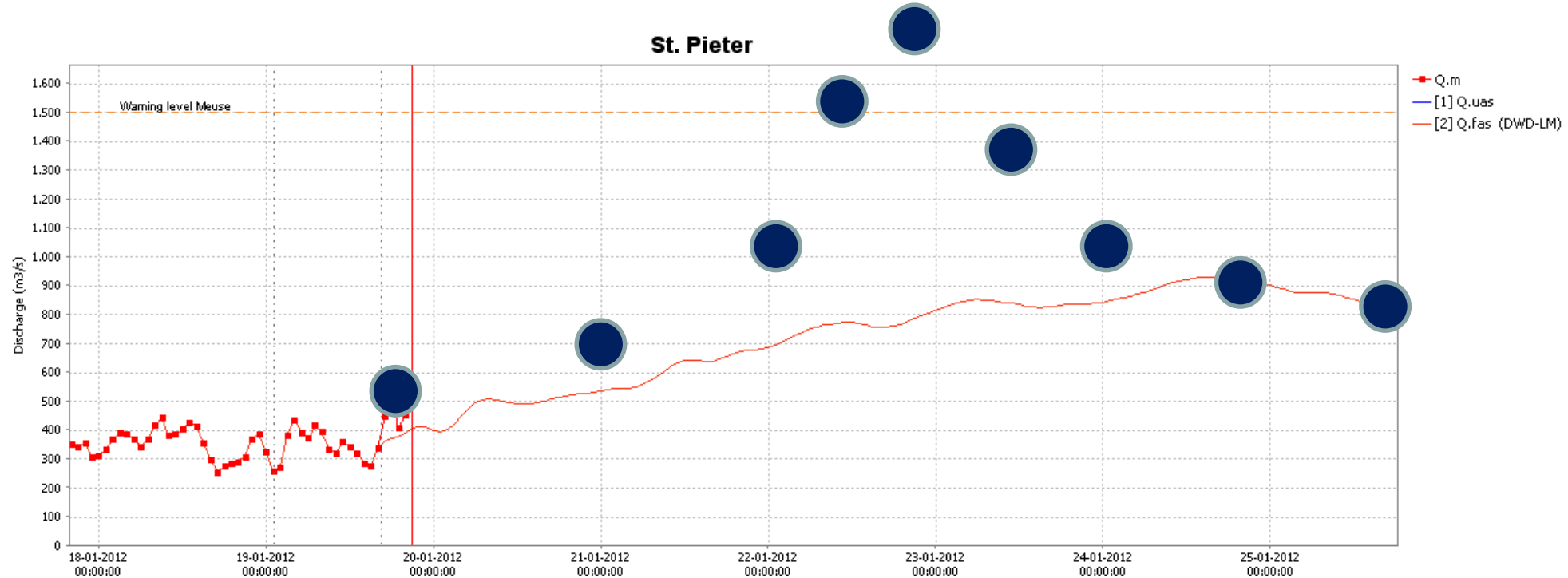
How is a hydrological forecast produced?



[1] 19-01-2012 01:00:00 Current Maas_Update [2] 19-01-2012 16:30:00 Current Maas_Forecast_DWD-LM

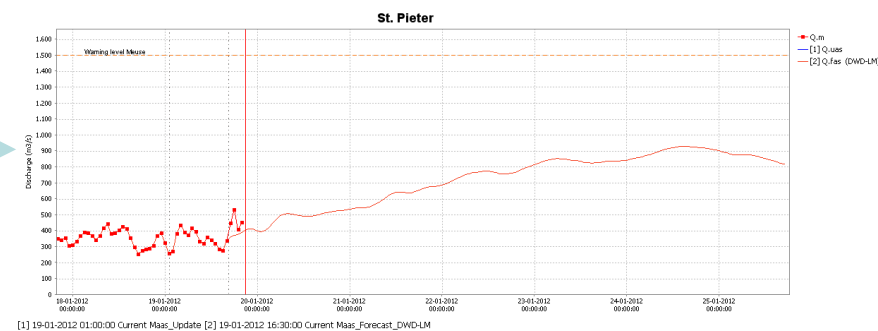
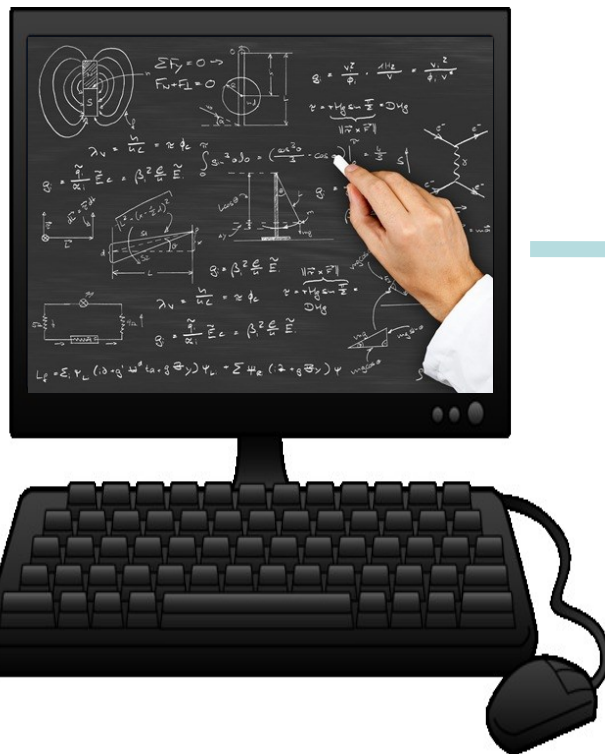
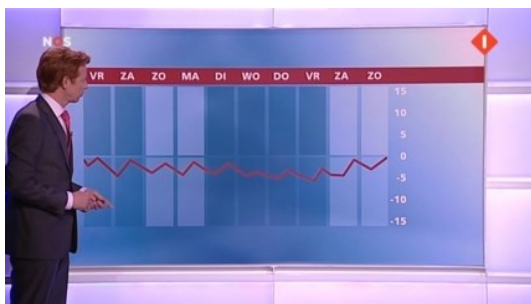
 Observation

How is a hydrological forecast produced?

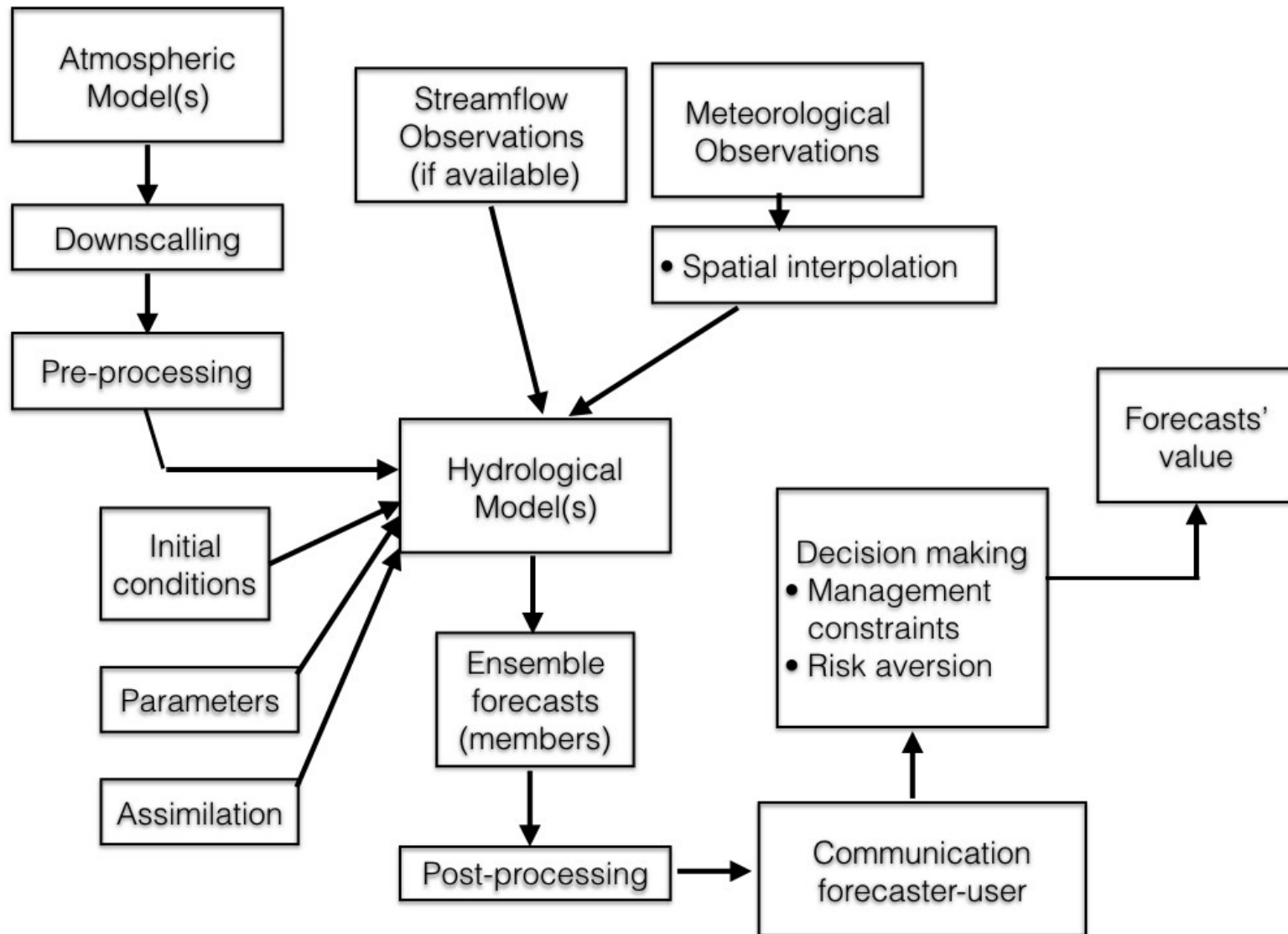


[1] 19-01-2012 01:00:00 Current Maas_Update [2] 19-01-2012 16:30:00 Current Maas_Forecast_DWD-LM

 Observation



Where are the uncertainties?



Managing uncertainties

- Uncertainty reduction → 'offline' activity
- Estimating uncertainties = probabilistic forecasting
 - ... accept that you'll still be wrong every now and then
 - ... but at least you'll know the probability thereof prior to making a decision





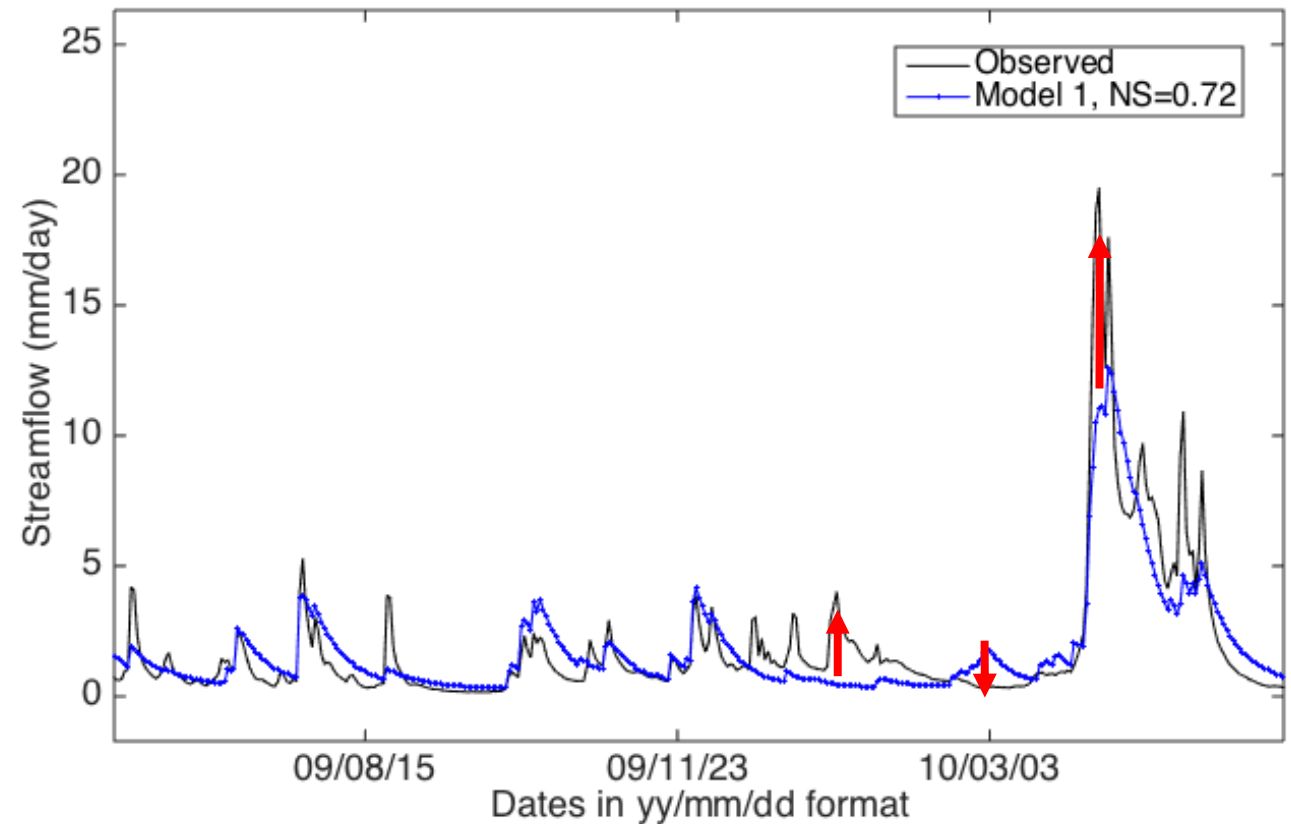
Techniques for reducing real-time predictive uncertainty

Short course on real-time hydrological forecasting



State variable updating

- The « true » initial state of a catchment (as represented by a model!) can't be known with certainty
- However, some information is known at time $t=0$
 - Observed streamflow
 - Snow water equivalent?
 - Etc
- Solution: use the available information to correct the state variables.
 - To artificially increase snowmelt: raise temperature!
 - To increase streamflow during summer: increase precipitation!
 - Re-run the model and save state variables



Data assimilation

- Updating state variables in a more systematic and reproducible fashion
 - Kalman filter (and many variants)
 - Particle filter (also many variants)
 - Variational methods
 - Etc.

Data assimilation

- Updating state variables in a more systematic and reproducible fashion
 - Kalman filter (and many variants)
 - Kalman gain: computed by minimizing the error of the simulation
 - Setting the derivative of the analysis error to 0

$$\mathbf{K}_t = \mathbf{P}_t \mathbf{H}^T \left(\mathbf{H} \mathbf{P}_t \mathbf{H}^T + \mathbf{R}_t \right)^{-1}$$

Gain at time step t

Model error covariance matrix

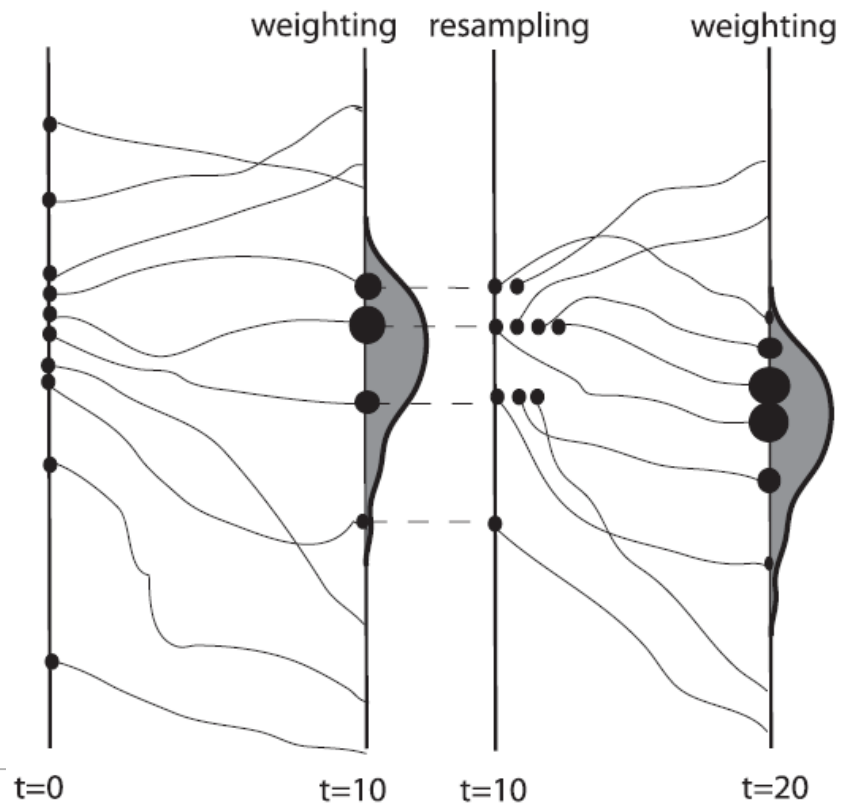
Observation model: relates the state vector to the observations

Covariance of observation noise

- **Compromise:** the gain is a weighting factor between the observations and the model's simulation
- Many assumptions: e.g. normality of the distribution of errors

Data assimilation

- Updating state variables in a more systematic and reproducible fashion
 - Particle filter (also many variants)
 - One particle = one model simulation from a specific state vector
 - The simulations (particles) that are closer to the observation are given more weight



(Figure 2 from Van Leeuwen, 2009)



Techniques for estimating real-time predictive uncertainty

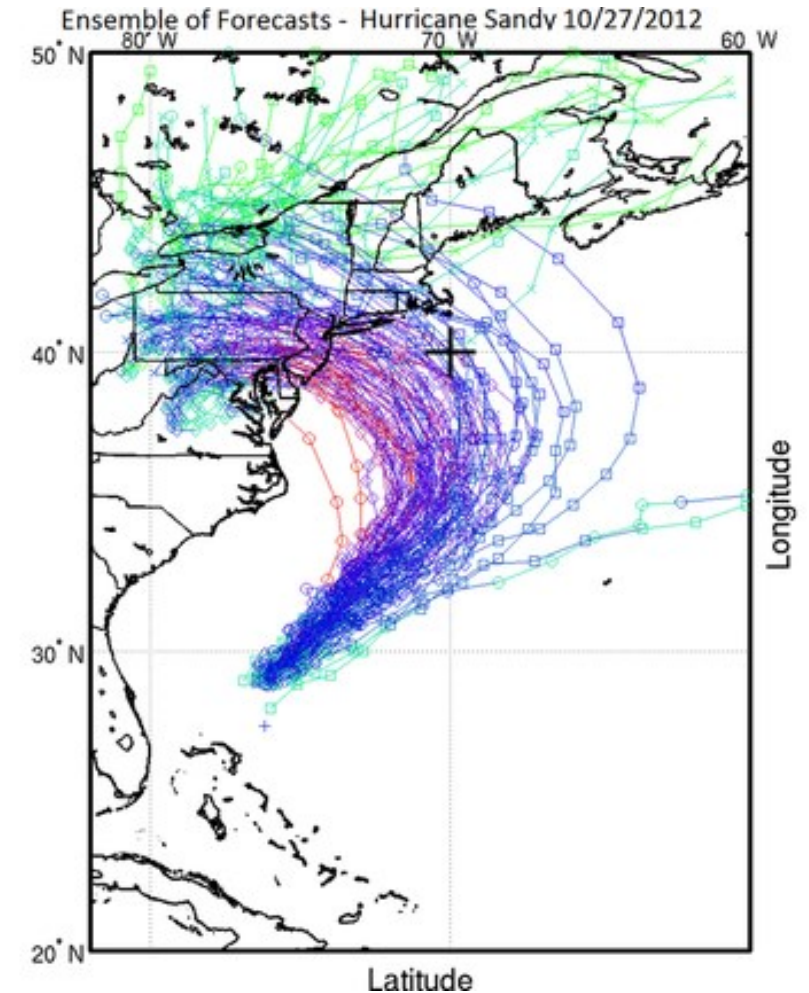
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Estimating predictive uncertainty: techniques

Roughly speaking two techniques available:

- Ensemble techniques
- Post-processing techniques

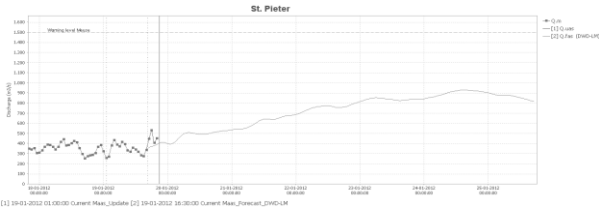
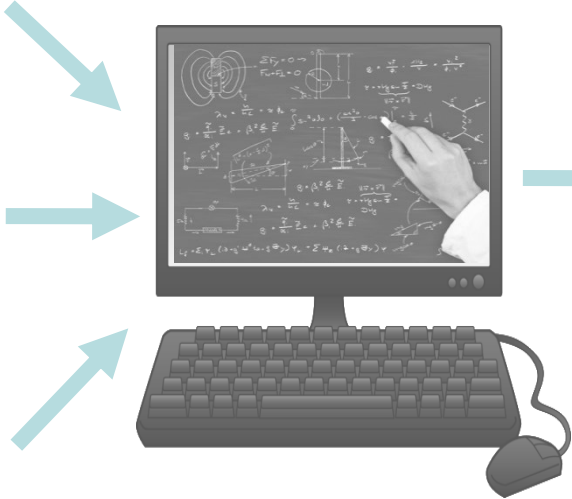
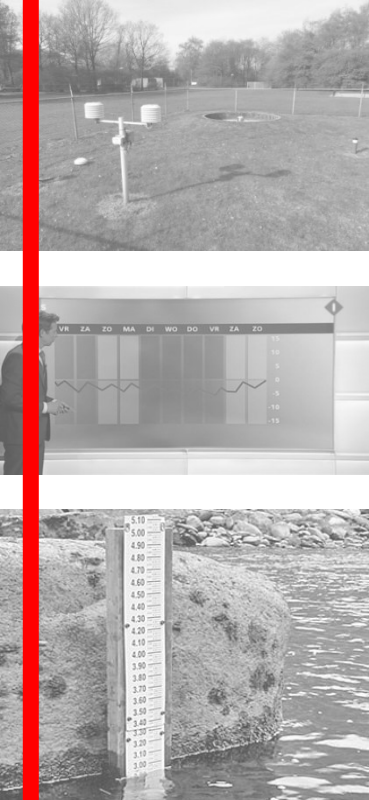
... and these may be, and often are, combined



Source: <http://www.mhfi.com/loads/1/3/8/7/13876358/7739921.png>

Estimating predictive uncertainty: techniques

Ensemble techniques



Post-processing techniques

Combinations possible!



Ensemble techniques

1. Use multiple, equally plausible inputs

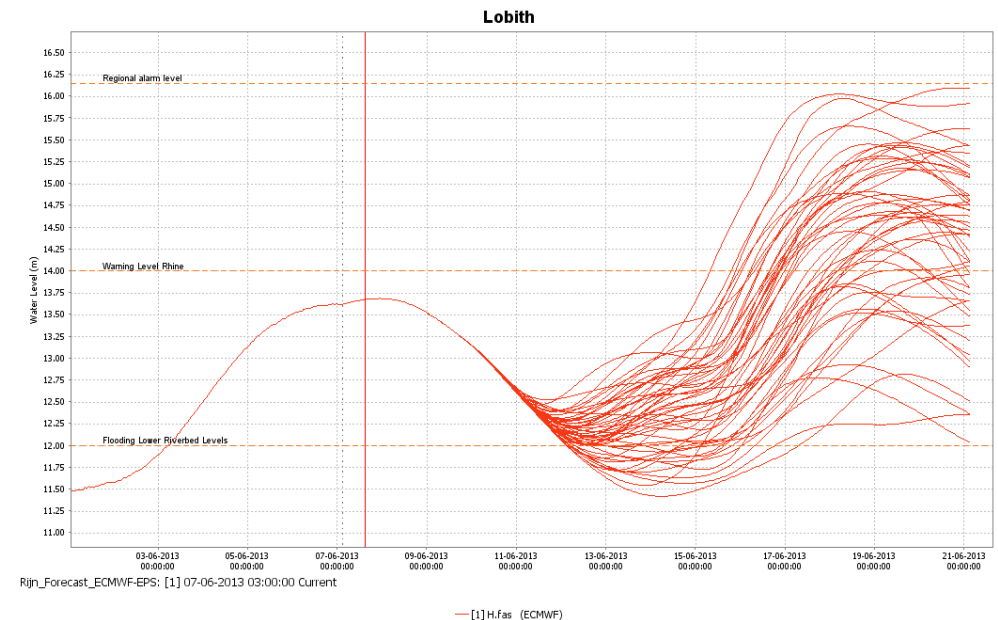
- Weather forecasts
- Initial conditions
- Parameters
- ...

2. Route all through a model:

- Using one single model
- Using multiple models (“multi-model”)

→ Model outputs will vary → “ensemble”

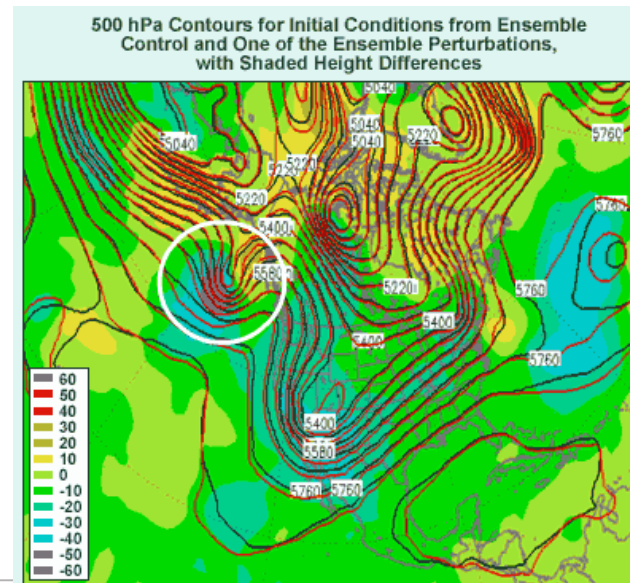
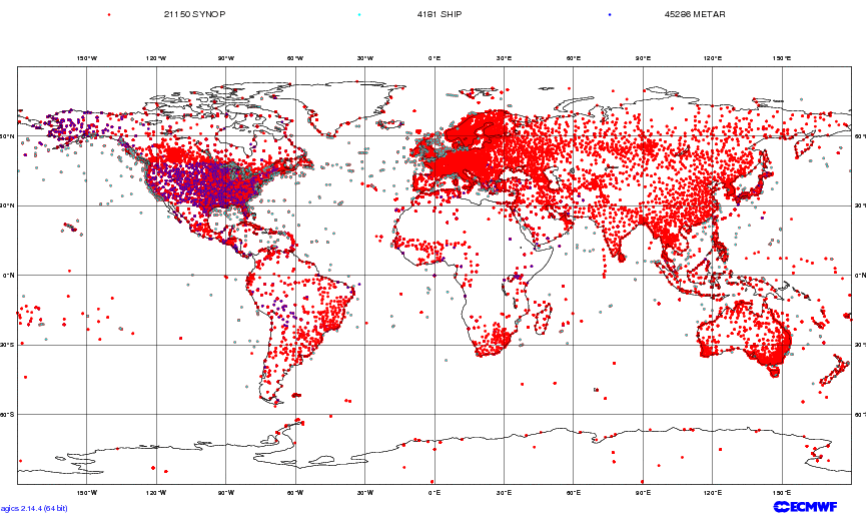
→ Individual model results are called “members”



Principle of ensemble NWP forecasting systems

- Future weather is highly dependent on current weather
- But we don't know *exactly* what the current weather is...
- Observations → best estimate
... but multiple good estimates possible
- These will each evolve to (sometimes very) different future weather

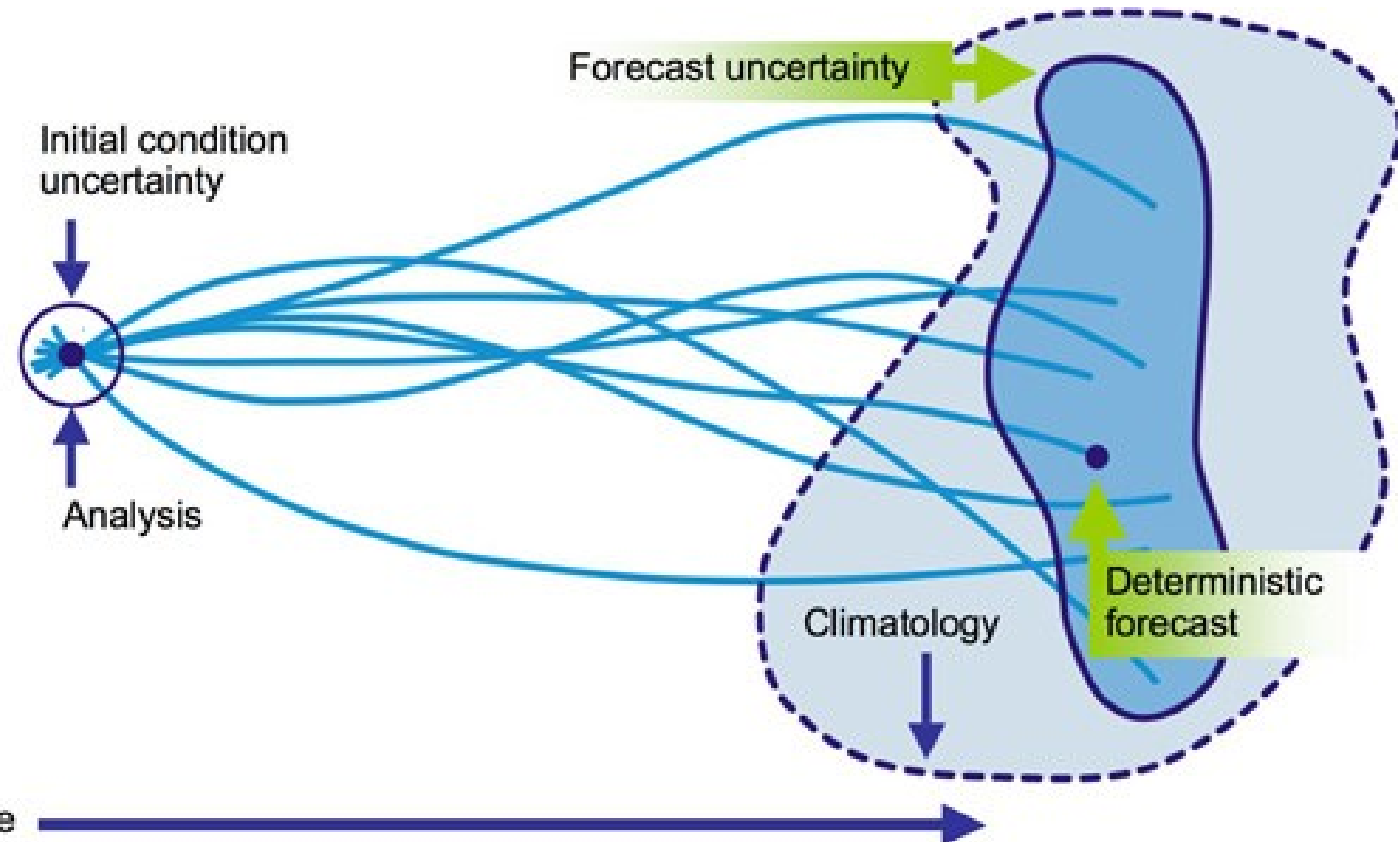
ECMWF Data Coverage (All obs DA) - Synop-Ship-Metar
01/Aug/2014; 00 UTC
Total number of obs = 70617



Source: http://www.meted.ucar.edu/nwp/pcu1/ensemble_webcast

Initial conditions in ensemble NWP forecasting

- “Monte Carlo” analysis:
 - Create a probability distribution of initial conditions
 - Draw an initial condition
 - Run your model
 - Repeat as often as you wish

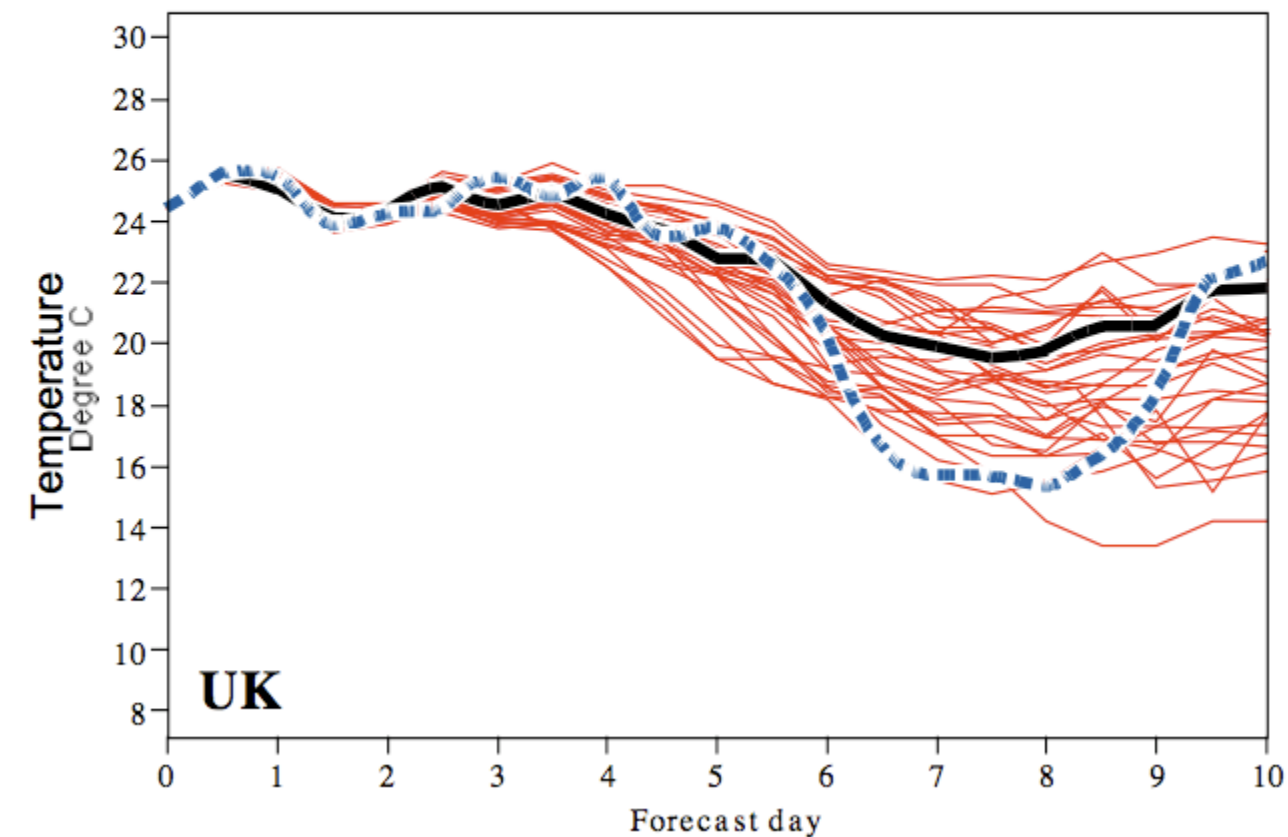


26th June 1995

ECMWF ensemble forecast - Air temperature

Date: 26/06/1995 London Lat: 51.5 Long: 0

Control Analysis Ensemble

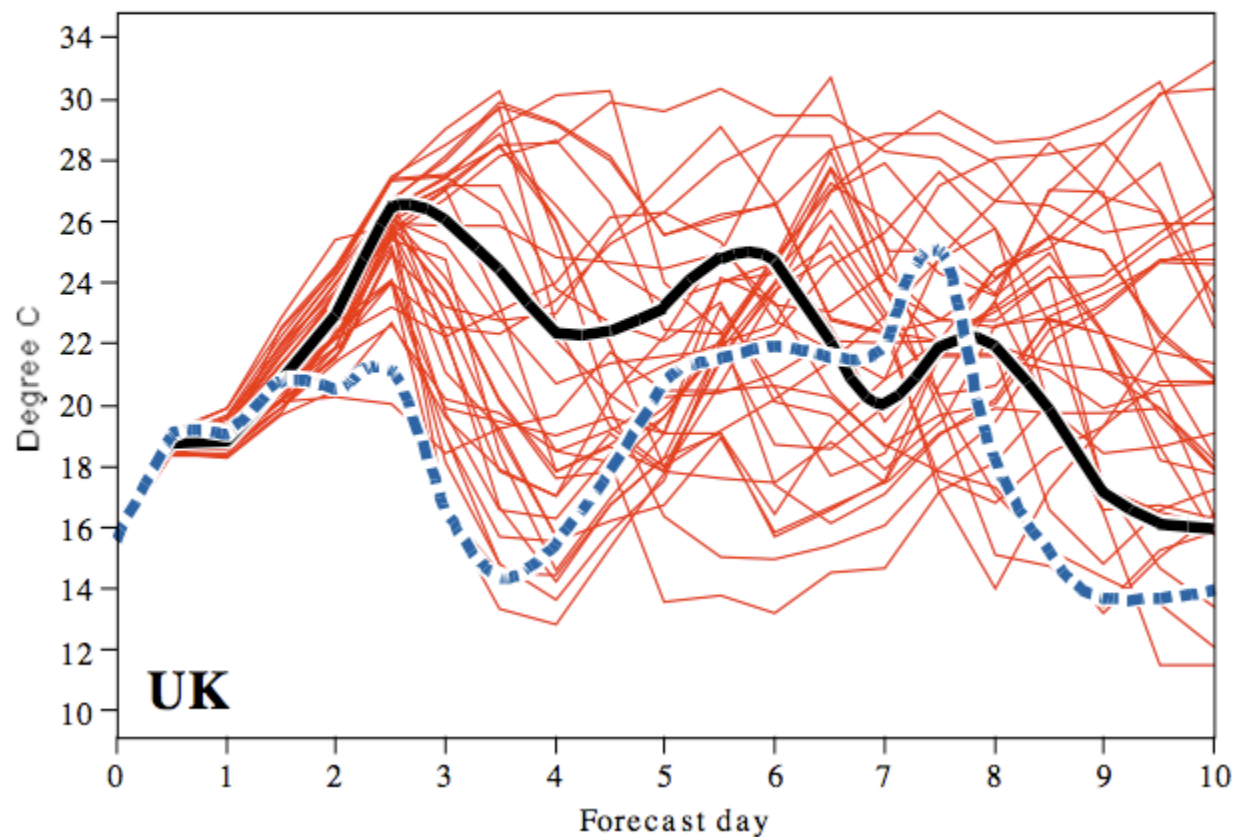


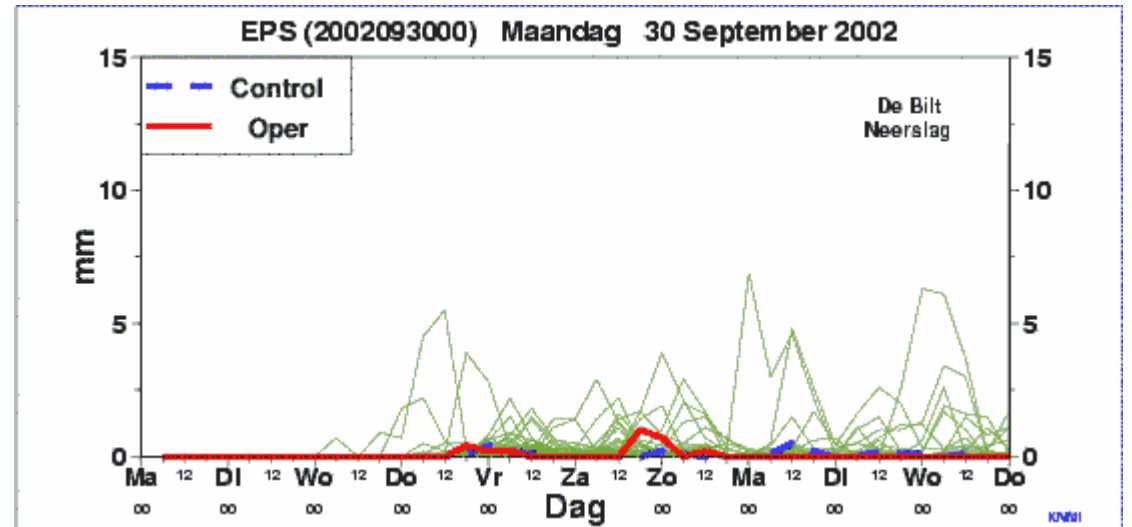
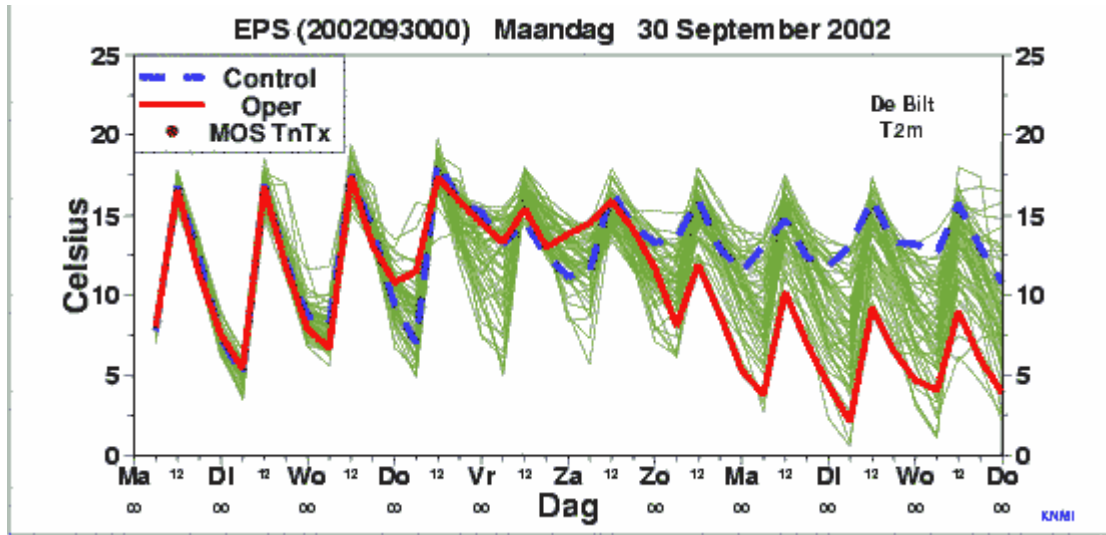
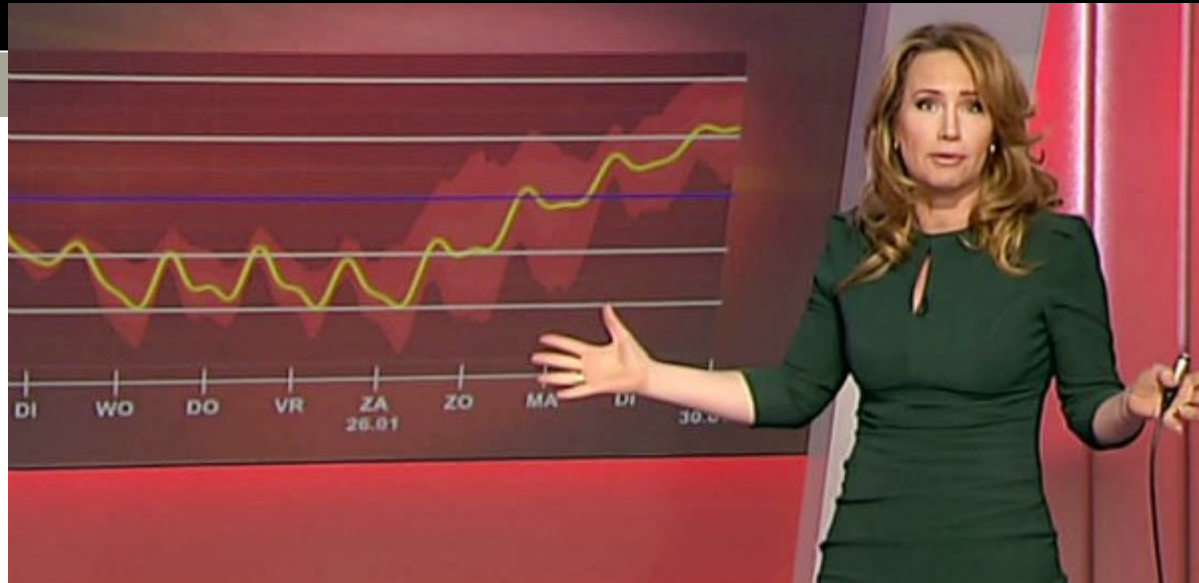
26th June 1994

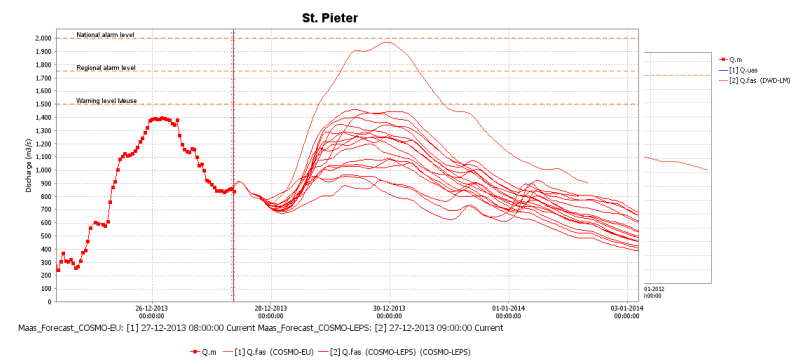
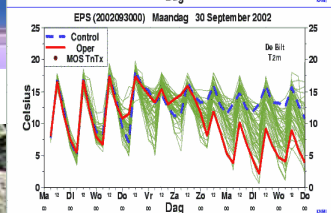
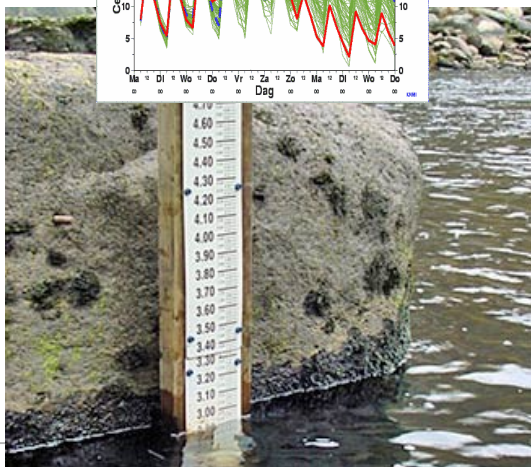
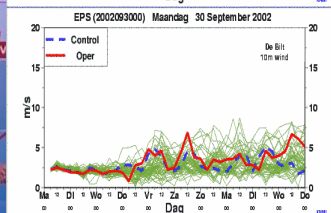
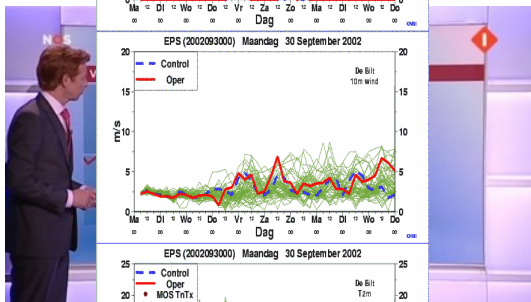
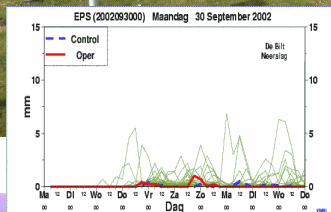
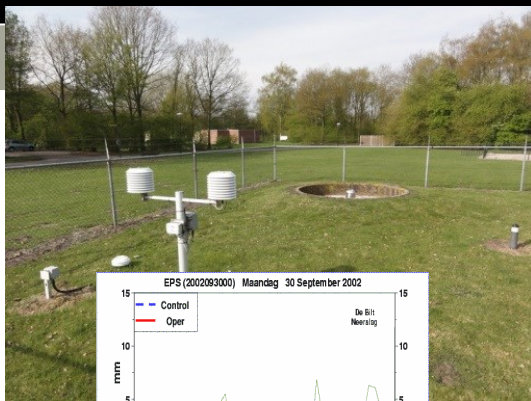
ECMWF ensemble forecast - Air temperature

Date: 26/06/1994 London Lat: 51.5 Long: 0

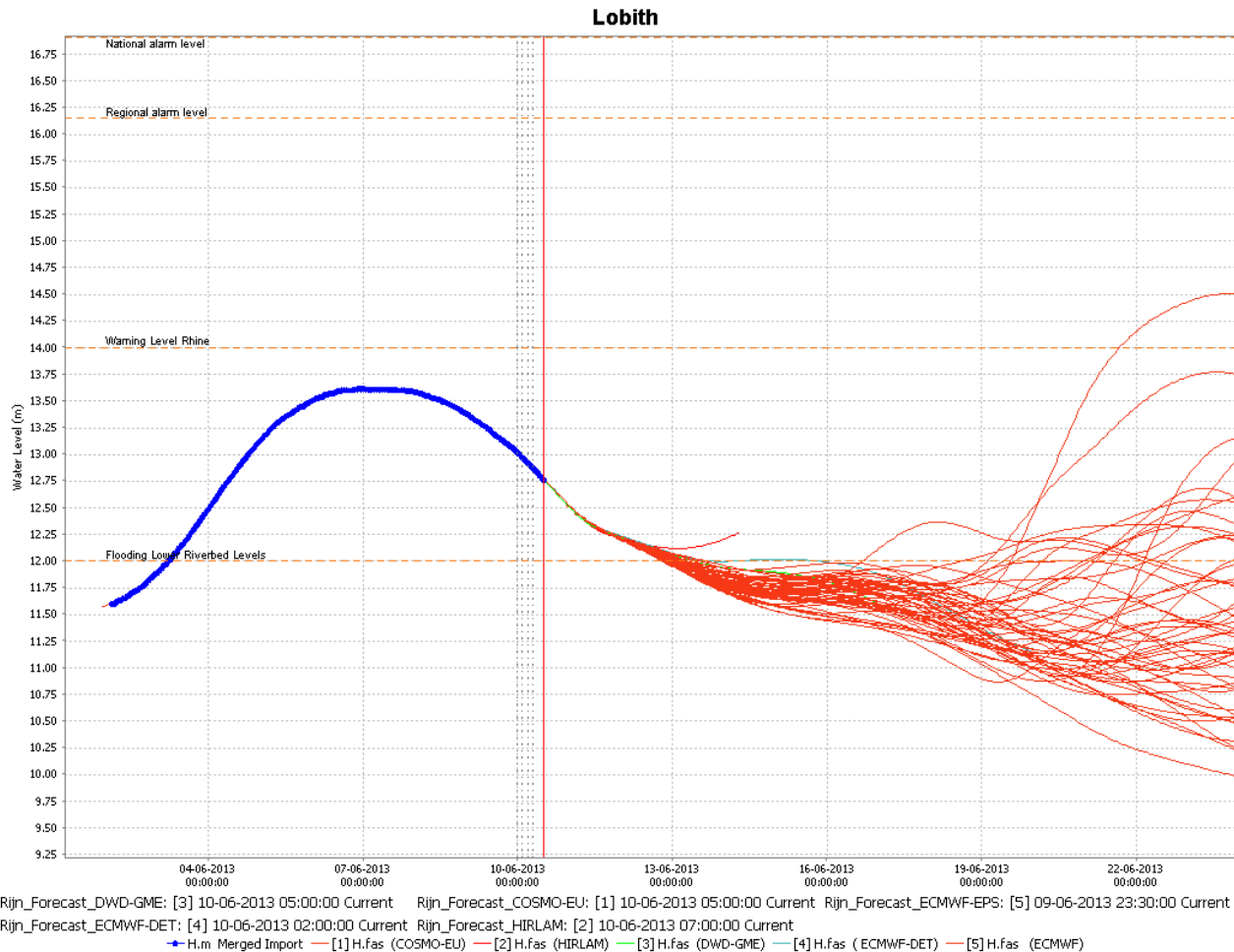
Control Analysis Ensemble







Interpretation of an ensemble forecast



**Which uncertainties
are represented by
the ensemble
spread?**

Which are NOT?

Ensemble Prediction Systems: pros and cons

- + Measure of forecasting uncertainty
- + Plausible traces, both temporally as well as spatially
- Single source of uncertainty only
- You need one of these:



Source: http://www.ecmwf.int/sites/default/files/Corinne_1567.jpg

Who runs ensemble NWP systems?

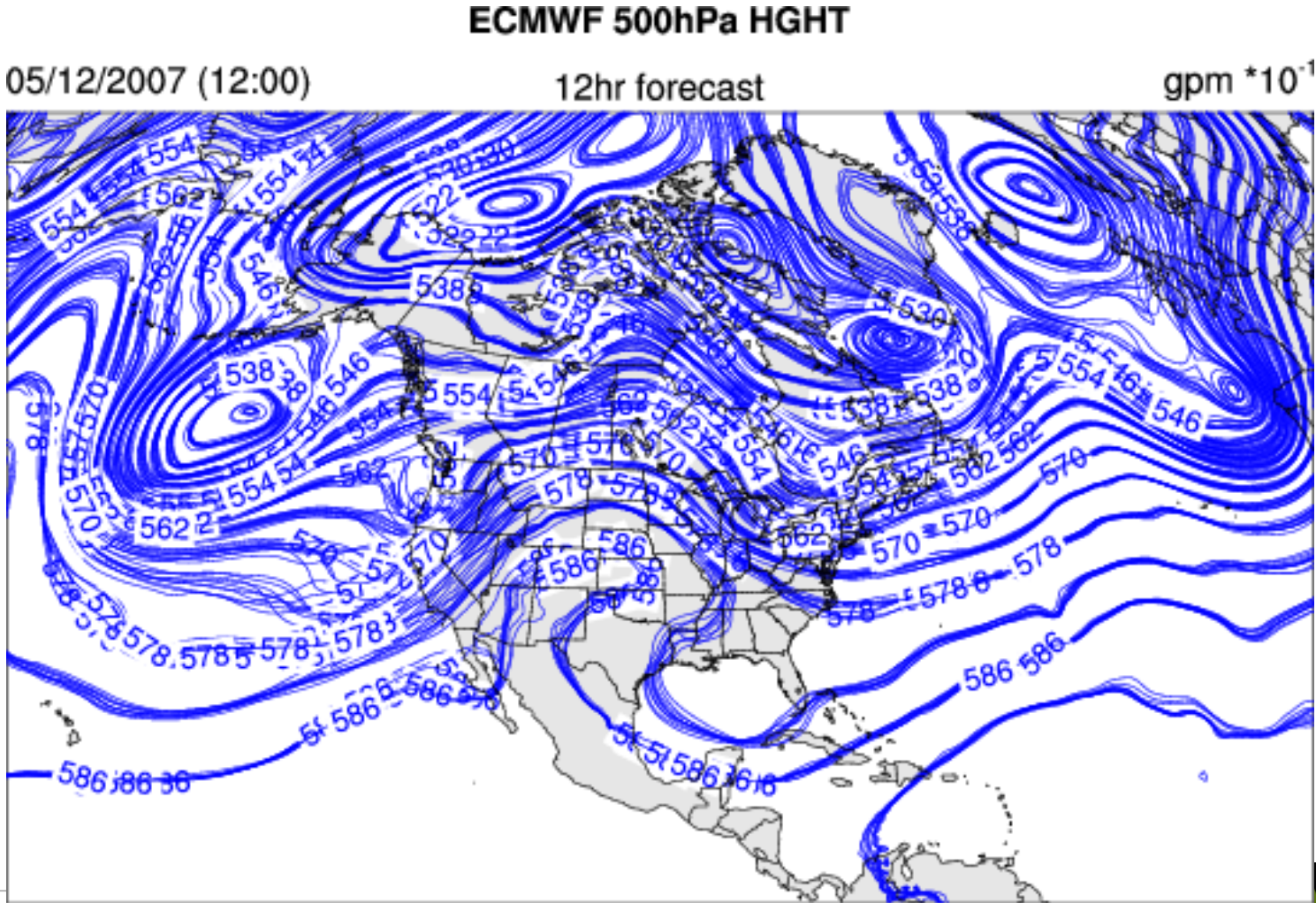
- European Centre of Medium-Range Weather Forecasts (ECMWF)
- US National Centres of Environmental Prediction (NCEP)
- UK Met Office
- Météo France
- Environment Canada
- Japan Meteorological Agency
- Australian Bureau of Meteorology
- China Meteorological Administration
- Korea Meteorological Administration
- CPTEC (Brazil)

ECMWF ensemble prediction system

- Global coverage (this is true for other EPSs, too)
- 51 members: 1 control + 50 perturbations
- Two forecasts daily: 00UTC and 12UTC
- 3-hour time steps up to 240h (10 days)
- 6-hour time steps up to 15 days



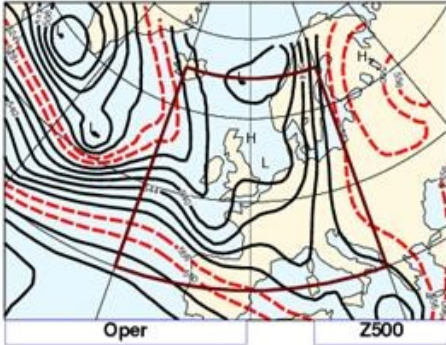
ECMWF ensemble prediction system



Spaghetti plots

ECMWF ensemble prediction system

ECMWF Forecast
from Monday 4 February 2013 00 UTC
for Wednesday 13 February 2013 12 UTC



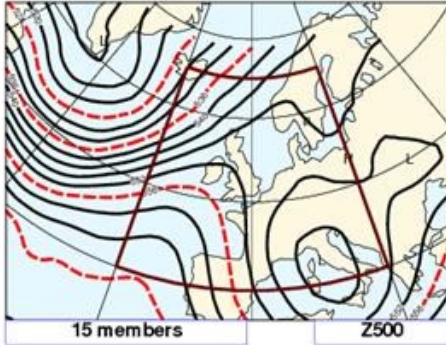
EC Cluster ; 2013020400 +228

4 5 6 8 9 10 13 14 16 21 22 26 31 44 46 47 49



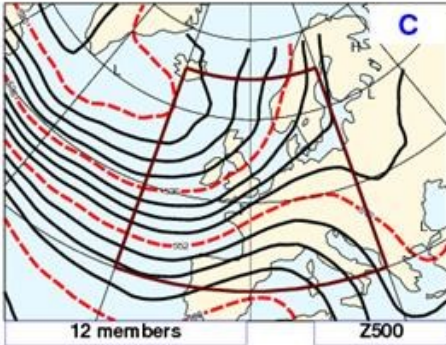
EC Cluster ; 2013020400 +228

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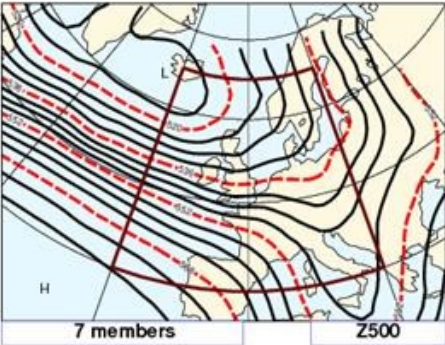
EC Cluster ; 2013020400 +228

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EC Cluster ; 2013020400 +228

7 17 23 27 33 43 50

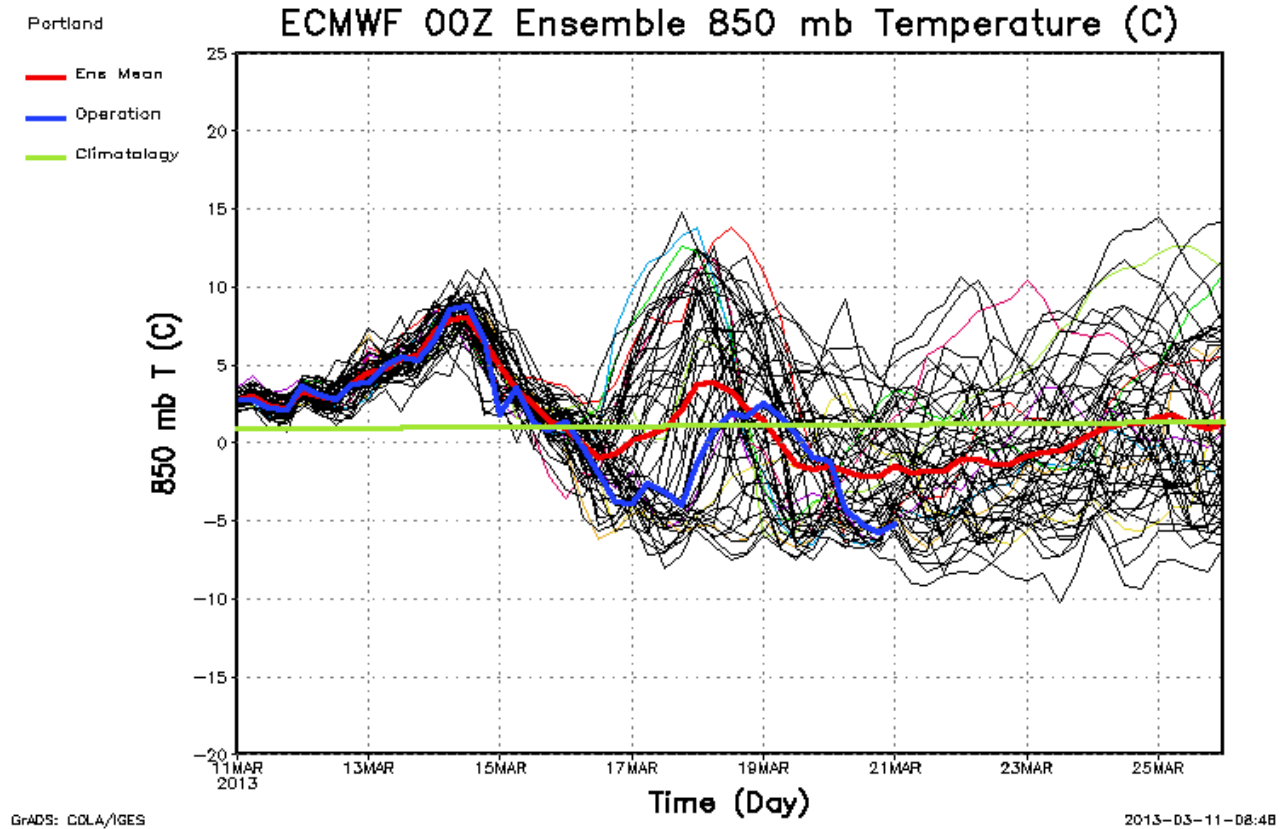


Clusters

Source: http://www.weer.nl/uploads/pics/cluster_wo.JPG



ECMWF ensemble prediction system

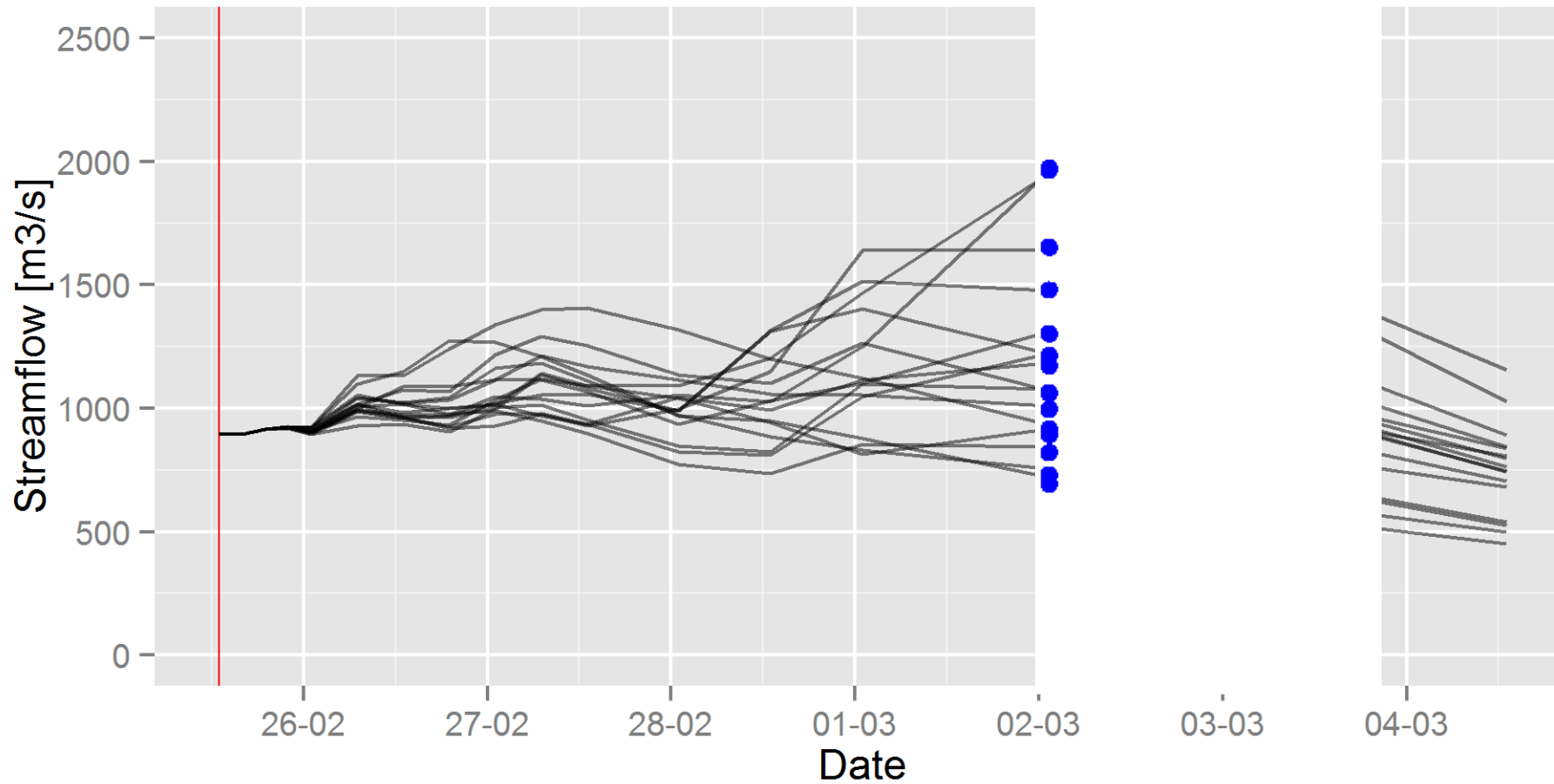


Source: http://fox12weather.files.wordpress.com/2013/03/tseries_850t_000-360_portland.png

Plumes

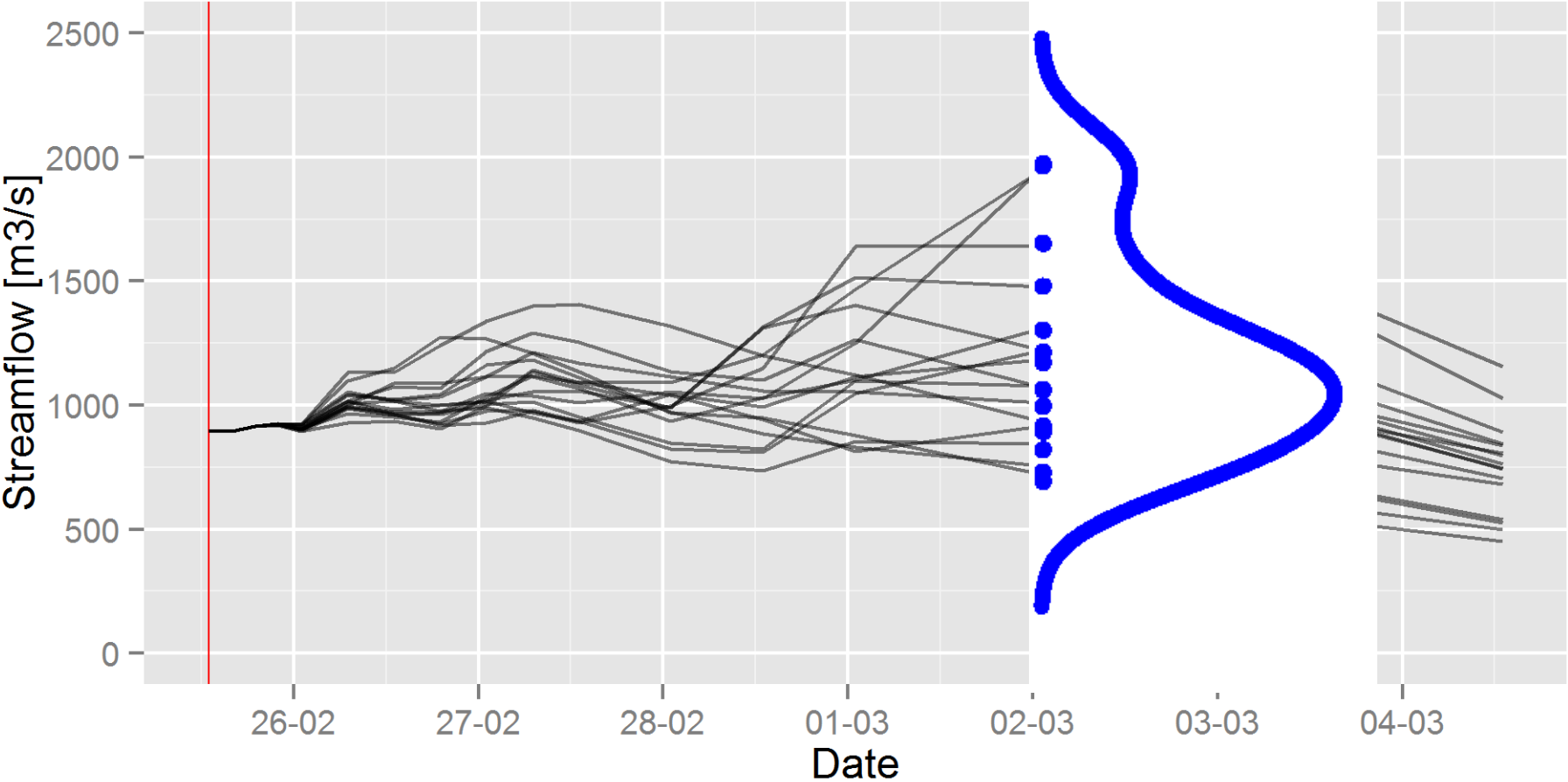


From ensembles to probabilities

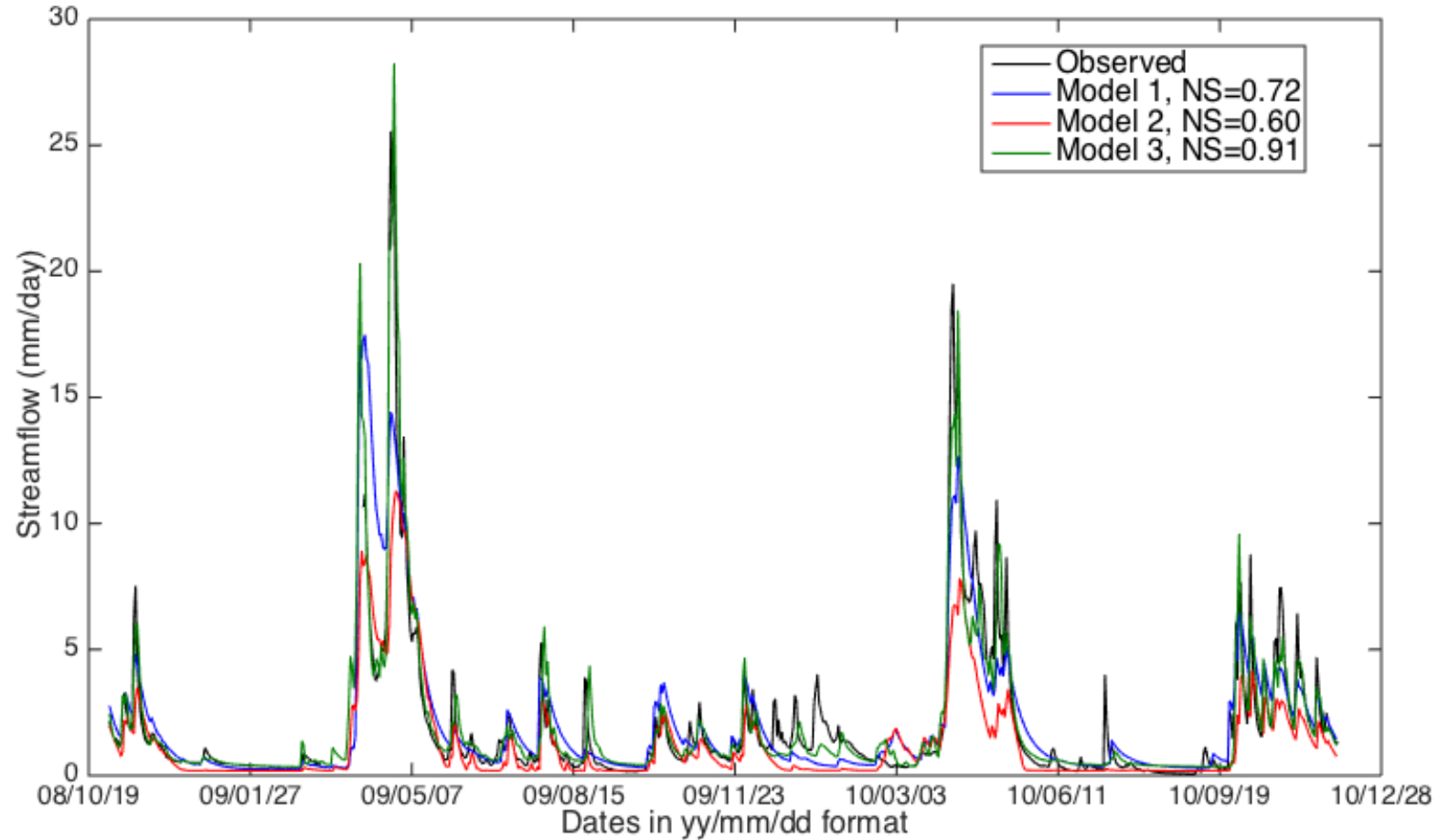


Assumption of equiprobability

From ensembles to probabilities

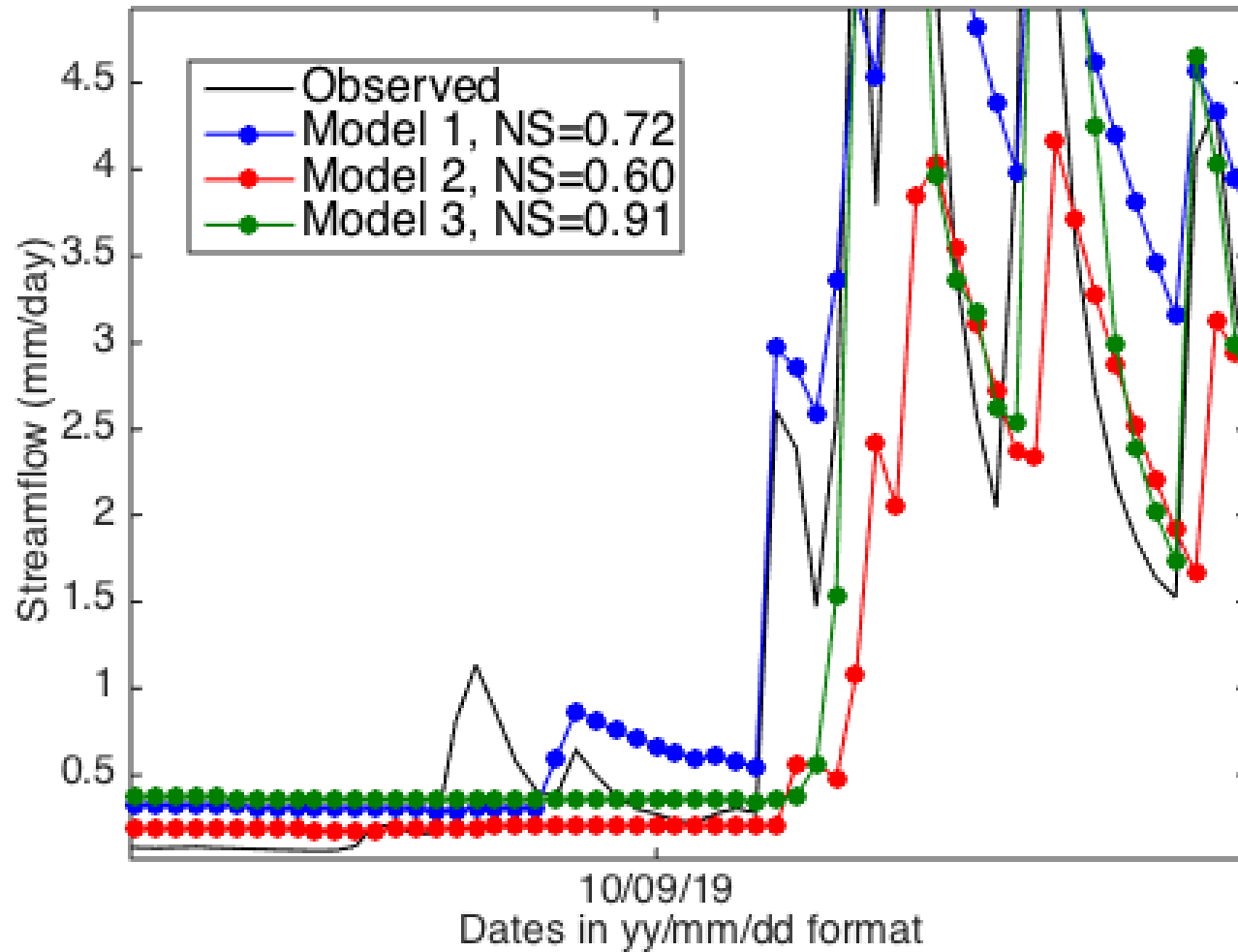


Multi-model ensemble: multiple hydrological models



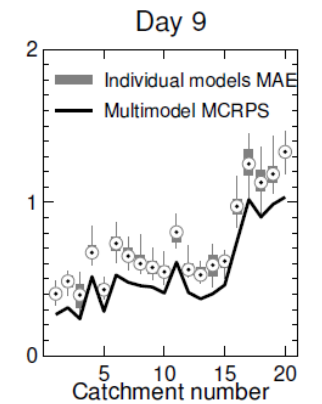
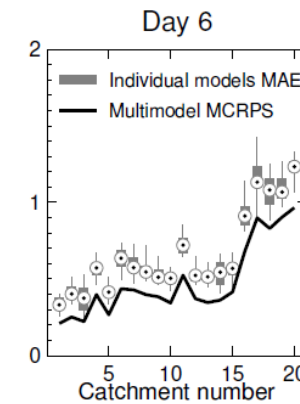
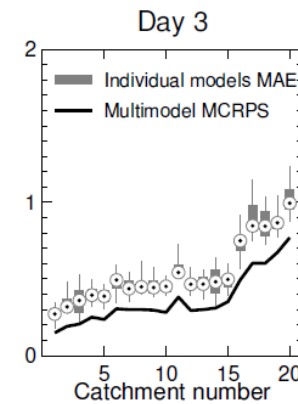
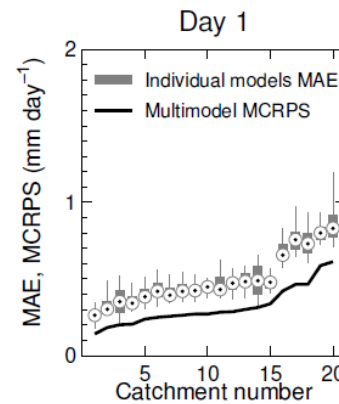
- Simulated hydrograph for the Trois-Pistoles catchment in Quebec, Canada

Multi-model ensemble: multiple hydrological models



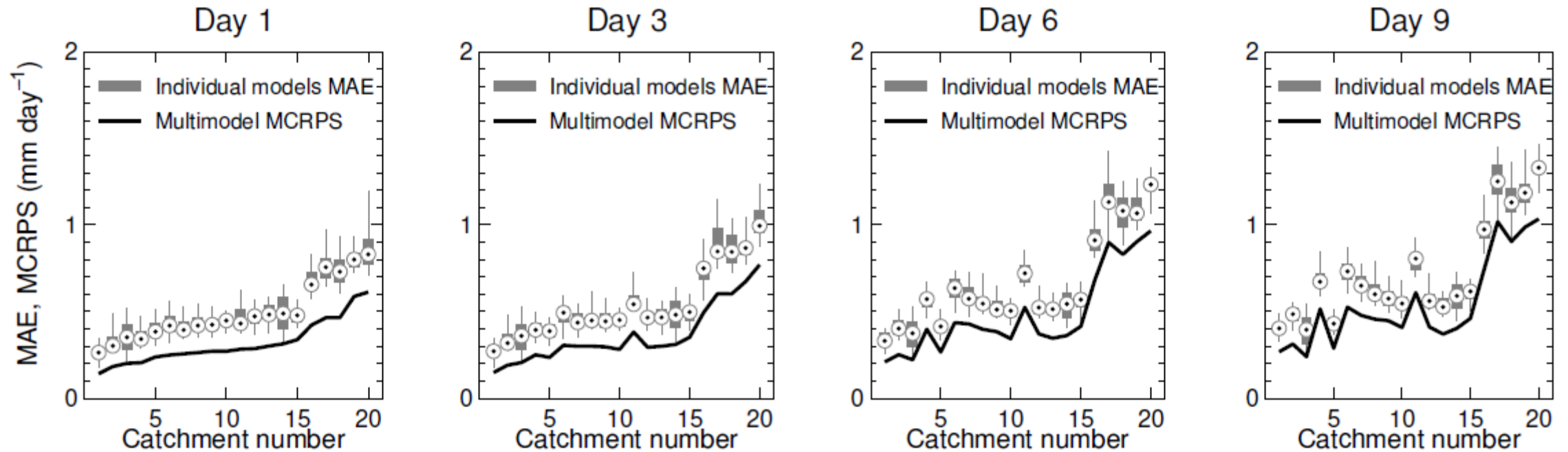
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Multi-model ensemble: multiple hydrological models



Thibault A., Anctil F. and Boucher M-A (2016): Accounting for three sources of uncertainty in ensemble hydrological forecasting, *Hydrology and Earth System Sciences*, **20**, 1809–1825

Multi-model ensemble: multiple hydrological models



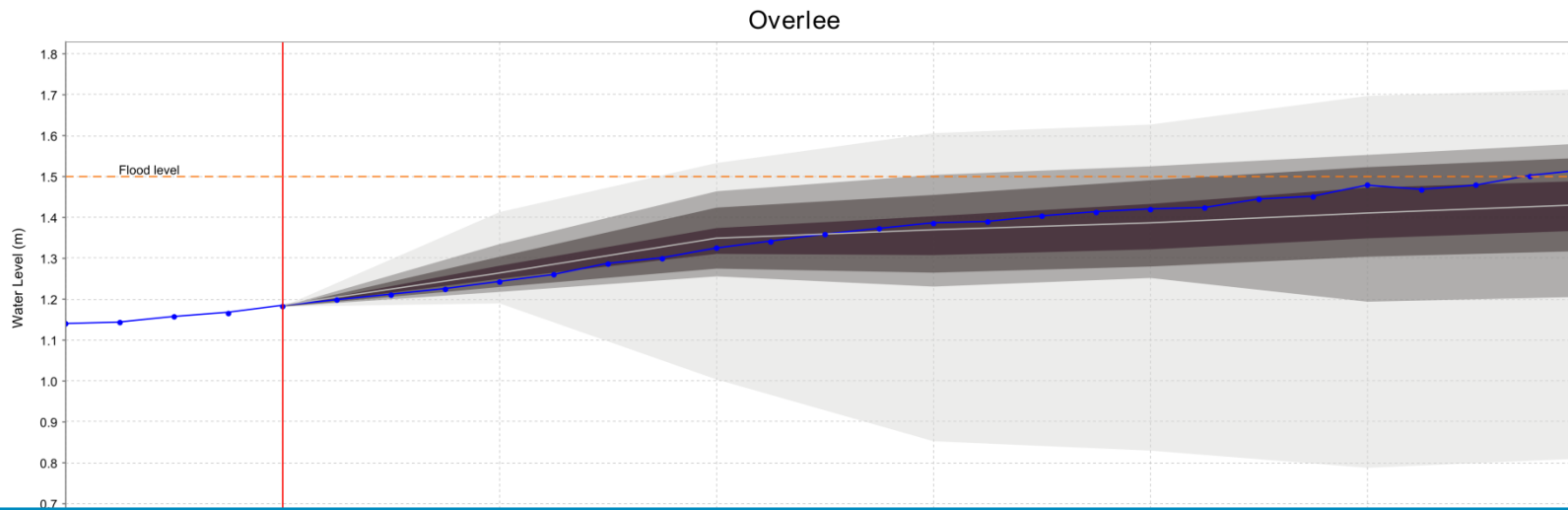
Thibault A., Anctil F. and Boucher M-A (2016): Accounting for three sources of uncertainty in ensemble hydrological forecasting, *Hydrology and Earth System Sciences*, **20**, 1809–1825

Test!

Spread of an ensemble is a result of...

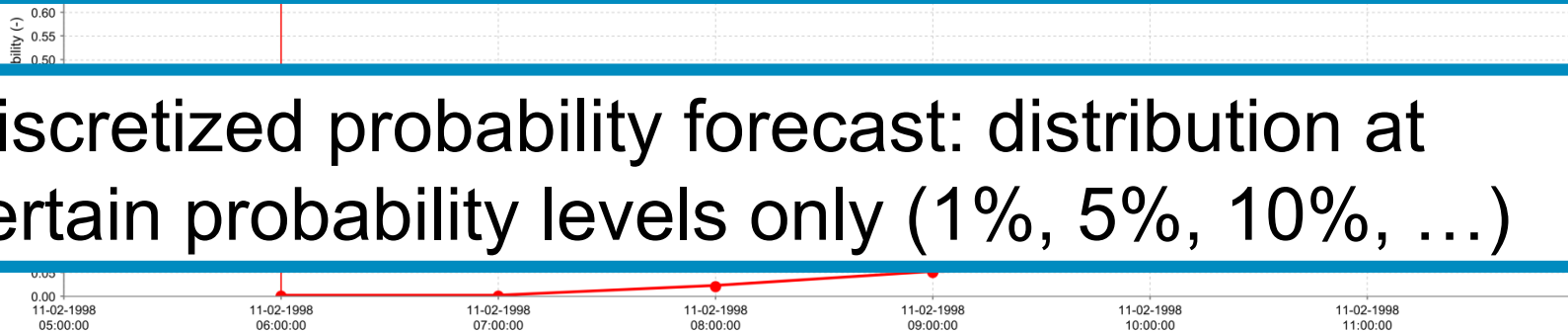
1. Model uncertainty
2. "Total uncertainty" in a forecast
3. A single or limited number of sources of uncertainty
4. Uncertain weather forecasts

Sample probability forecast



Probability forecast: a probability distribution of the future value of a variable.

Discretized probability forecast: distribution at certain probability levels only (1%, 5%, 10%, ...)



From probability forecasts to 'event probs'

- One could be interested in:
 - Discharge over 1250 m³/s
 - Water level below 4.0m
 - Annual income between €25,000 and €40,000
- In terms of probability:
 - Probability of exceedence of $Q=1250$ m³/s
 - Probability of non-exceedence of $H=4.0$ m
 - Probability of $25,000 \leq Y \leq 40,000$



Verification: how good are my forecasts?

Short course on real-time hydrological forecasting



What is forecast verification?

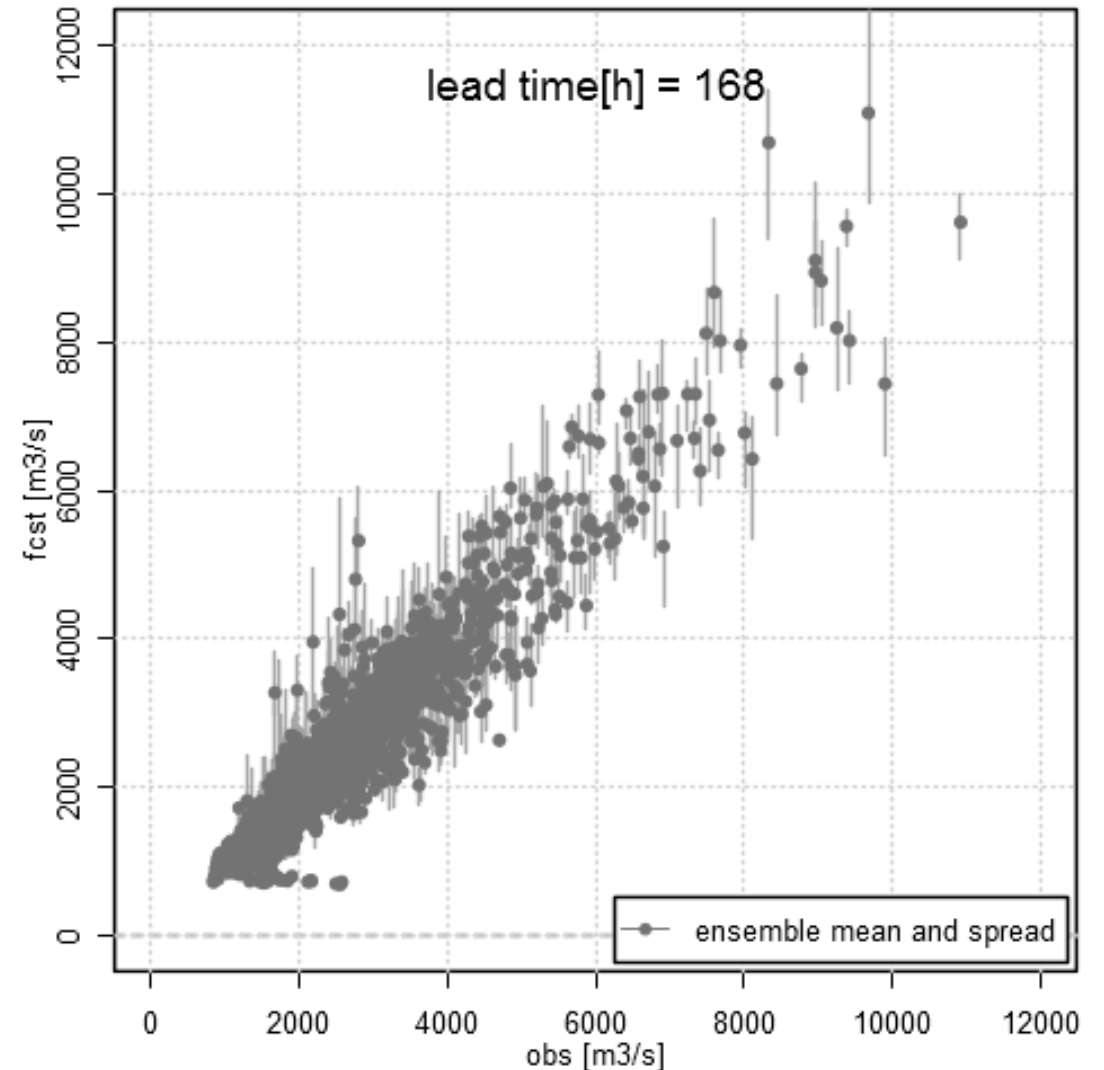
“Verification is the assessment and quantification of the relationship between a matched set of forecasts and observations.” (Stanski et al., 1989)

“Verification is the posterior assessment of the skill and value of the forecasts”

It ties into the question: “What is a good forecast?”

- Quality
- Value
- Consistency

(Murphy, 1993)



Why verify?

1. Administrative reasons
Provision of the rationale for (additional) investments in forecasts
2. Scientific reasons:
Where can the forecasts be improved?
3. Economic reasons:
What is the value to an end user?

(Jolliffe and Stephenson, 2012; Brier & Allen, 1951; Stanski et al., 1989)

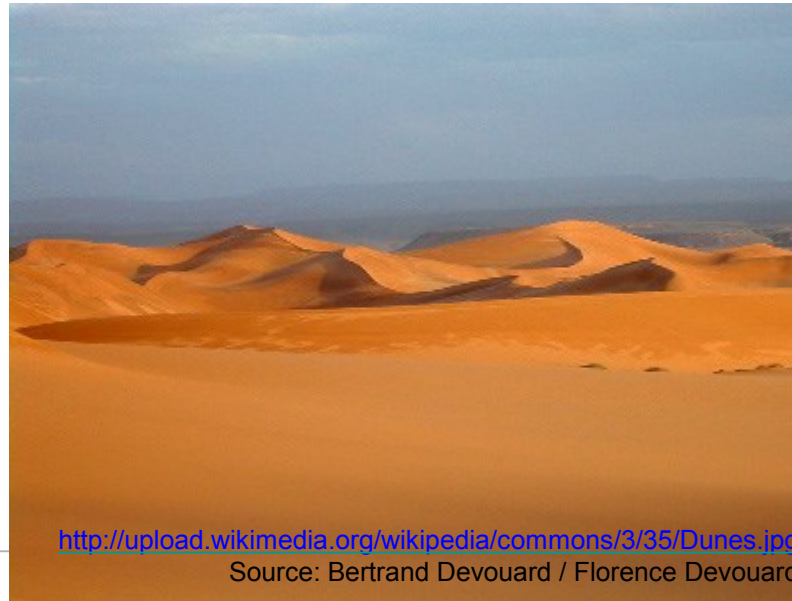


Forecast quality versus forecast value

- Quality: high correlation between forecasts and observations
- Value: degree to which an end user can make better decisions

Classic example: forecast of a sunny day over Sahara desert

- Quality?
- Value?



What to expect from a probability forecast?

- *Reliability*: correspondence of predicted probabilities with observed relative frequencies
- *Sharpness*: tendency to produce 0% and 100% probability forecasts

(there are more considerations: see [Murphy, 1993](#))

What Is a Good Forecast? An Essay on the Nature of Goodness in Weather Forecasting

ALLAN H. MURPHY

College of Oceanic and Atmospheric Sciences, Oregon State University, Corvallis, Oregon

(Manuscript received 11 August 1992, in final form 20 January 1993)

ABSTRACT

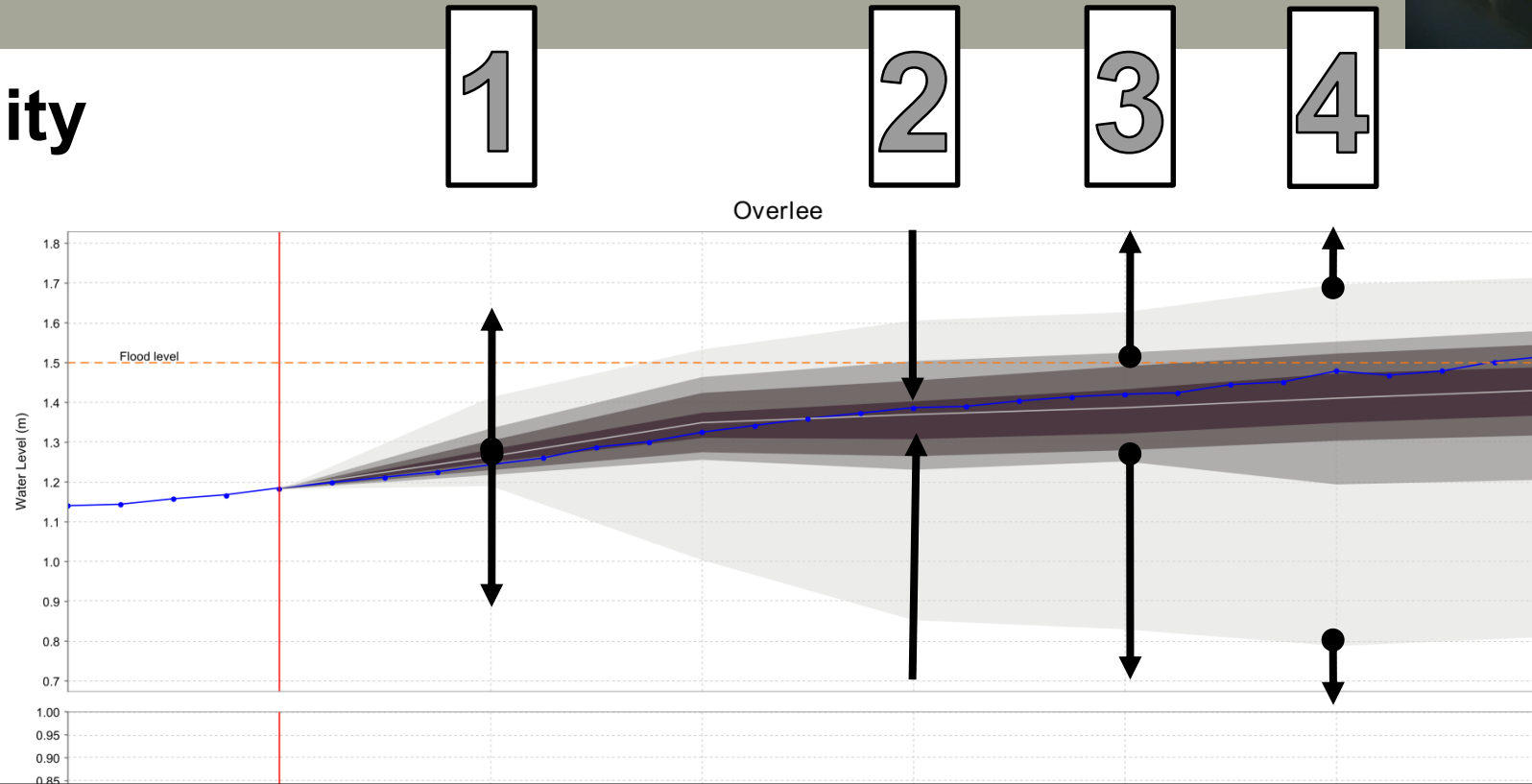
Differences of opinion exist among forecasters—and between forecasters and users—regarding the meaning of the phrase “good (bad) weather forecasts.” These differences of opinion are fueled by a lack of clarity and/or understanding concerning the nature of goodness in weather forecasting. This lack of clarity and understanding complicates the processes of formulating and evaluating weather forecasts and undermines their ultimate usefulness.

Three distinct types of goodness are identified in this paper: 1) the correspondence between forecasters’ judgments and their forecasts (type 1 goodness, or *consistency*), 2) the correspondence between the forecasts and the matching observations (type 2 goodness, or *quality*), and 3) the incremental economic and/or other benefits realized by decision makers through the use of the forecasts (type 3 goodness, or *value*). Each type of goodness is defined and described in some detail. In addition, issues related to the measurement of consistency, quality, and value are discussed.

Relationships among the three types of goodness are also considered. It is shown by example that the level of consistency directly impacts the levels of both quality and value. Moreover, recent studies of quality/value relationships have revealed that these relationships are inherently nonlinear and may not be monotonic unless



Reliability

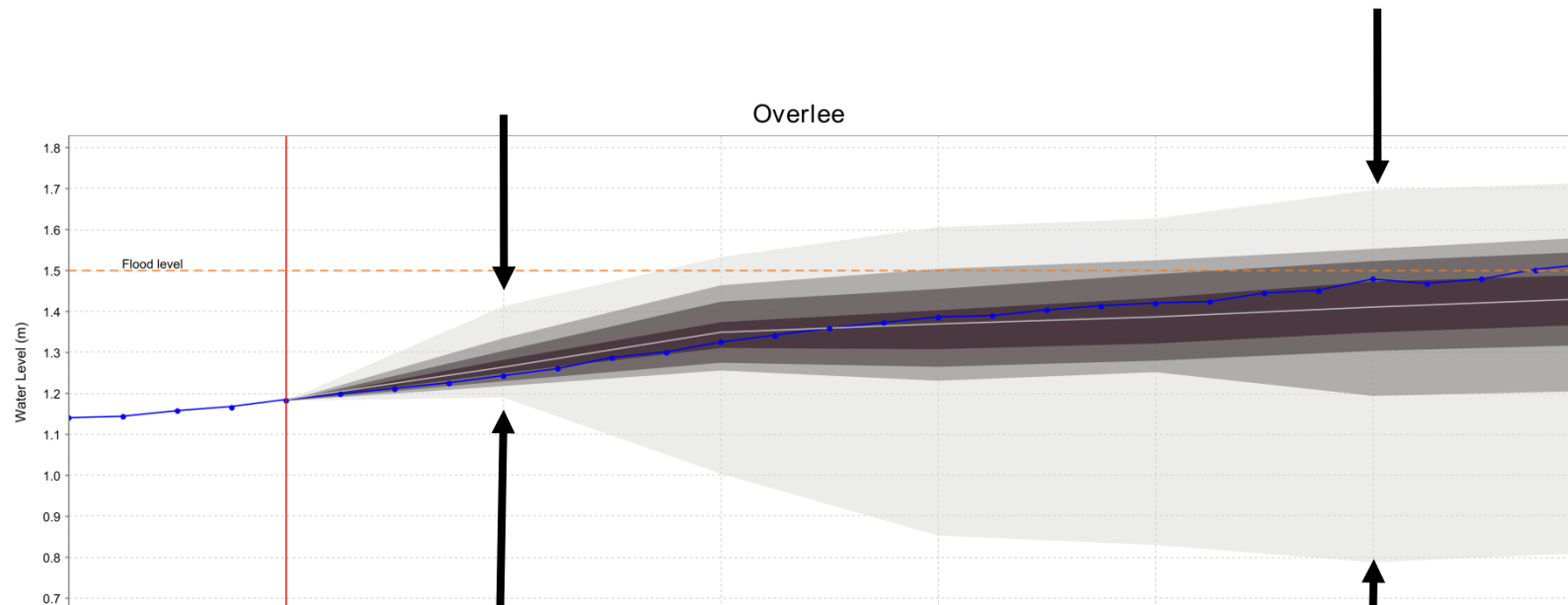


1. Half of the observations above the median; half below
 2. 50% of the observations between Q25 and Q75
 3. 10% of the observations between Q90; 10% below Q10
 4. 1% of the observations above Q99; 1% below Q1
- Et cetera...

0.00 11-02-1998 05:00:00 11-02-1998 06:00:00 11-02-1998 07:00:00 11-02-1998 08:00:00 11-02-1998 09:00:00 11-02-1998 10:00:00 11-02-1998 11:00:00

Sharpness

- ...measure of the width of a predictive distribution
- What is ideal? Under which conditions?



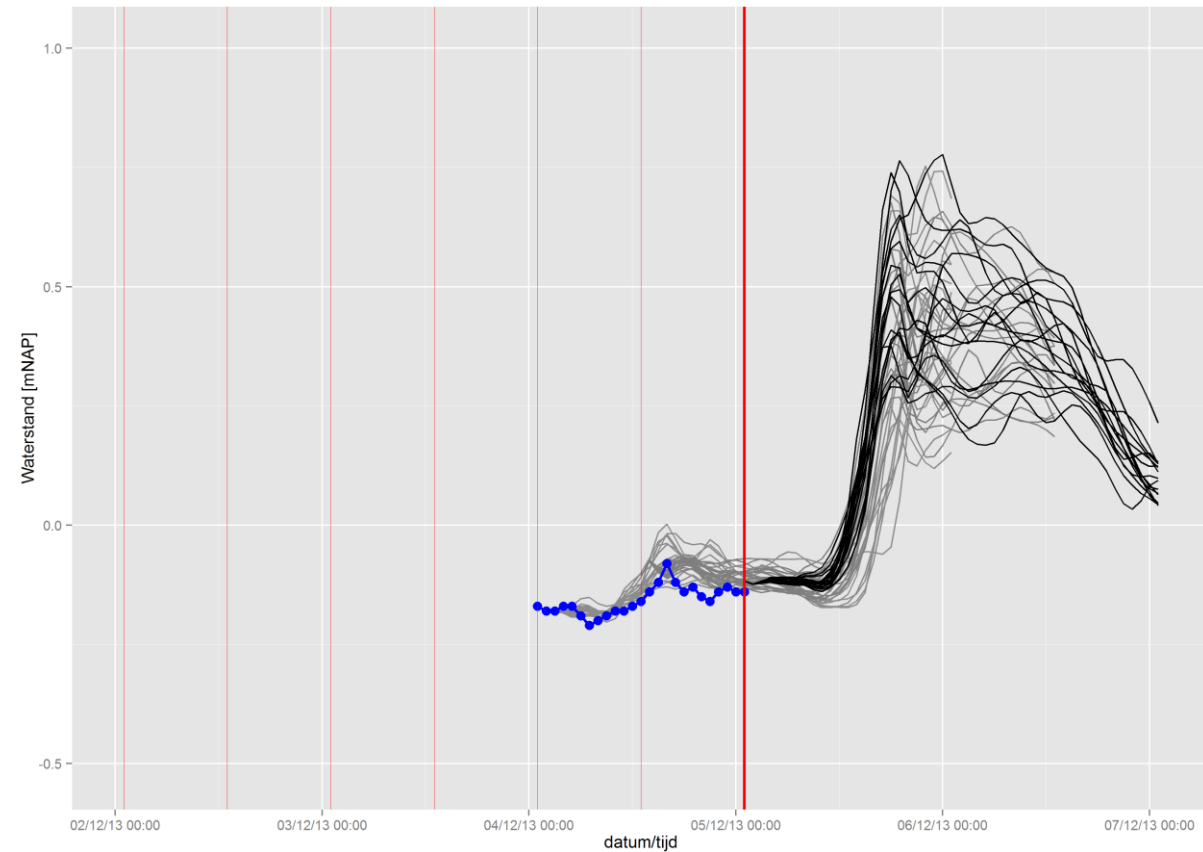
Verification: (possible) approach

- Qualitative: “Eyeball verification”: take a look at forecasts and observations
- Summary metrics:
 - Graphical verification measures
 - Numerical: metrics and skill scores



Visual inspection: hydrographs

- Example: water levels at Kampen
- Interpretation:
 - T0 (thick red line) always on same location
 - Blue = observation
 - Black/grey= forecast
 - Animation:
 - Time progresses; figure “moves” to the left
 - Previous T0s: thin red lines
 - Forecasts become lighter with age



Visual inspection: hydrographs

- What do you notice? Think of...
 - Initial conditions
 - Bias
 - Spread
 - Reliability

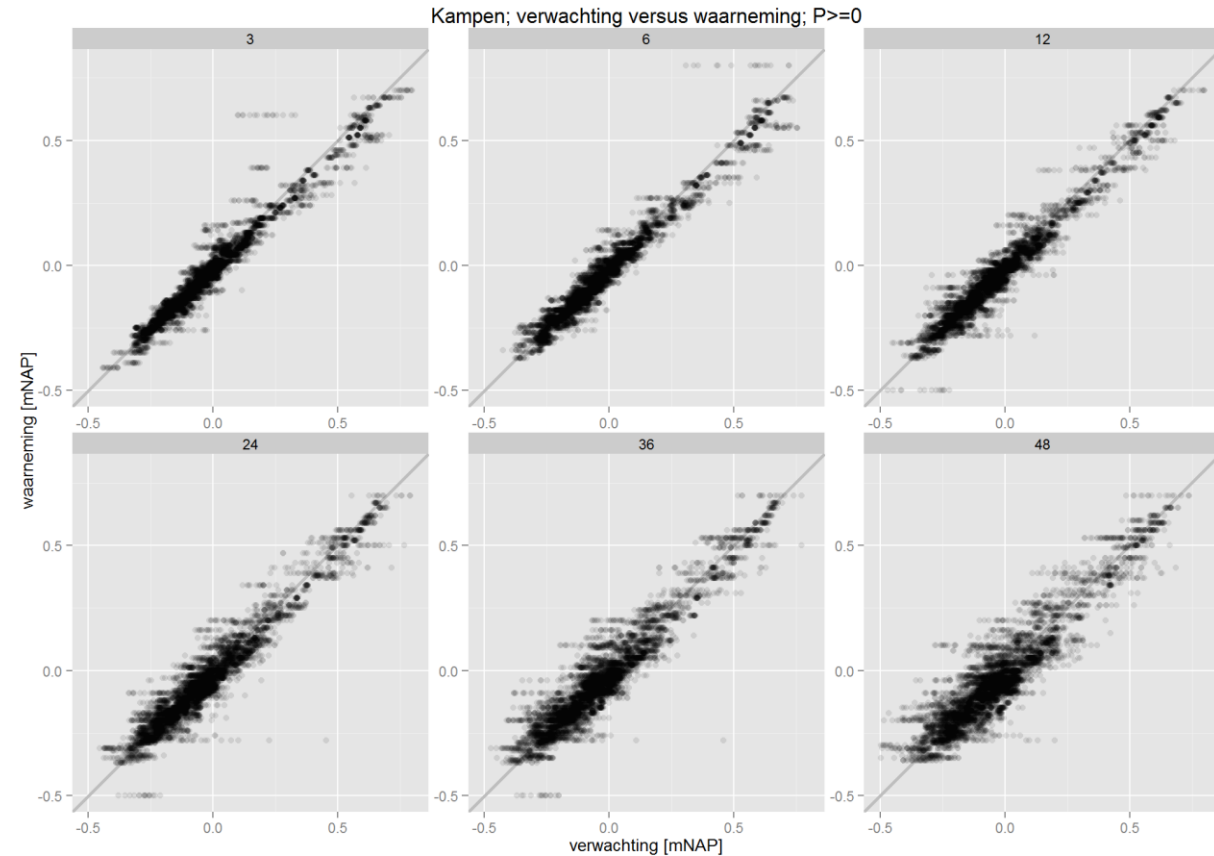
Kampen: https://youtu.be/Px_zQsyQJhk

Ramspolbrug: <https://youtu.be/R-7klljaOlo>

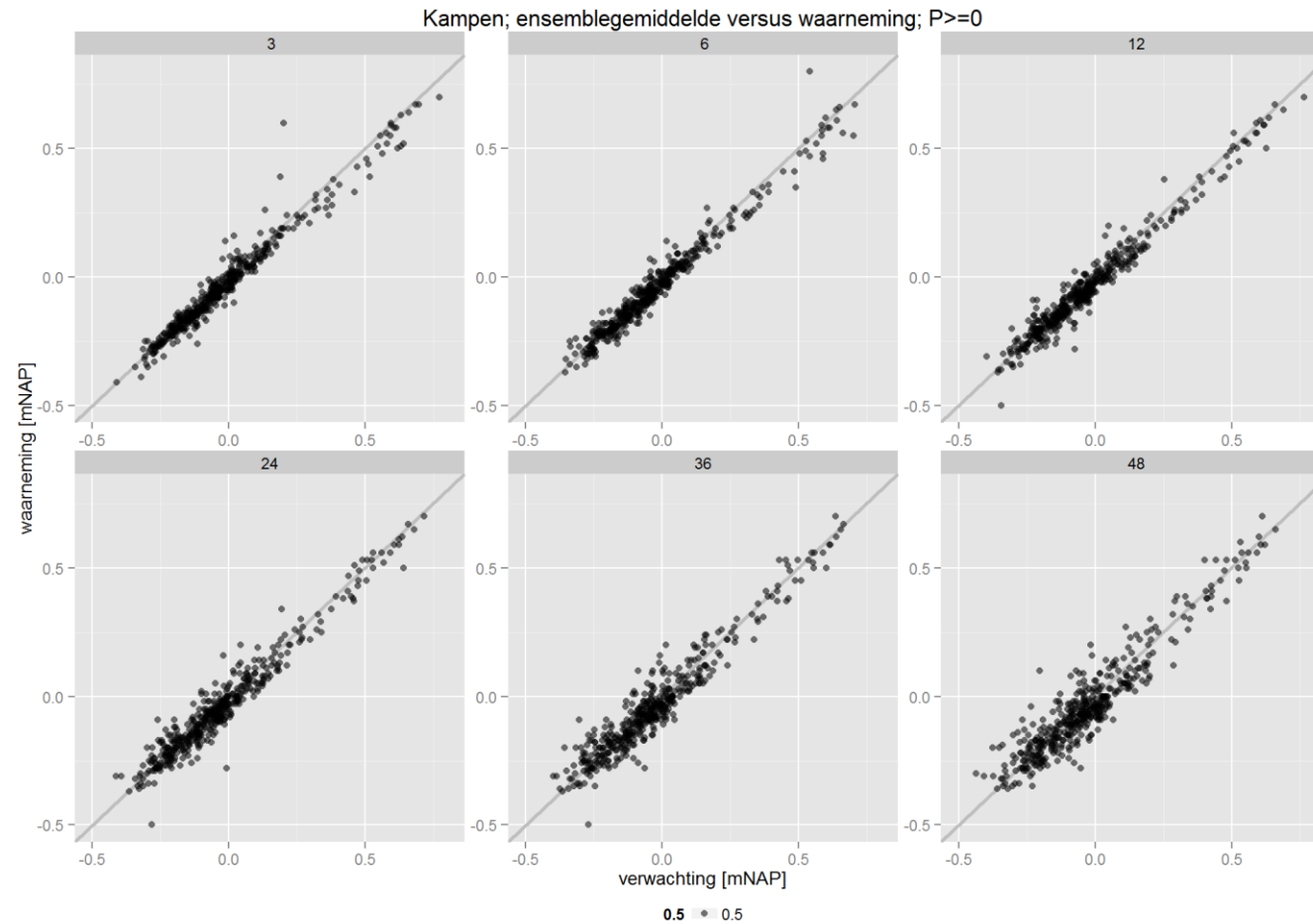
Nijkerkersluis West: <https://youtu.be/p8qBDQMj6Bo>

Visual inspection: scatters (forecast v observation)

- All available fcst, obs pairs in a single figure
- Separate plots for separate leadtimes
- Horizontal axis: forecast
Vertical axis: observation
- Where would we like to see the points?
- Ensemble: multiple forecasts for every observation
 - transparency helps to identify this
 - complicates interpretation nonetheless

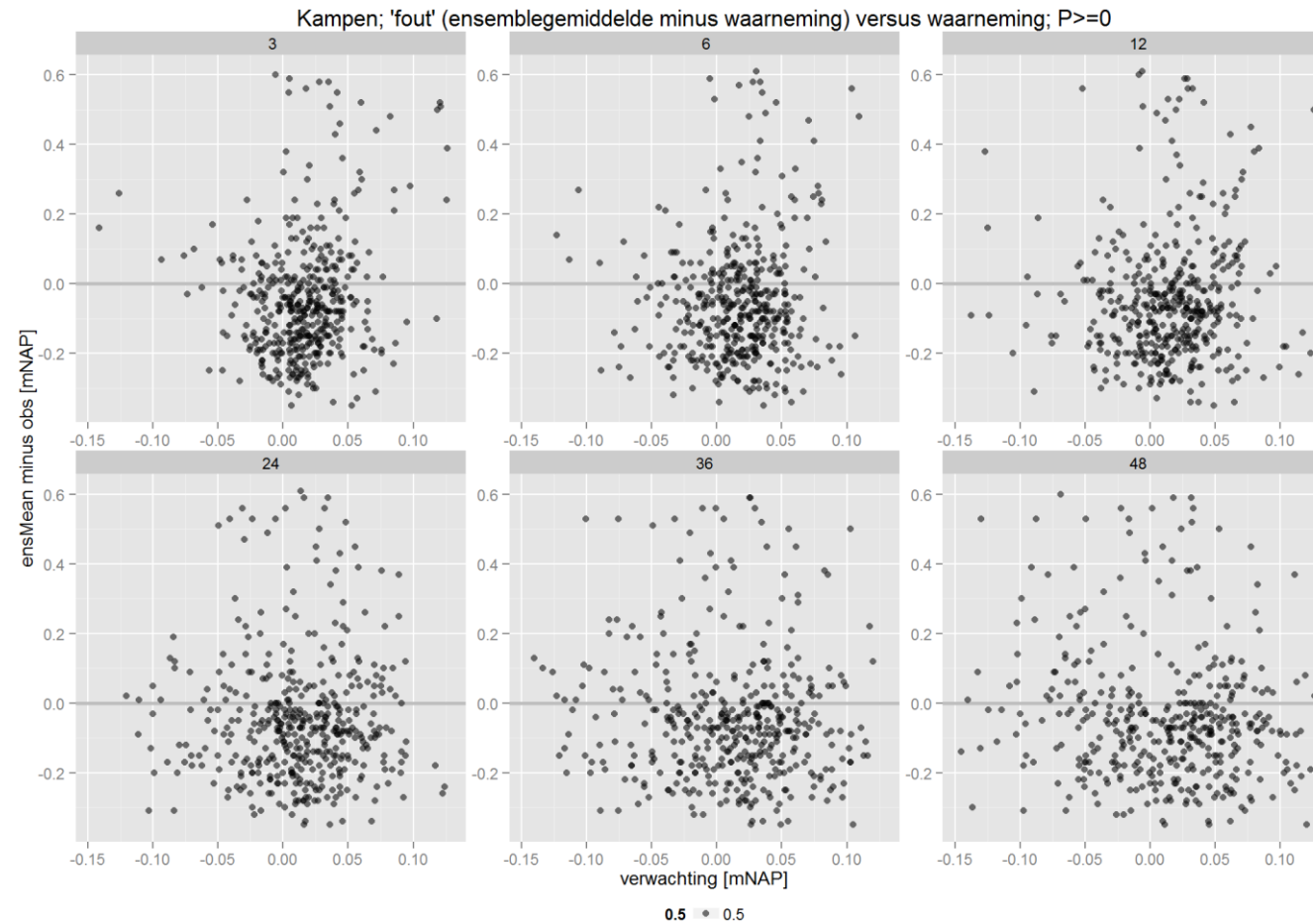


Visual inspection: scatters (ensemble mean v observation)



- What do you notice?

Visual inspection: scatters ('error' versus observation)



- What do you notice?
- Can these forecasts be bias-corrected?

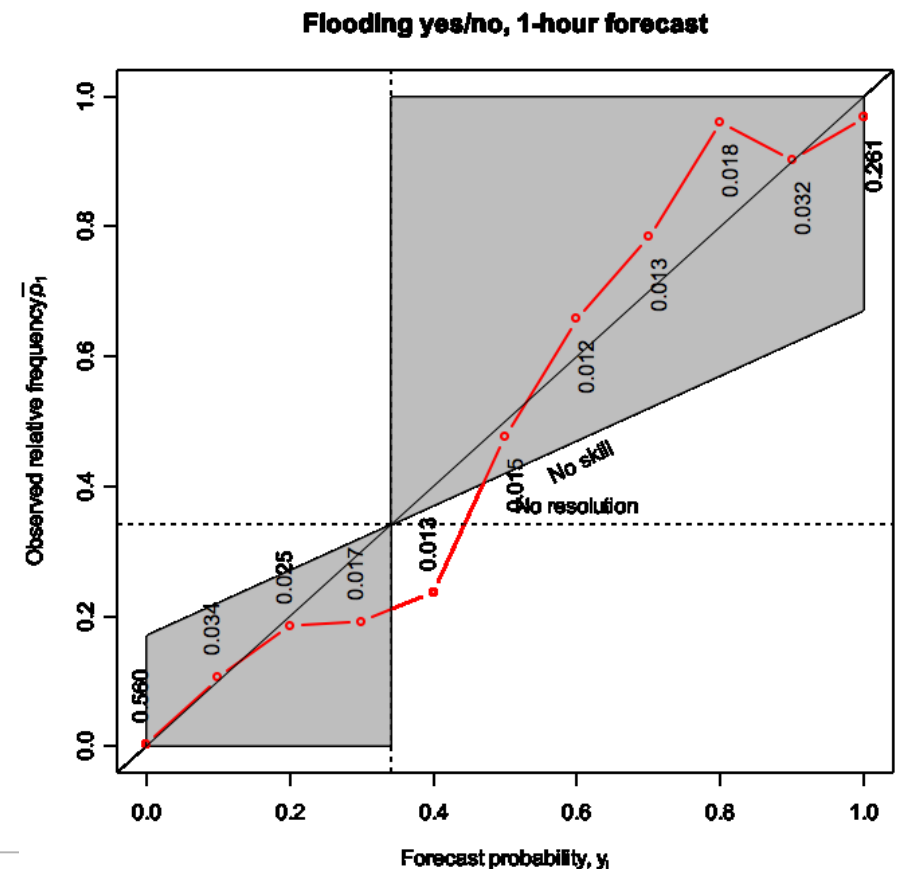
Verification: (possible) approach

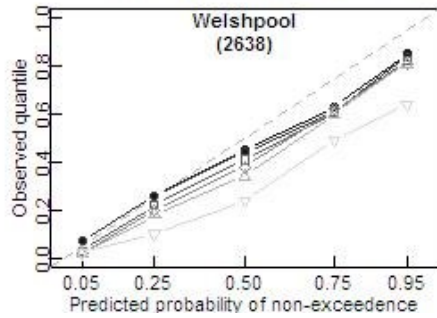
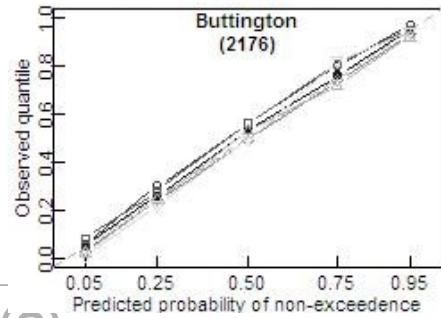
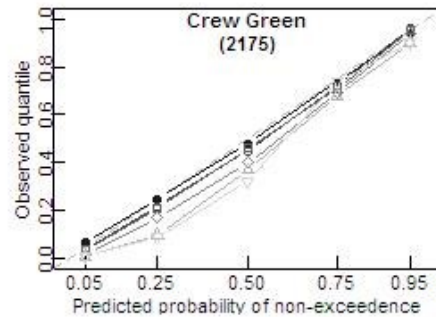
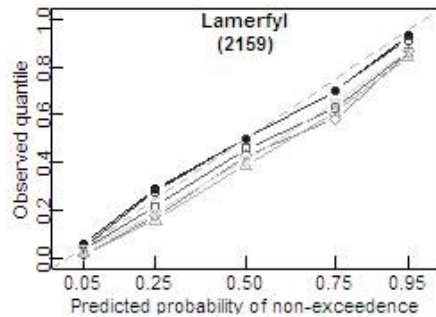
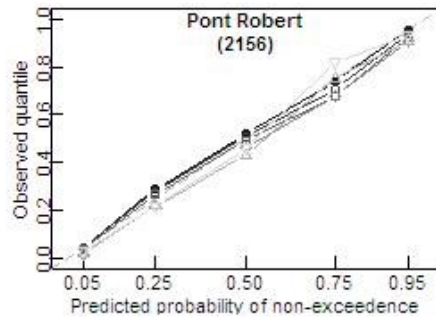
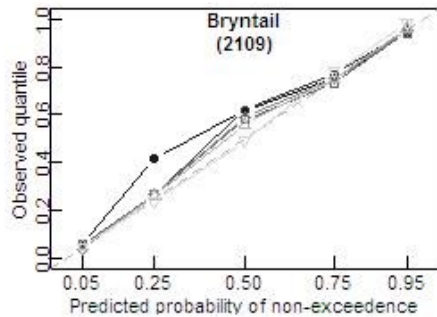
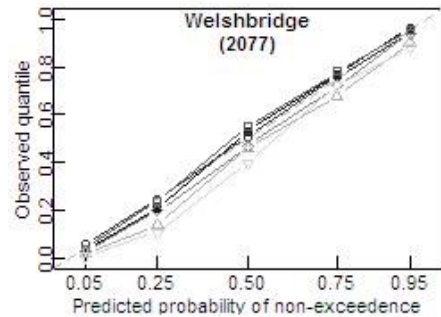
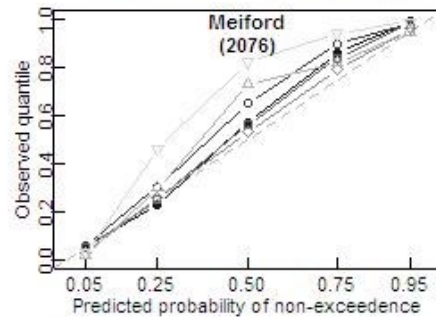
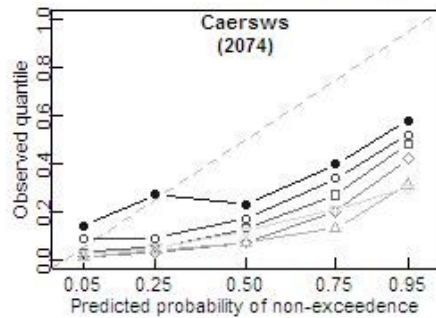
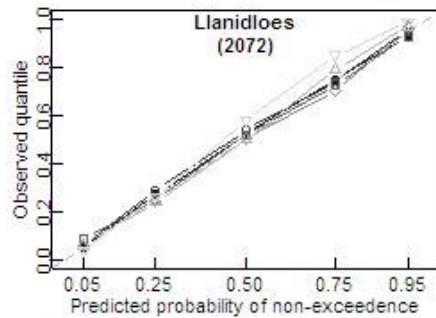
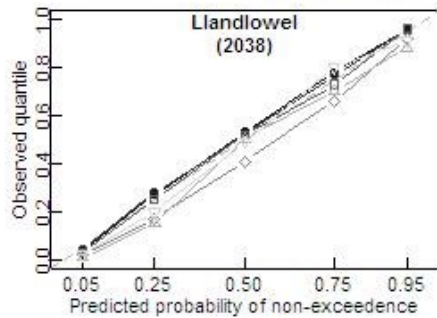
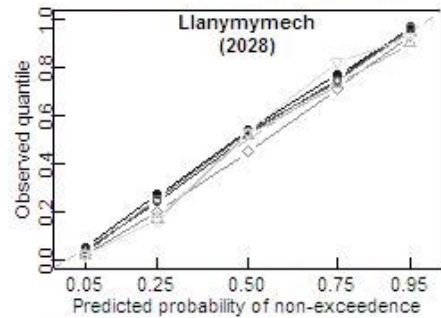
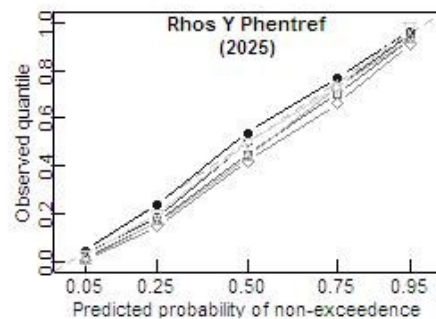
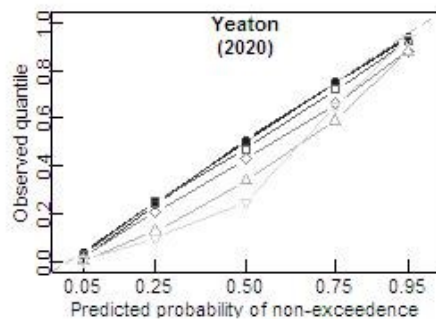
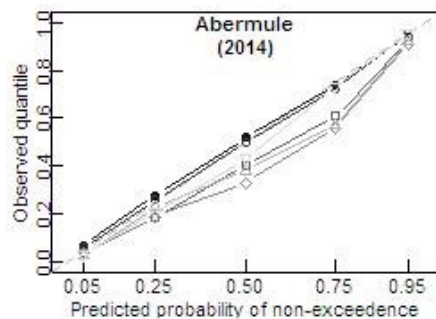
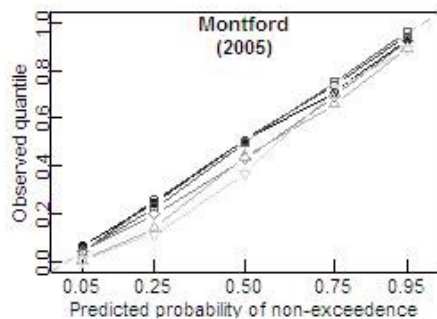
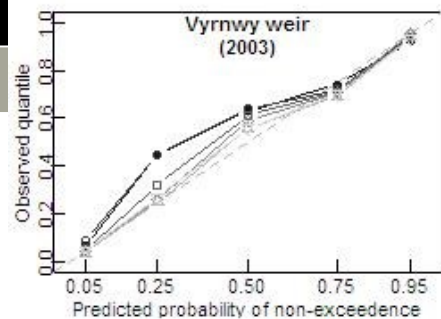
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Reliability plots

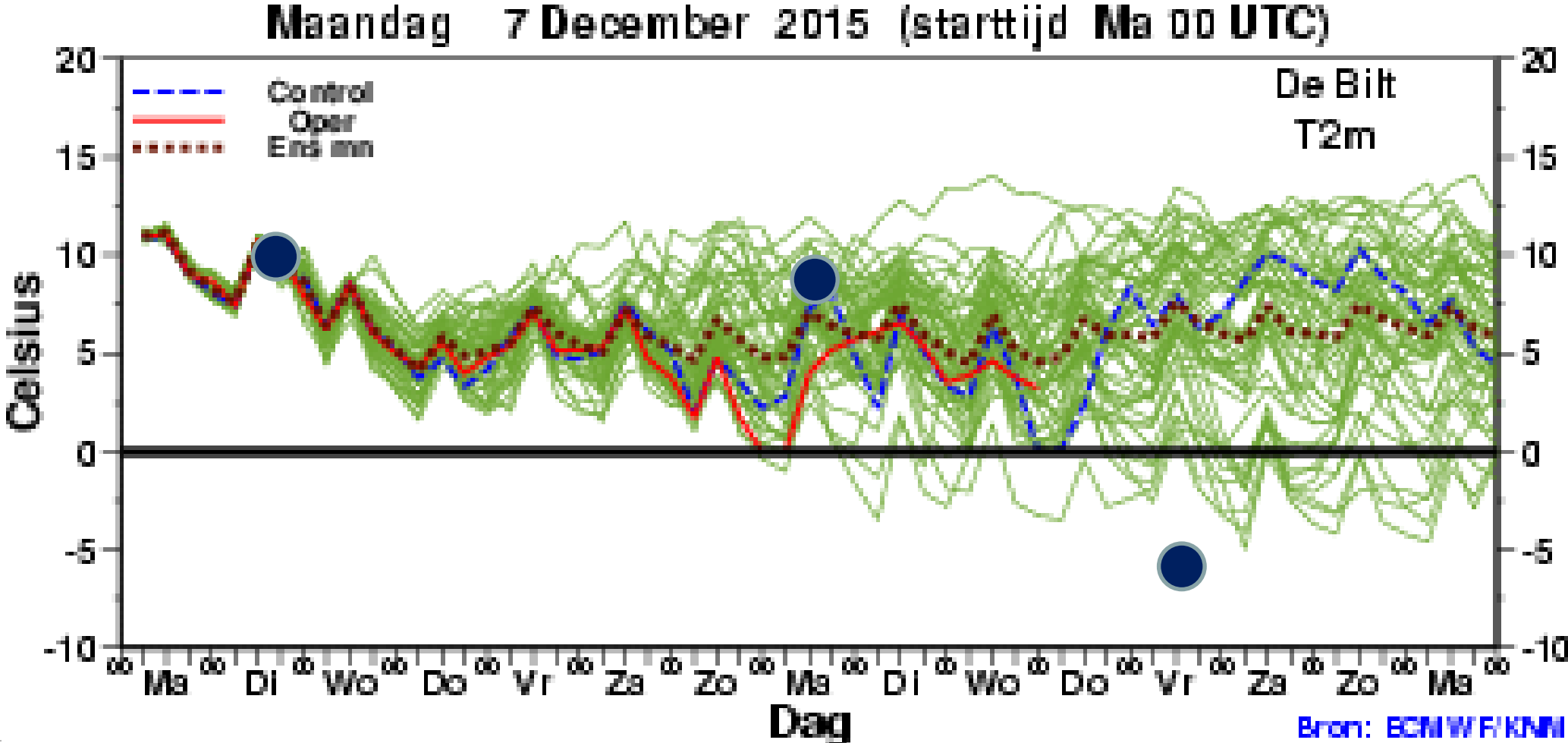
- Reliability: correspondence of predicted probabilities with observed relative frequencies
- Graphical measure: reliability plots
 - Horizontal axis: event probabilities
 - Vertical axis: observed relative frequencies
- Important! How many verification pairs were used to determine the points on the graph?





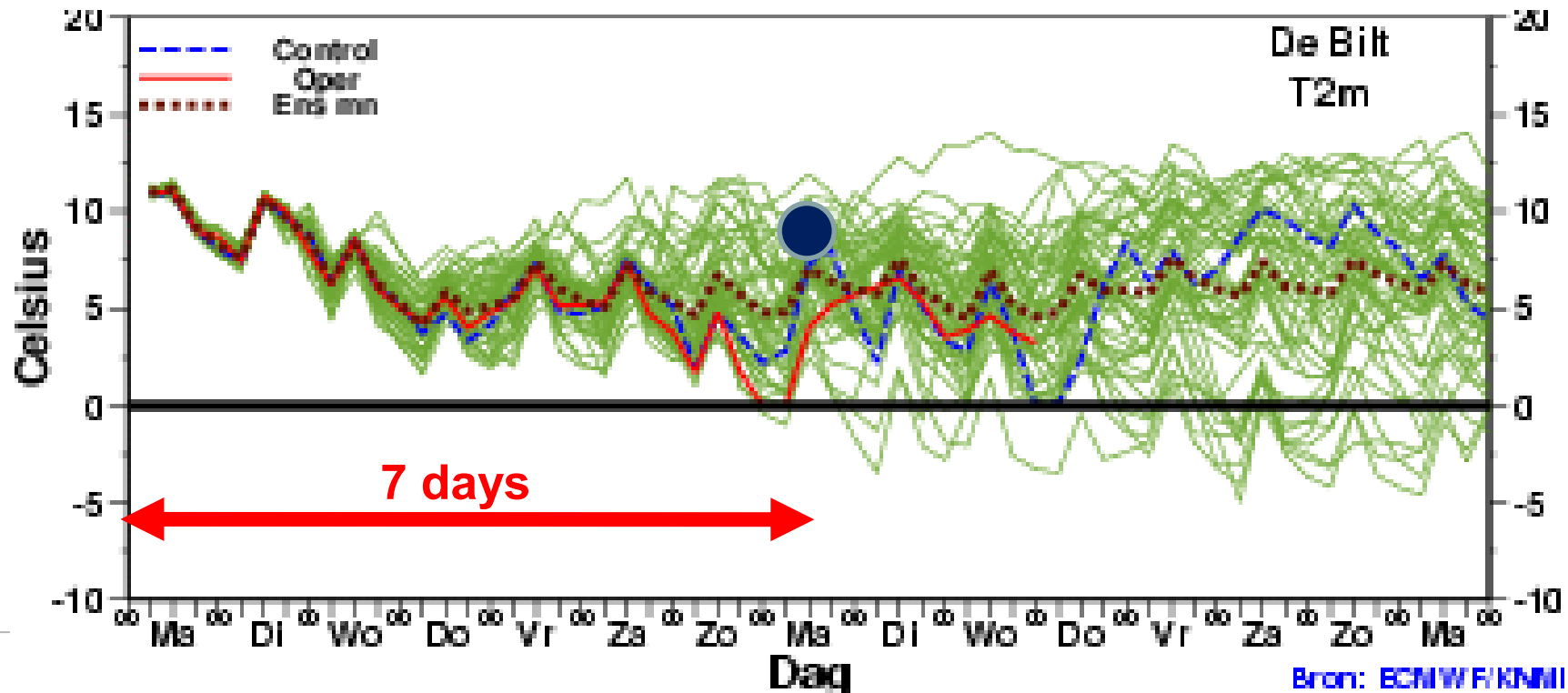
- Lead-time = 3 hours
- Lead-time = 6 hours
- Lead-time = 12 hours
- ◇ Lead-time = 24 hours
- △ Lead-time = 36 hours
- ▽ Lead-time = 48 hours

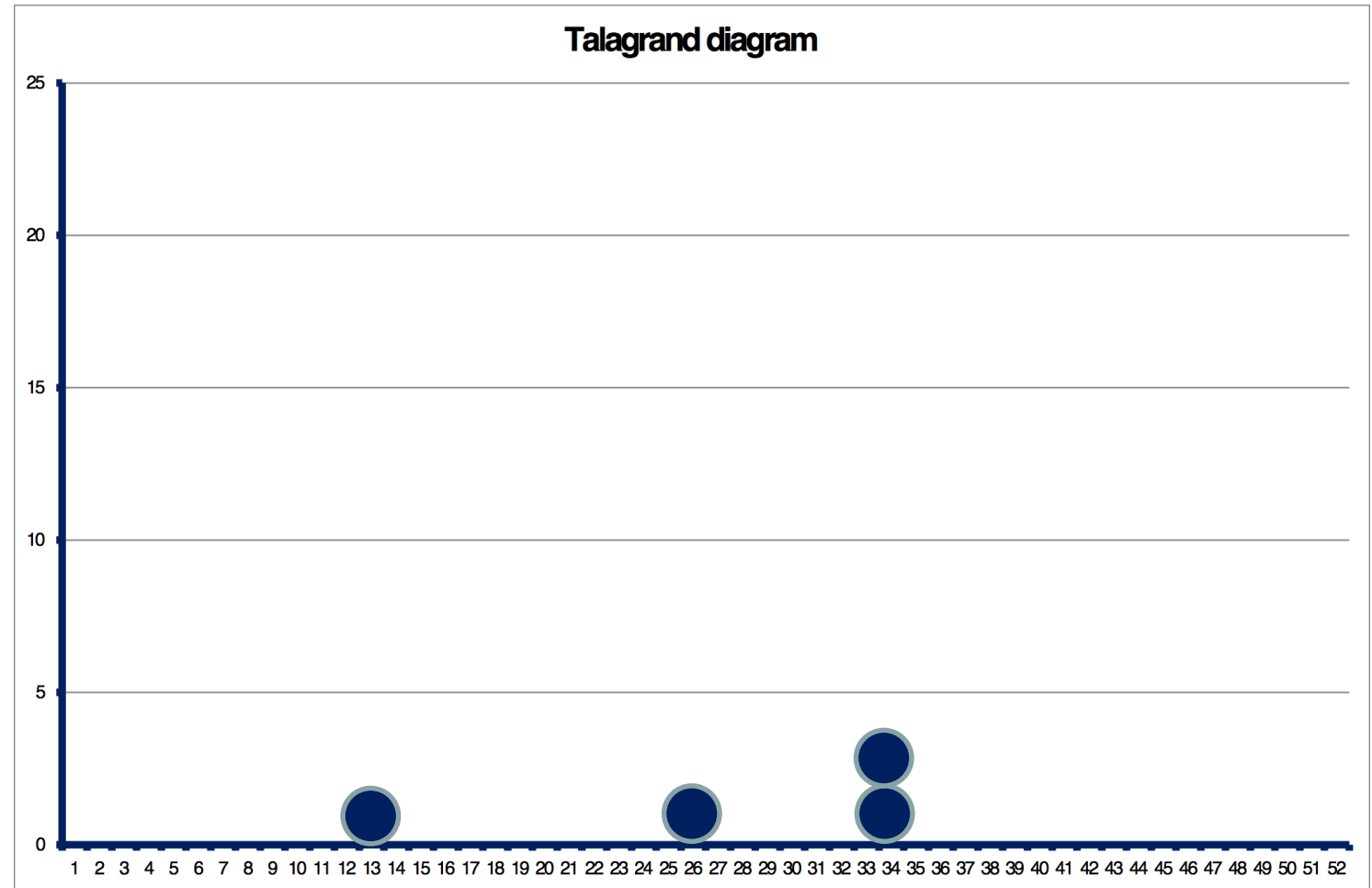
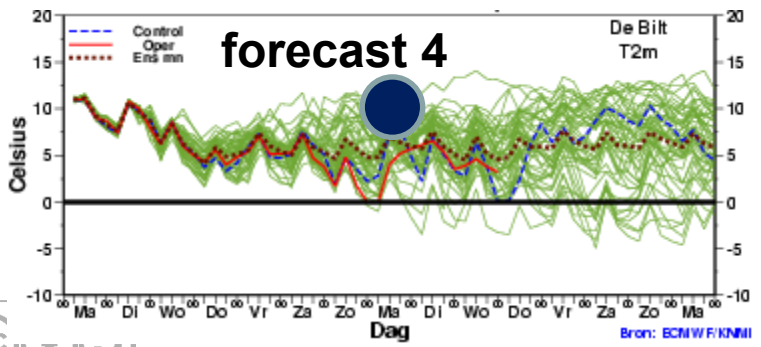
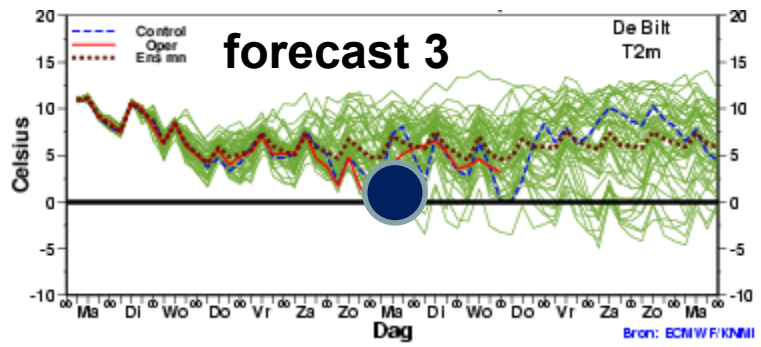
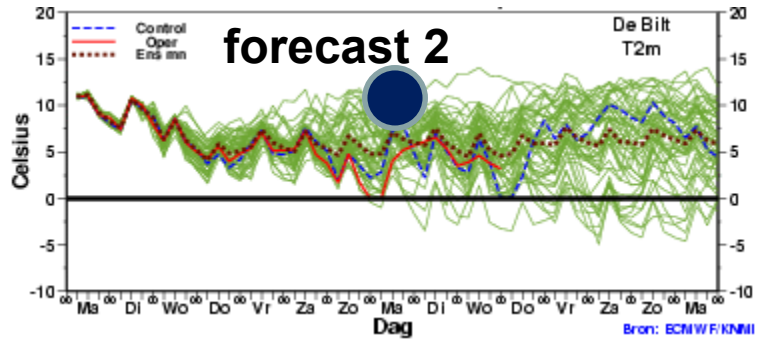
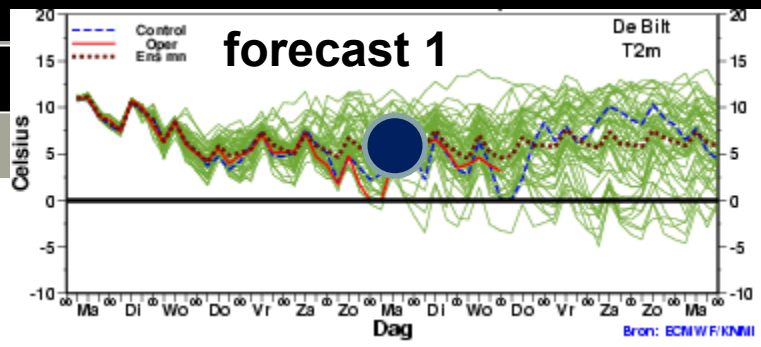
Rank histograms (“Talagrand diagrams”)



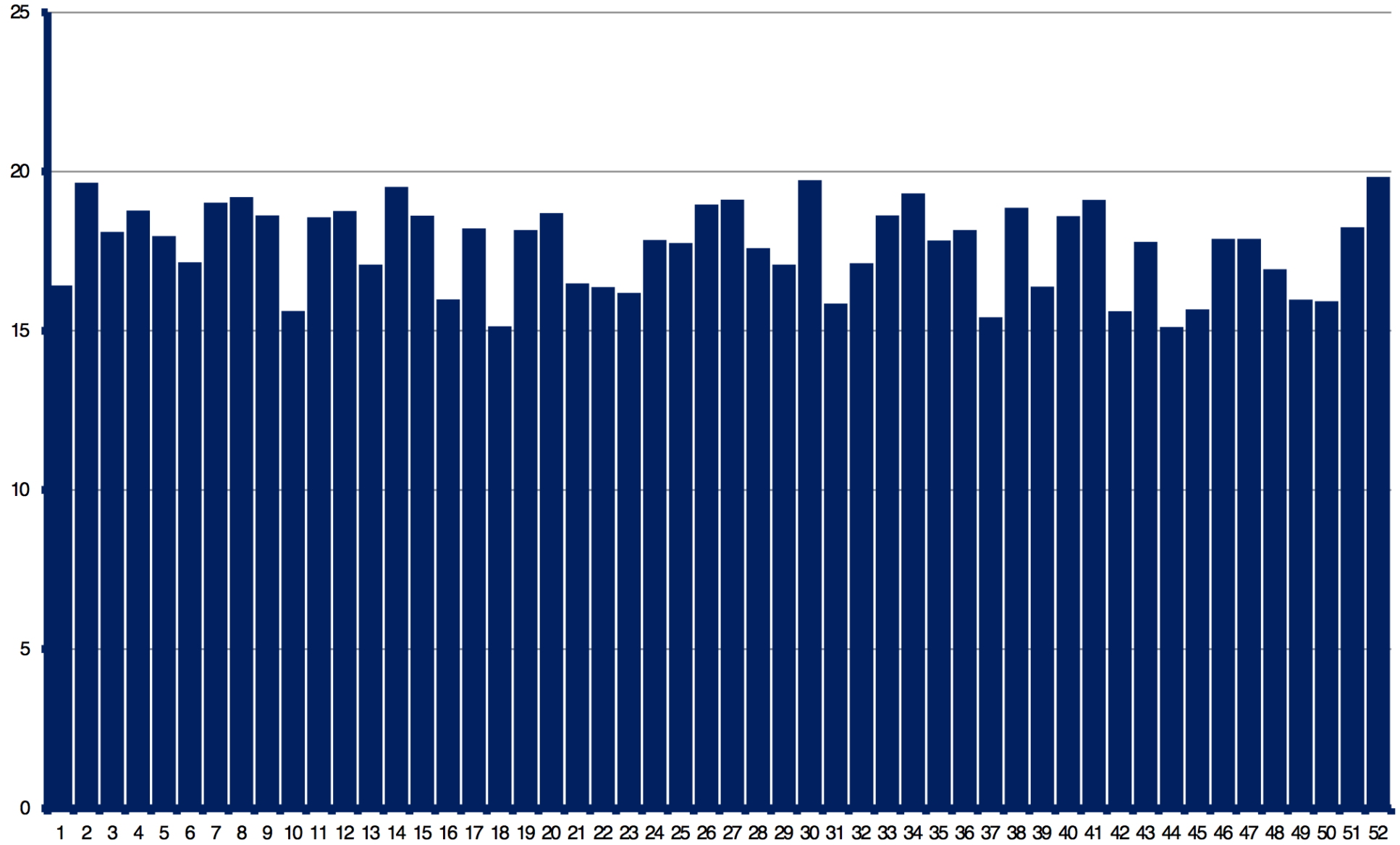
Rank histograms (“Talagrand diagrams”)

- Here, we are interested in forecast quality at the 7 day / 168h lead time
- We look at multiple forecasts for which we have observations available
- Key: record *between which ensemble members* the observation has occurred

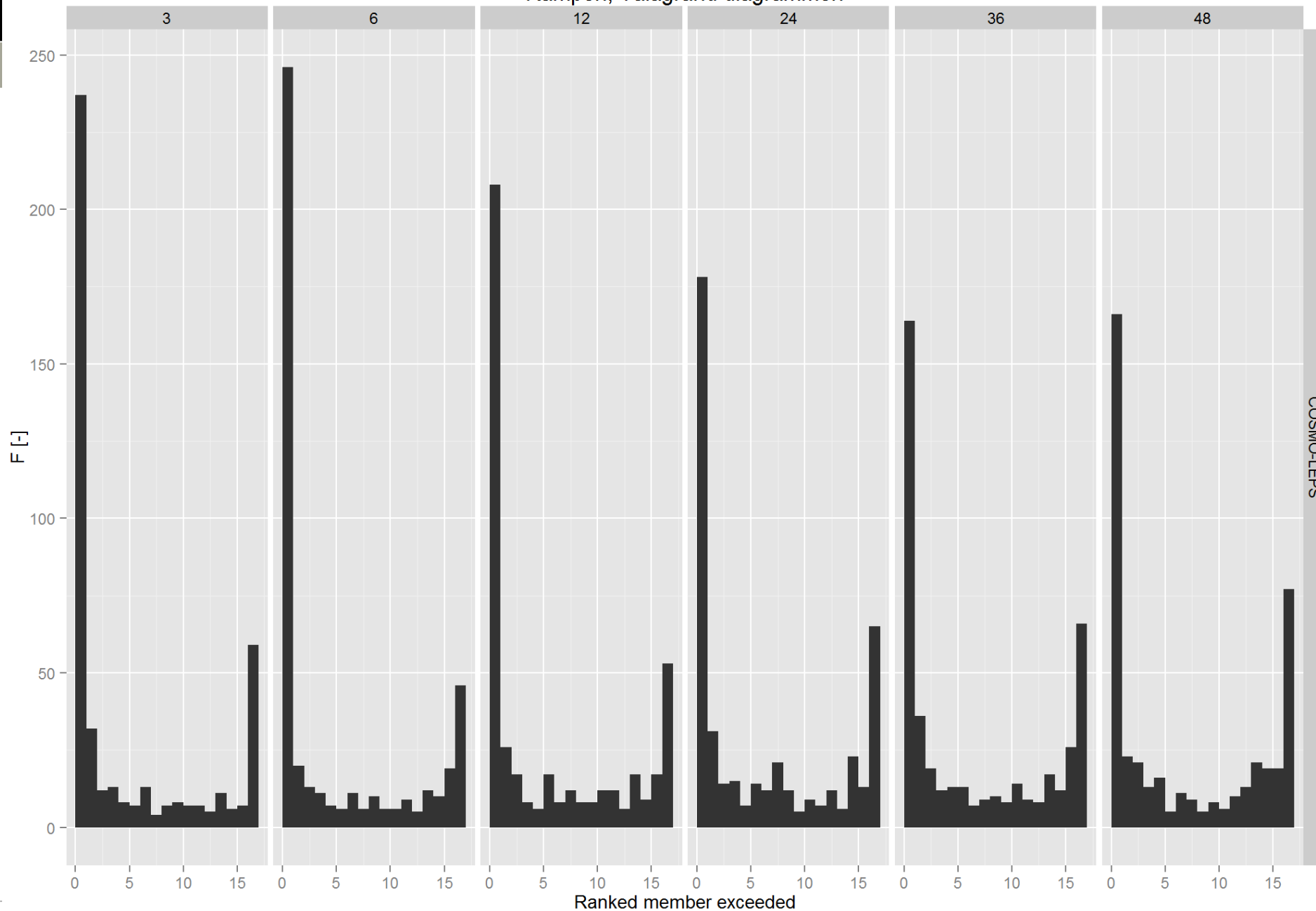




Talagrand diagram



Kampen; Talagrand diagrammen



COSMO-LEPS

Verification: (possible) approach

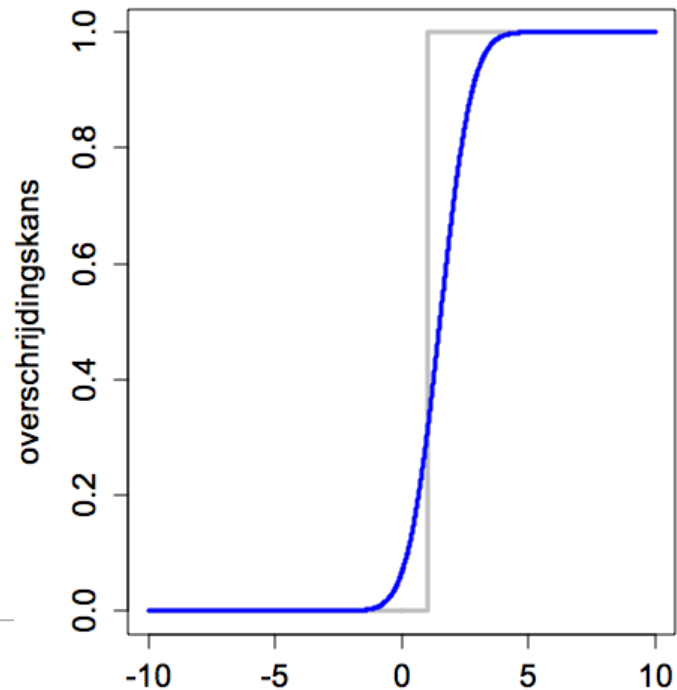
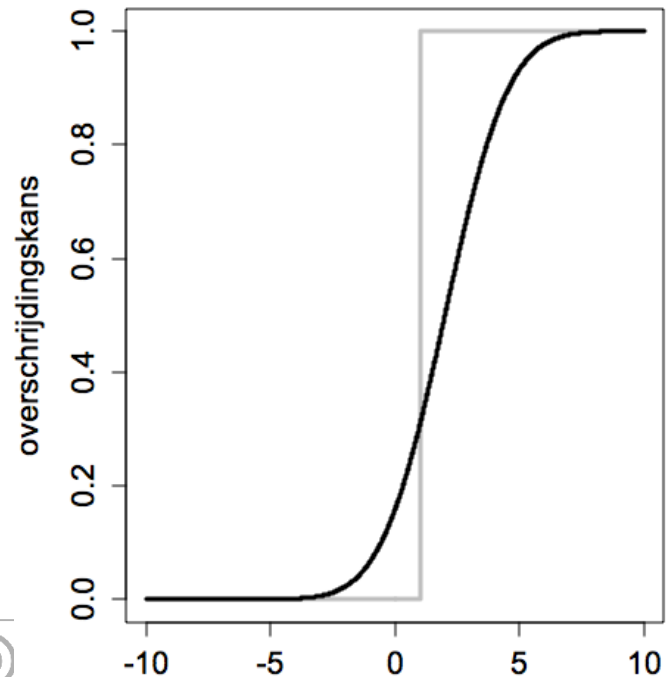
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Approach

A magnifying glass with a black handle and a silver rim is positioned over the word 'Approach'. The lens of the magnifying glass is centered over the letters 'ppro', making them appear larger and more prominent than the rest of the word.

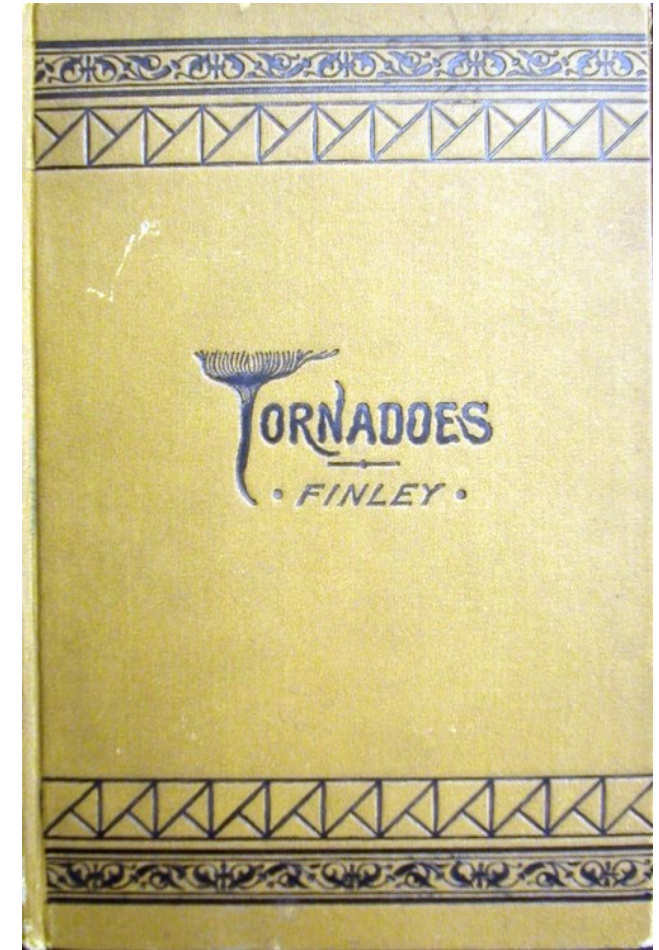
Continuous Ranked Probability Score

- Measure for both *reliability* and *sharpness*
- Area of the difference between the forecast and observed CDF
- Hersbach, 2000 for details and decomposition



“Finley’s tornadoes”

Forecast	Observation		Total
	Tornado	No tornado	
Tornado	28	72	100
No tornado	23	2680	2703
Total	51	2752	2803



Scores and “skills”

- Finley’s tornado forecasts: “96.6% accurate”
 - Critics: 98.1% accuracy if always predicting non-occurrence
 - Quality versus a baseline is important: skill
-
- Best possible skill score: 1
 - Quality of your forecast equal to that of baseline: skill = 0
 - Quality of your forecast worse than that of baseline : skill < 0
-
- Finley’s tornadoes: skill = $(96.6 - 98.1) / (100 - 98.1) = -0.79$

Supplemental materials: software

- [Verification package](#) in R (UCAR) + vignette
- EVS: [Ensemble Verification System](#) (NOAA-NWS-OHD)
- MET: [Model Evaluation Tools](#) (UCAR)

characteristic	R	EVS	MET
deterministic forecasts	yes	yes	yes
probabilistic forecasts	yes	yes	yes
open source	yes	yes	yes
ensemble inputs	no	yes	yes
spatially gridded input	no	no	yes
GUI	no	yes	no
Delt-FEWS-PI as input	no	yes	no
command line	yes	yes	yes

Short break! (10 minutes)

After the break, we'll play a game.

**A risk-based decision-making
game relevant to water
management.
Try it yourself!**

2013. This game was prepared by Louise Crochemore (IRSTEA), Florian Pappenberger (ECMWF), Schalk Jan van Andel (UNESCO-IHE), Maria-Helena Ramos (IRSTEA) and Andy Wood (NOAA). If you use this game, the authors would be grateful for feedback on your usage and results so as to help improve future versions of the game and justify further development efforts. Special thanks to Kevin Werner (NWS), a key designer of the original game on which this one is based.

Contact: maria-helena.ramos@irstea.fr

This game is part of HEPEX activities: www.hepex.org

START

General instructions: use full screen mode. Always click on the appropriate links in each slide.
Do not use Page Up, Page Down or arrow keys for scrolling.



Risk-based decision-making: a game

Short course on real-time hydrological forecasting

A risk-based decision-making game relevant to water management.

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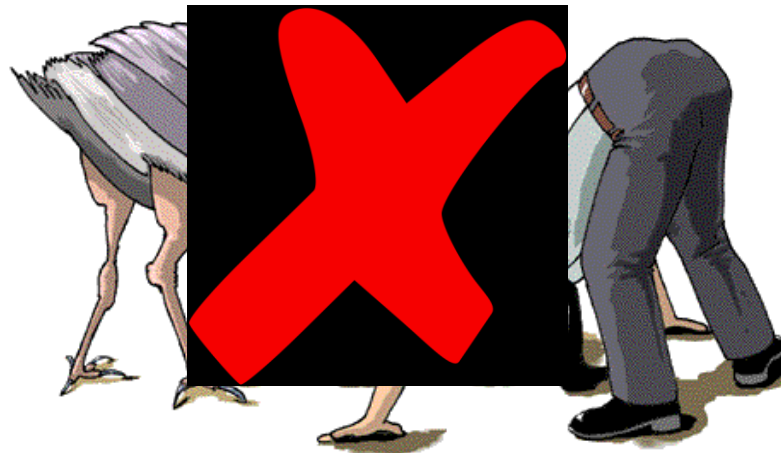


Probabilistic forecasts and decision making

Short course on real-time hydrological forecasting

Rationale for probabilistic forecasts

1. Explicitly show inherent uncertainties
2. Enable risk-based decision-making
3. Extending forecast lead time
4. Separation of responsibilities between



The “contingency table”

- Summarizes binary forecasts (...) and corresponding observations
- Is used to calculate metrics (next slide)

Forecast	Observation		Total
	Tornado	No tornado	
Tornado	Hit	False alarm	Σ forecast events
No tornado	Miss	Quiet	Σ forecast non-events
Total	Σ events	Σ non-events	Σ pairs

Estimation of the *value* of forecasts

- Hits, misses, false alarms, quiet → first step
- If you can quantify consequences of each, you're nearly there...

	Frequency	Consequences
hit	h	C+Lu
false alarm	f	C
miss	m	Lu + La
quiet	q	--

- Here:
 - C: cost of warning response
 - Lu: unavoidable damage
 - La: avoidable damage
- Expected value $E = h(C+Lu) + fC + m(La+Lu)$

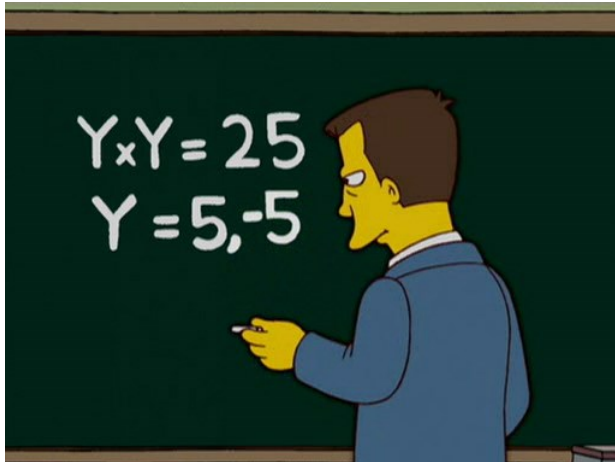
Generic risk criterion:

Damage mitigation: $E1 = C + P \times (L - \Delta L)$

NO damage mitigation: $E2 = P \times L$

Damage mitigation measures are initiated if the expected value of this decision is lower than the case where we do NOT mitigate:

$$\begin{aligned} E1 &\leq E2 \\ C + P \times (L - \Delta L) &\leq P \times L \\ C + P \times L - P \times \Delta L &\leq P \times L \\ C - P \times \Delta L &\leq 0 \\ C &\leq P \times \Delta L \\ C / \Delta L &\leq P \\ P &\geq C / \Delta L \end{aligned}$$



The “contingency table” and prob forecasts

- Binary forecasts → probabilistic forecasts have to be ‘converted’ by means of a criterion
- Essentially, this means that the quality of a decision is assessed
- Example: issue warning if $P(\text{tornado}) \geq 60\%$
 $P(\text{tornado}) = 50\% \rightarrow$ no warning
 $P(\text{tornado}) = 65\% \rightarrow$ warning
- Then fill a contingency table for every criterion of interest

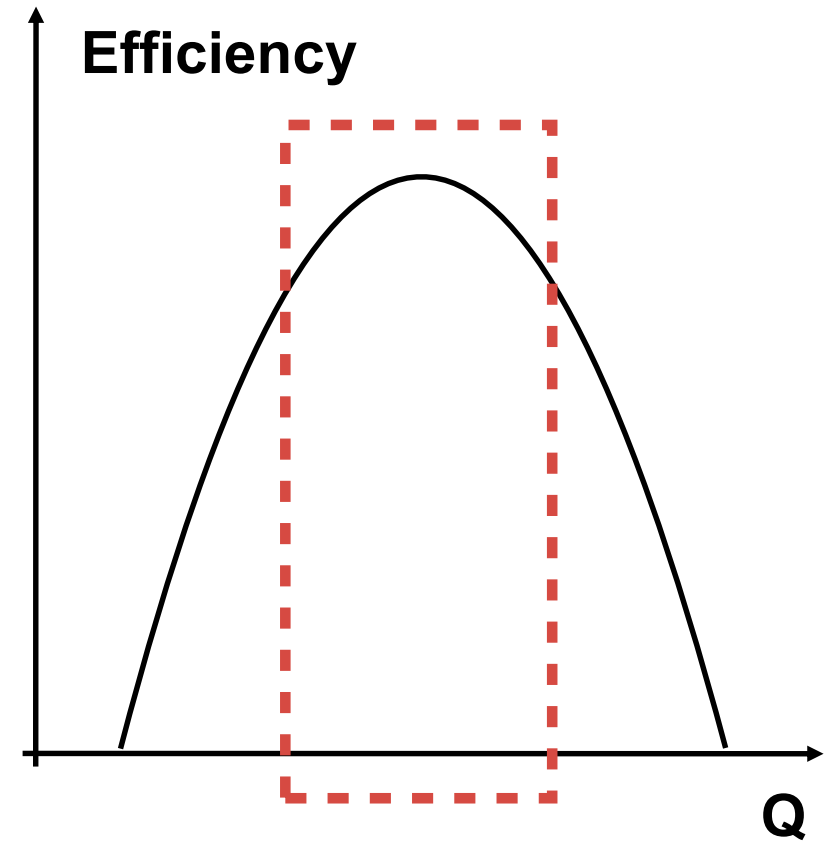
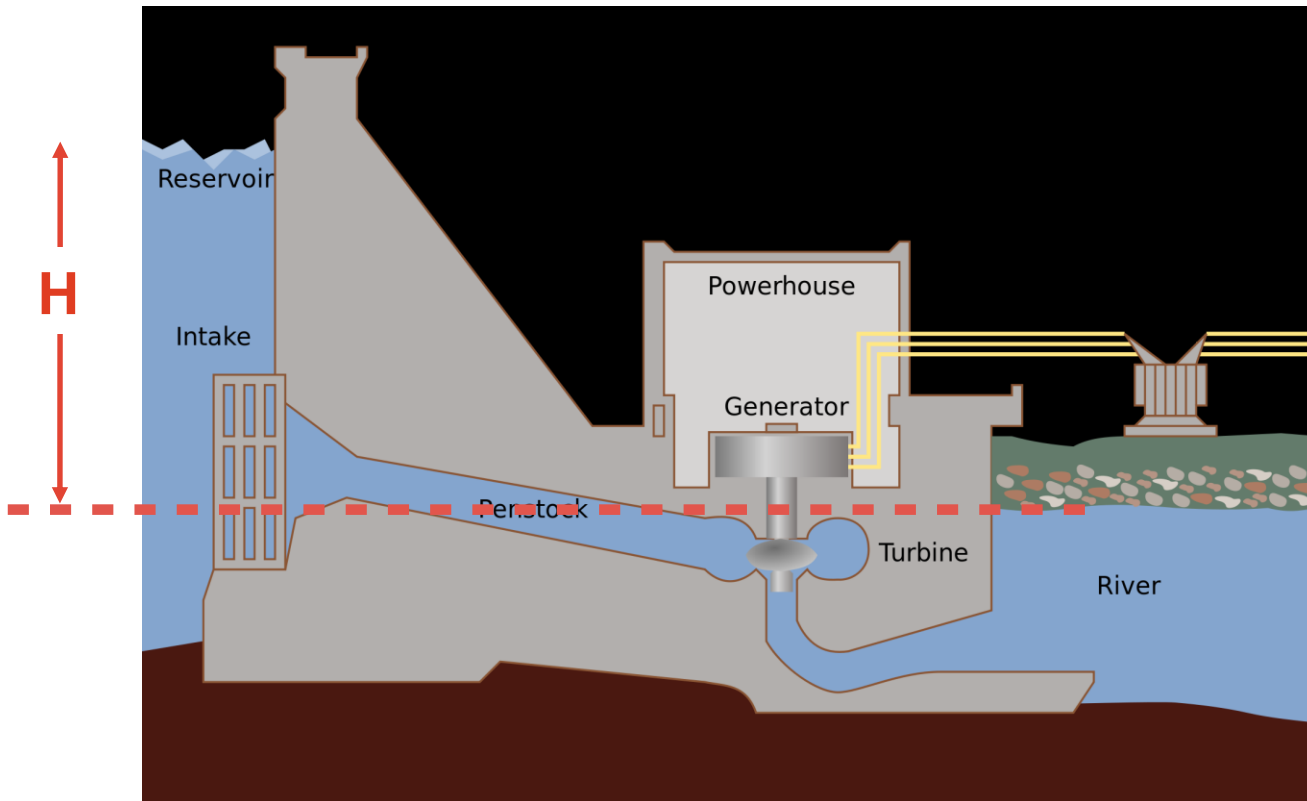
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Tornado	Hit	False alarm	Σ forecast events
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Total	Σ events	Σ non-events	Σ pairs

The context of hydropower production



Daniel-Johnson Dam. Source: Hydro-Québec ([hydroquebec.com](https://www.hydroquebec.com)) autorisation for non-commercial reuse

The context of hydropower production





The context of hydropower production

- We want to...
 - Keep the reservoir high...
 - ... But not *too* high (avoid flooding, spilling, etc)
 - Maximize turbines' efficiency
 - Release some water for the ecosystem
 - Lower the reservoir sometimes (e.g. before spring freshet)
 - Fill the reservoir before the winter period
 - Avoid conflicts with other users of the reservoir and river

The context of hydropower production

WATER RESOURCES RESEARCH, VOL. 21, NO. 12, PAGES 1797-1818, DECEMBER 1985

Reservoir Management and Operations Models: A State-of-the-Art Review

WILLIAM W-G. YEH

Civil Engineering Department, University of California, Los Angeles

The objective of this paper is to review the state-of-the-art of mathematical models developed for reservoir operations, including simulation. Algorithms and methods surveyed include linear programming (LP), dynamic programming (DP), nonlinear programming (NLP), and simulation. A general overview is first presented. The historical development of each key model is critically reviewed. Conclusions and recommendations for future research are presented.

Water Resour Manage (2016) 30:3609–3625
DOI 10.1007/s11269-016-1377-8



Performance of Deterministic and Probabilistic Hydrological Forecasts for the Short-Term Optimization of a Tropical Hydropower Reservoir

Fernando Malvardi Ego¹ · Dirk Schwaneberg² ·
Rodrigo Alvarado³ · Alberto Assis dos Reis⁴ ·
Walter Colitzmann¹ · Steffi Nussman³

Risk based decision making: disclaimers apply!

- “Risk” is optimal if there are many decisions. But are there?
 - Risk requires quantification of
 - Flood damage €€€
 - Damage reduction €€€
 - Cost of damage mitigation €€€
- Tricky! Especially in real-time.





Using forecasts: some issues, considerations

Short course on real-time hydrological forecasting

Visualization of probability forecasts

- Often considered as a complicated issue
- Often discussed in the scientific literature

HYDROLOGICAL PROCESSES
Hydrol. Process. 27, 132–146 (2013)
Published online 23 April 2012 in Wiley Online Library
(wileyonlinelibrary.com) DOI: 10.1002/hyp.9253

Visualizing probabilistic flood forecast information: expert preferences and perceptions of best practice in uncertainty communication

Florian Pappenberger,^{1*} Elisabeth Stephens,² Jutta Thielen,³ Peter Salamon,³ David Demeritt,⁴
Schalk Jan vanAndel,⁵ Fredrik Wetterhall¹ and Lorenzo Alfieri³

¹ European Centre for Medium Range Weather Forecasts, Reading, UK

² University of Bristol, Bristol, UK

³ Joint Research Centre of the European Commission/IRCIpsa, Italy

⁴ King's College London, London, UK

⁵ UNESCO-IHE Institute for Water Education, Delft, The Netherlands

Abstract:

The aim of this article is to improve the communication of the probabilistic flood forecasts generated by hydrological ensemble prediction systems (HEPS) by understanding perceptions of different methods of visualizing probabilistic forecast information.

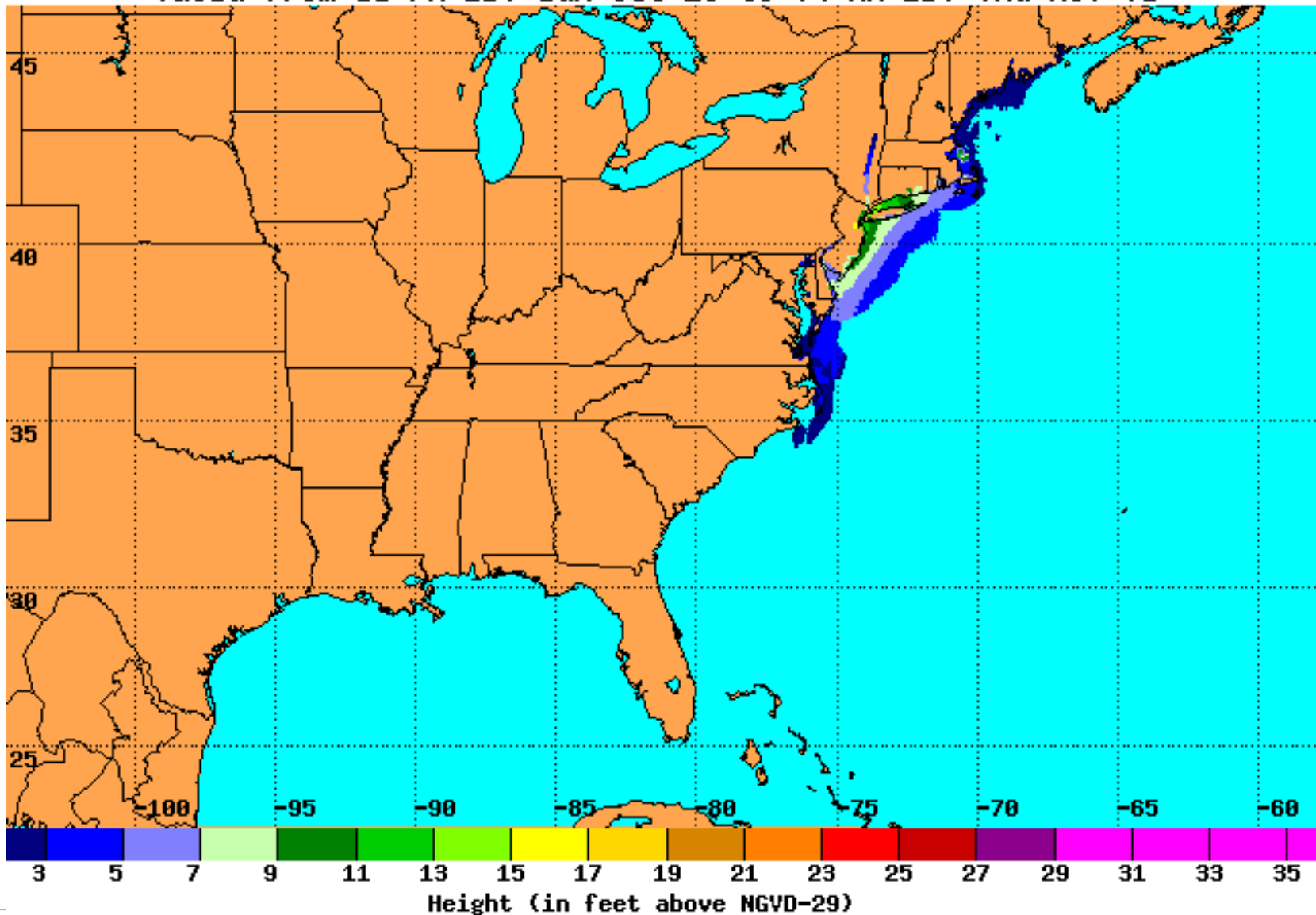
Visualization: what's the problem???

- 'Curse of dimensionality'
 - Visualisation nearly always done in 2d (screen, paper)
 - Probability forecasts are highly dimensional:
 - > Location X and Y
 - > Time
 - > Variable (precipitation, river stage, streamflow rate, wind speed)
 - > Probabilities
- More dimensions than one can plot
 - à No single visualization gives answer to all possible questions
 - à choices have to be made, and communicated!
- Note: for point locations, problem is slightly less complicated



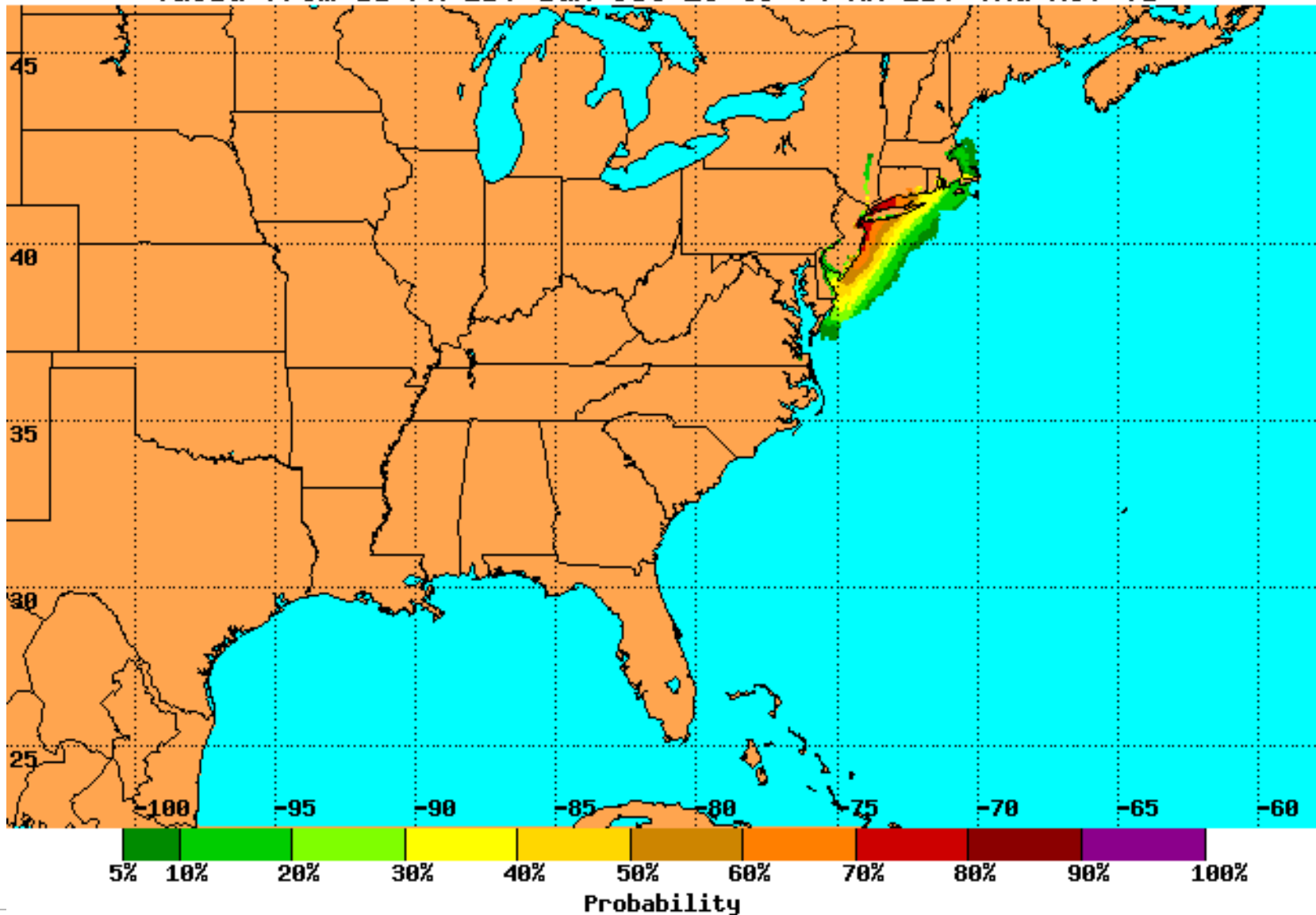


Tropical Cyclone Storm Surge Heights (NGVD-29)
That Have a 1 in 10 Chance of Being Exceeded
Hurricane Sandy (2012) Advisory 27
Valid from 11 PM EDT Sun Oct 28 to 04 AM EDT Thu Nov 01





Tropical Cyclone Storm Surge Probability
of ≥ 4 feet (NGVD-29)
Hurricane Sandy (2012) Advisory 27
Valid from 11 PM EDT Sun Oct 28 to 04 AM EDT Thu Nov 01

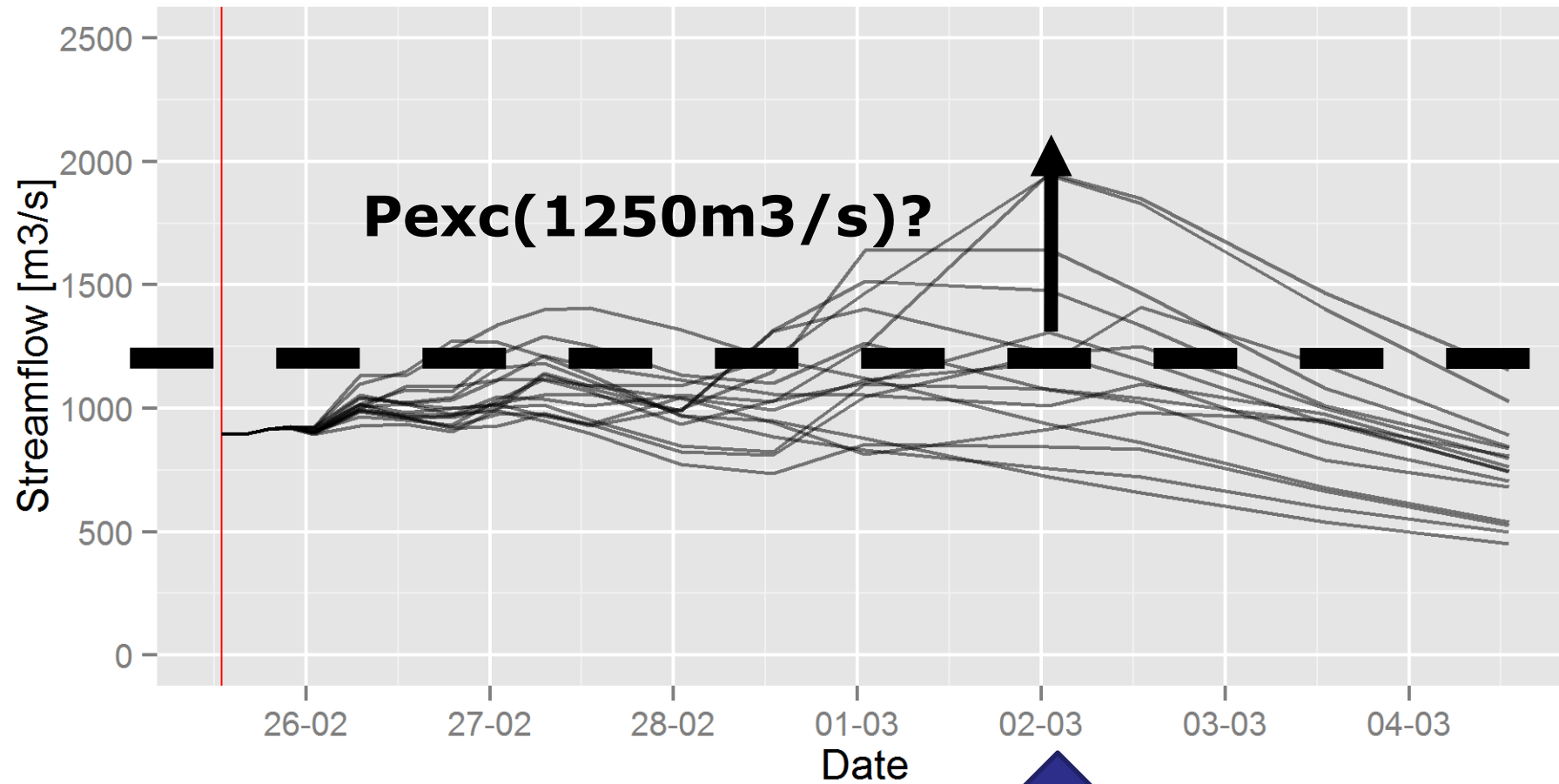


Visualization: ensemble plots

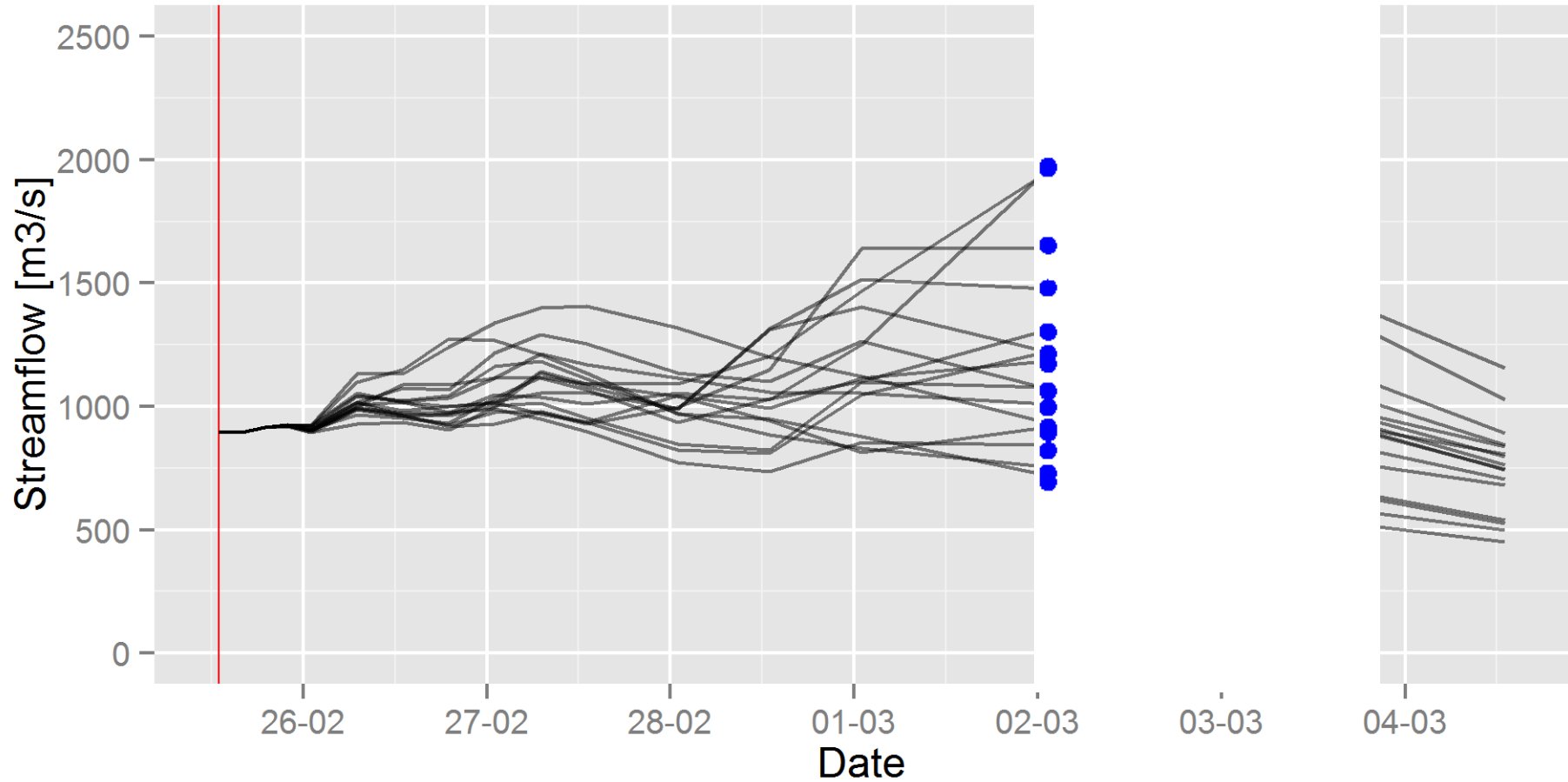
- '*curse of dimensionality*' is reduced somewhat (x,y combined)
- However...

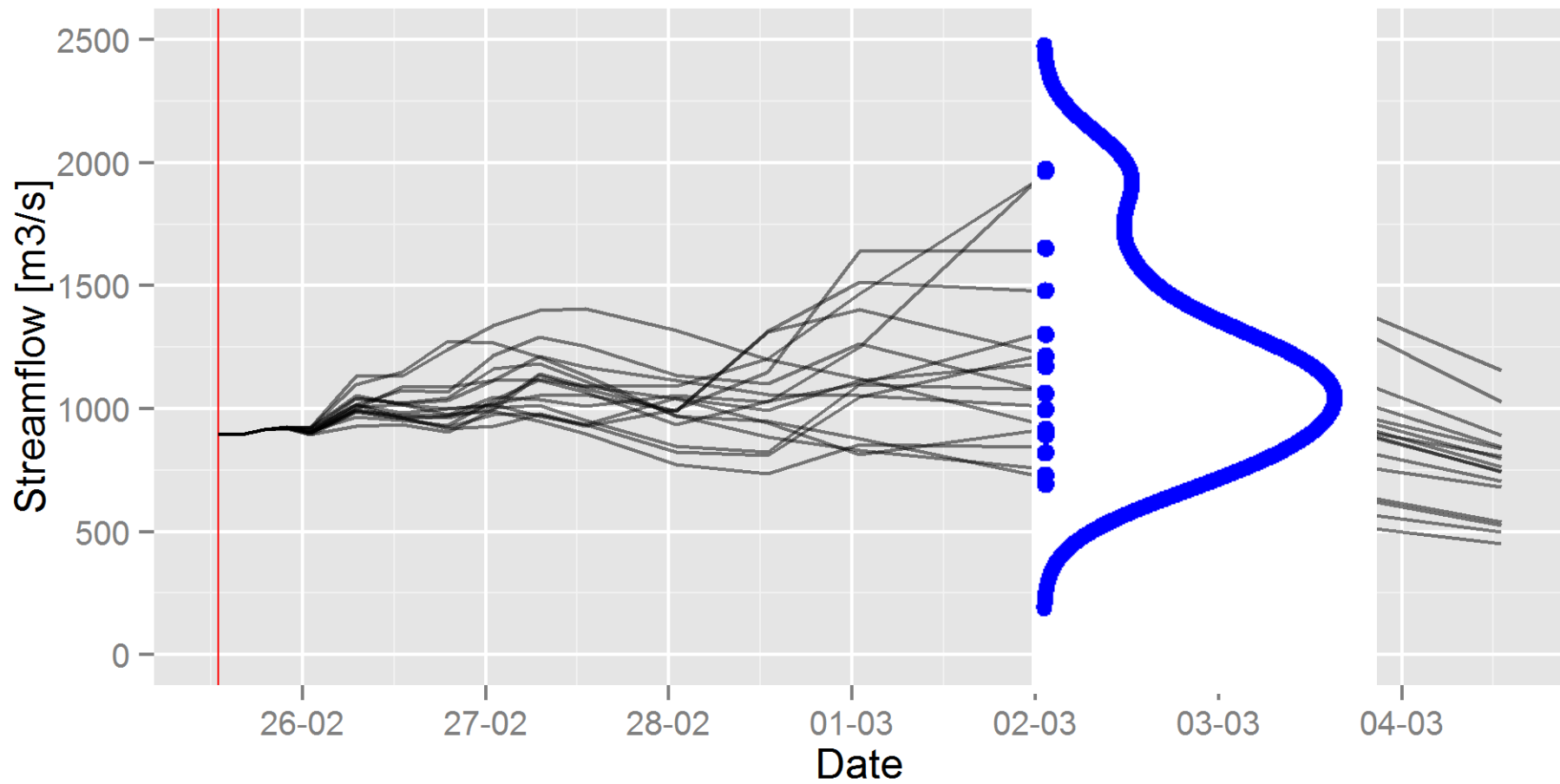
**“What is the probability of
streamflow
exceeding 1,250m³/s
at St Pieter
on March 2nd?”**

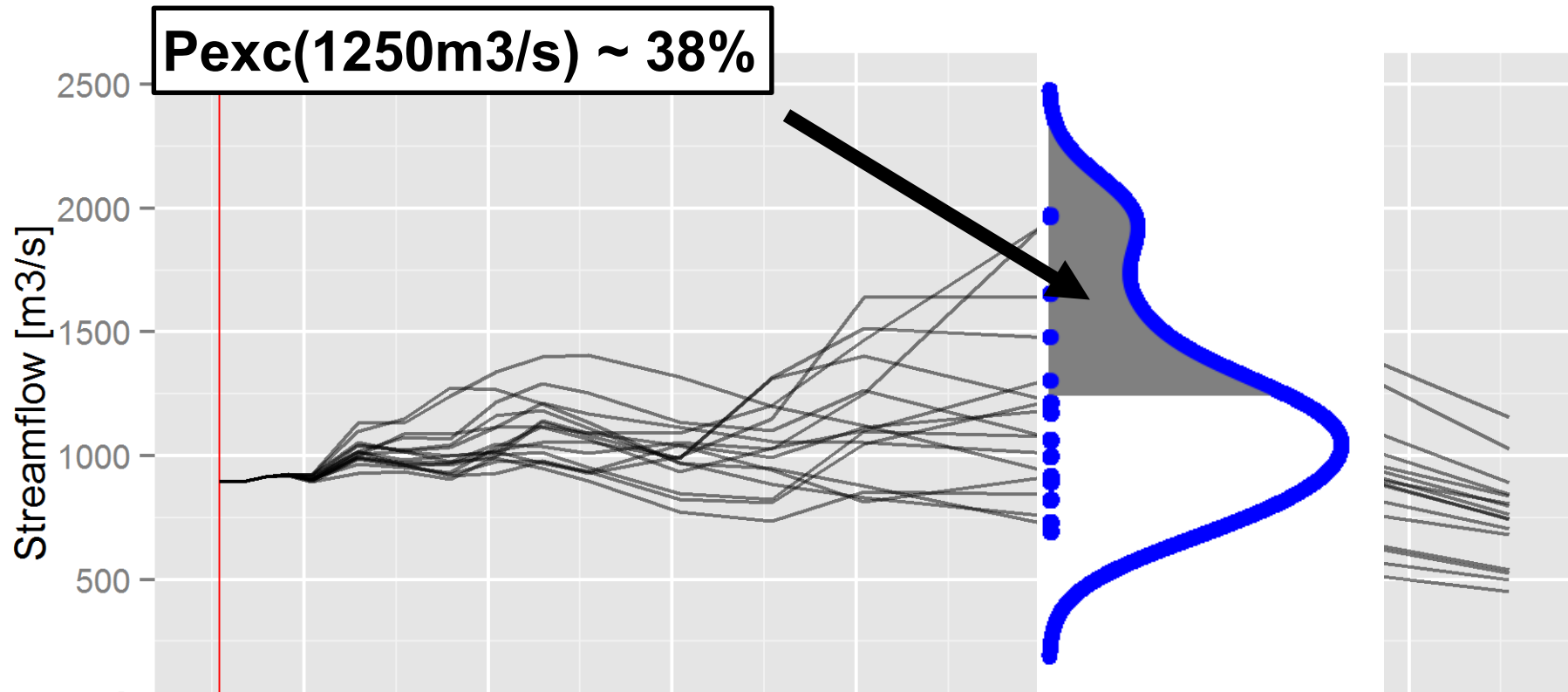
On March 2nd,
what is the probability of $Q \geq 1250 \text{ m}^3/\text{s}$?



The "solution"....



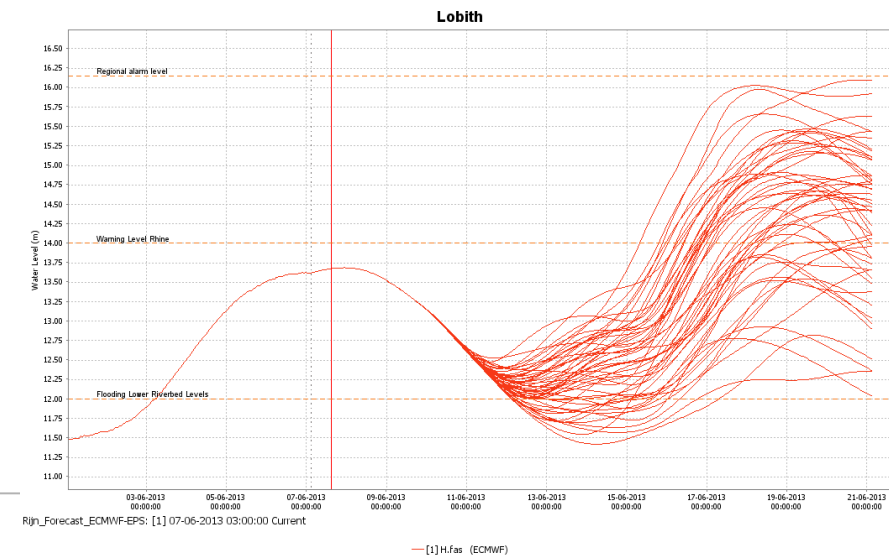




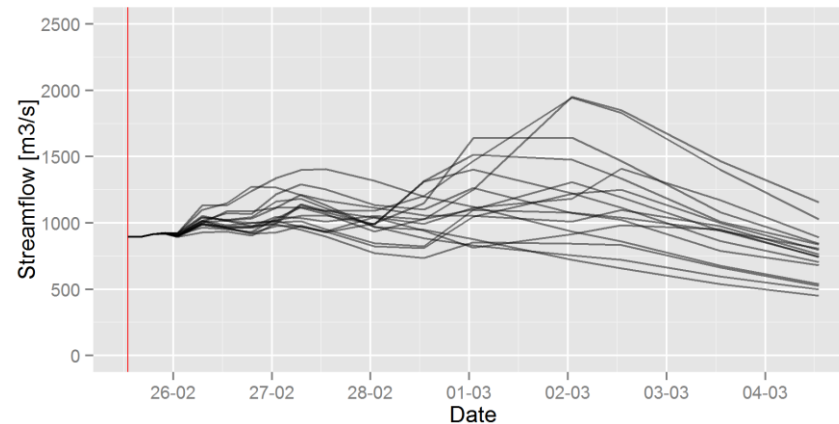
**For the untrained forecast user,
this may be too much to ask**

The problem with using ensembles...

- Statistical manipulation may be too much to ask from an untrained forecast user
 - (S)he may be rusty on Statistics 101
 - Counting the number of lines above/below a threshold is not trivial
 - (S)he may not know how many members there are
- Forecasters can provide P_{exc} (some thresholds) but probably not P_{exc} (all possible thresholds)



Summary: the problem with using ensembles...



does not directly provide the answer to

**At March 2nd,
what is the probability of $Q \geq 1250$ m³/s?**

Subjective interpretation of probabilities

EFAS FLOOD ALERT for Germany - Elbe, section Eger - Schwarze Elster

Written by Sprokkereef Eric
Sunday, 02 June 2013 16:25

EFAS FLOOD ALERT REPORT

=====

Dear Partner,

EFAS predicts a high probability of flooding for **Germany - Elbe, section Eger - Schwarze Elster (Elbe basin)** from Tuesday 4th of June 2013 onwards.

According to the latest forecasts (2013-06-02 00 UTC) up to 100% EPS (VAREPS) are exceeding the high threshold (> 5 year simulated return period) and up to 2% EPS (VAREPS) exceeding the severe threshold (>20 year simulated return period).

Compared to the VAREPS mean, the ECMWF deterministic forecast is comparable and the DWD deterministic forecast is lower.

The higher resolution COSMO-LEPS forecasts indicate lower risk for flooding than VAREPS.

The earliest flood peak is expected for Wednesday 5th of June 2013.

Please monitor the event on the EFAS-IS interface (<http://www.efas.eu>)

The EFAS Dissemination center is looking forward to receive your feedback for this EFAS Alert.

Regards,

The EFAS Dissemination center

Email: dissemination@efas.eu

EFAS forecaster on duty



Deltares

Subjective interpretation of probabilities

- Not everybody has same interpretation of “high”, “low”, etc prob
- IPCC solution: agree on the terminology used

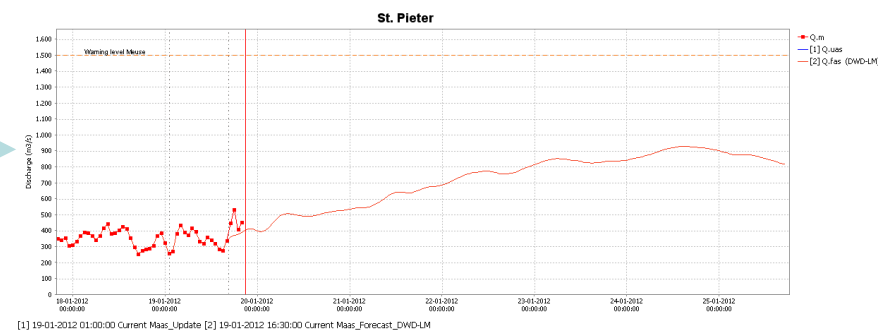
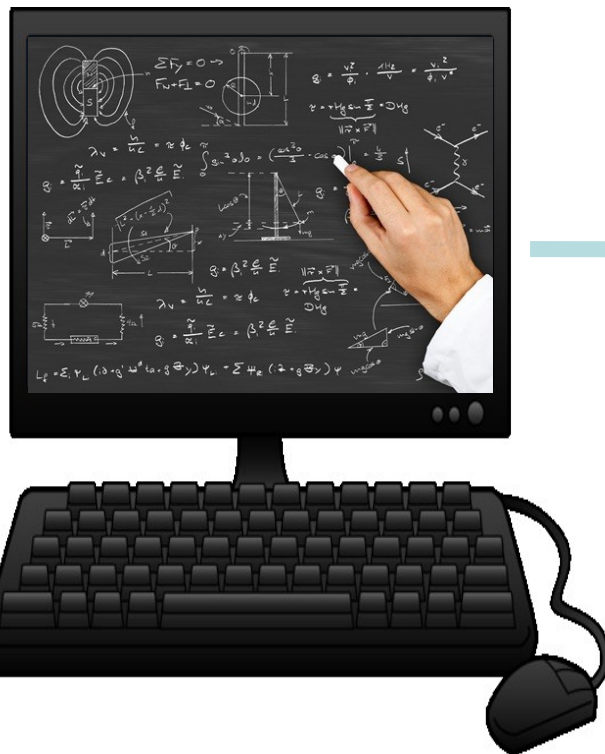
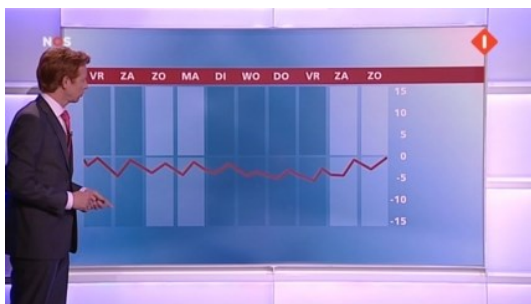
Likelihood Terminology	Likelihood of the occurrence/ outcome
Virtually certain	> 99% probability
Extremely likely	> 95% probability
Very likely	> 90% probability
Likely	> 66% probability
More likely than not	> 50% probability
About as likely as not	33 to 66% probability
Unlikely	< 33% probability
Very unlikely	< 10% probability
Extremely unlikely	< 5% probability
Exceptionally unlikely	< 1% probability

Source: http://www.ipcc.ch/publications_and_data/ar4/wg1/en/ch1s1-6.html



Open challenges: a very much non-exhaustive list

Short course on real-time hydrological forecasting



Where are the uncertainties?

Floods - Ice jams

2016



<http://www.lapresse.ca/actualites/201602/27/01-4955316-quebec-consent-une-aide-financiere-aux-sinistres-des-inondations.php>

2017



<http://www.journaldequebec.com/2017/04/11/rivieres-sous-haute-surveillance-des-orages-a-venir-font-craindre-le-pire>



Probability forecasts: current “State of the art”

- Lots of recent research into techniques for estimating uncertainties: ensembles, post-processing, combinations
- As yet unresolved:
 - Reliable probability forecasts for extreme events – skill measure to actually assess extremes?
 - How to manage change?
 - Effective USE of probability forecasts: decision making, visualization, communication, etc.



Some resources to go further...

Short course on real-time hydrological forecasting



Relevant papers in peer reviewed literature: General

- Cloke, HL and F. Pappenberger. “Ensemble Flood Forecasting: A Review.” *Journal of Hydrology* 375, no. 3–4 (2009): 613–26.
- Inness, Peter. *Operational Weather Forecasting*. Hoboken, NJ: John Wiley & Sons, 2013.
- Krzysztofowicz, R. «The case for probabilistic forecasting in hydrology », *Journal of Hydrology*, 249 (2001): 2-9
- World Meteorological Organization. «Guidelines on Ensemble Prediction Systems and Forecasting», Report WMO-No. 1091, 23 pages, 2012



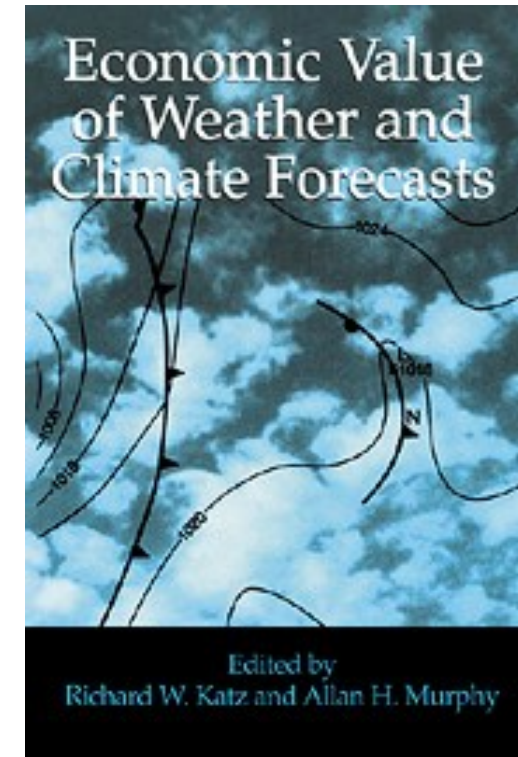
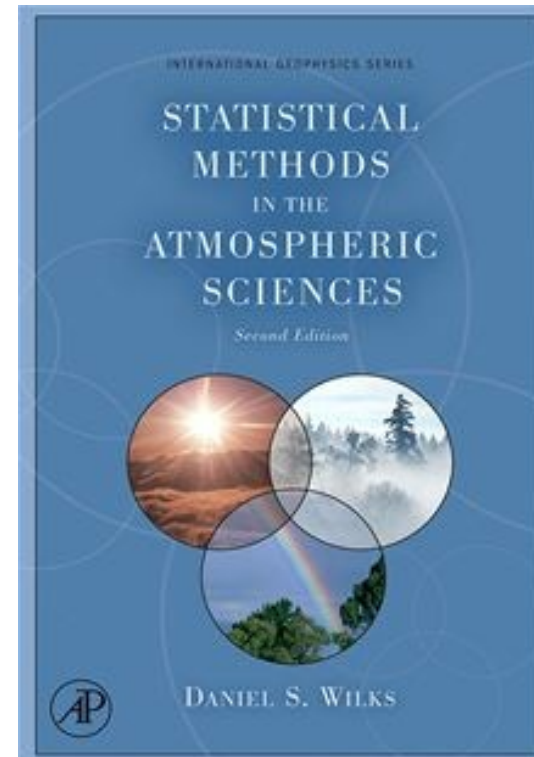
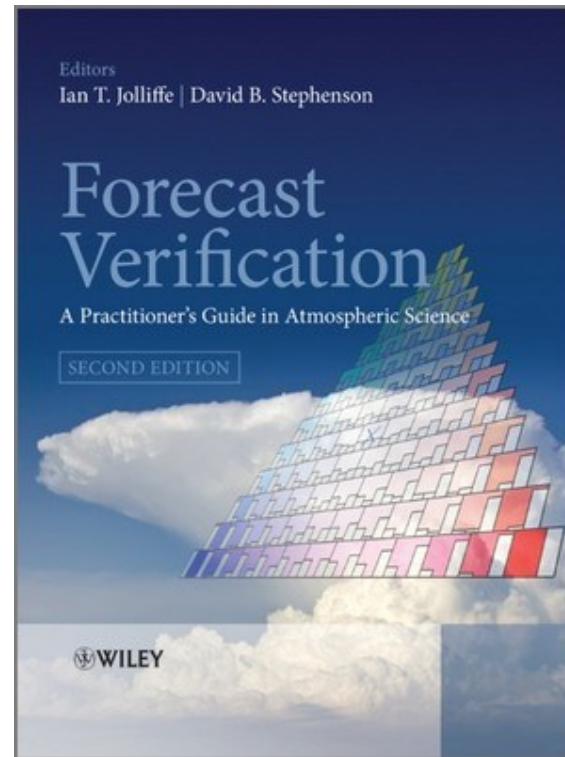
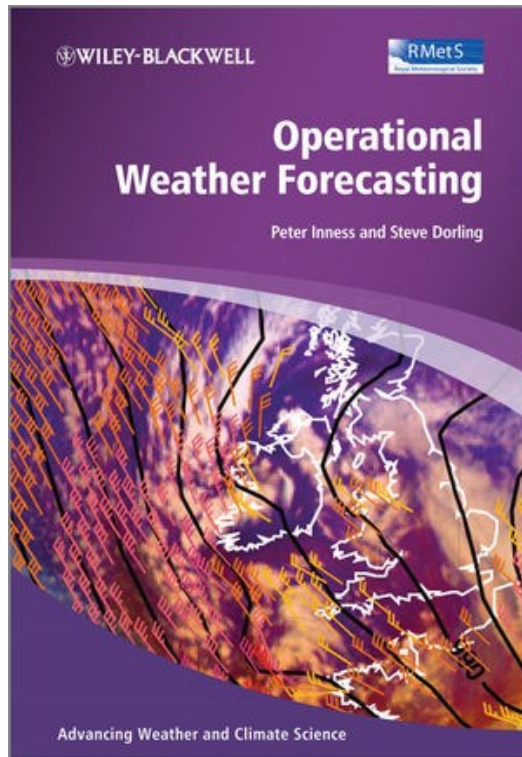
Relevant papers in peer reviewed literature: Data assimilation

- van Leeuwen, P.J. « Particle Filtering in Geophysical Systems », *Monthly Weather Review*, 137, (2009): 4089-4114.
- Evensen, G. « The Ensemble Kalman Filter: theoretical formulation and practical implementation, *Ocean Dynamics*, 53, (2003): 343-367.
- Mandel, J. « Efficient implémentation of the Ensemble Kalman Filter » Report, University of Colorado at Denver and Health Sciences Center, Denver, 9 pages, 2006.

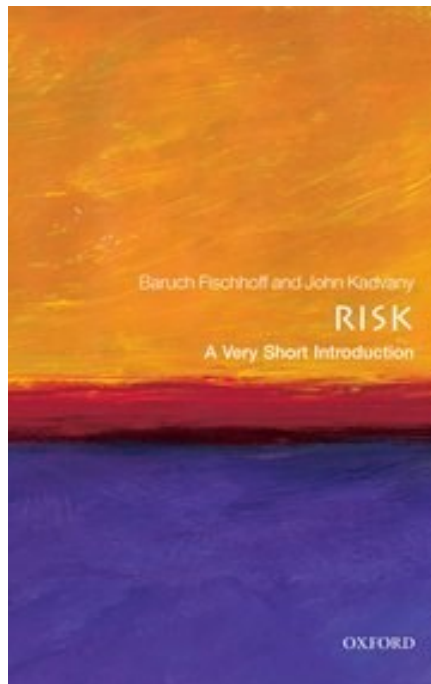
Relevant papers in peer reviewed literature: Verification

- Brown, James D., Julie Demargne, Dong-Jun Seo, and Yuqiong Liu. 'The Ensemble Verification System (EVS): A Software Tool for Verifying Ensemble Forecasts of Hydrometeorological and Hydrologic Variables at Discrete Locations'. *Environmental Modelling & Software* 25, no. 7 (2010): 854 – 872.
- Hersbach, Hans. 'Decomposition of the Continuous Ranked Probability Score for Ensemble Prediction Systems'. *Weather and Forecasting* 15, no. 5 (October 2000): 559–570. doi:10.1175/1520-0434(2000)015<0559:DOTCRP>2.0.CO;2.
- Mason, S.J., and N.E. Graham. 'Conditional Probabilities, Relative Operating Characteristics, and Relative Operating Levels'. *Weather and Forecasting* 14 (1999): 713–725.
- Mason, S.J. 'Understanding Forecast Verification Statistics'. *Meteorological Applications* 15, no. 1 (2008): 31–40.
- Murphy, A.H. 'The Finley Affair: A Signal Event in the History of Forecast Verification'. *Weather and Forecasting* 11, no. 1 (1996): 3–20.
- Murphy, A.H. 'What Is a Good Forecast? An Essay on the Nature of Goodness in Weather Forecasting'. *Weather and Forecasting* 8, no. 2 (1993): 281–293.
- Murphy, A.H., and R.L. Winkler. 'A General Framework for Forecast Verification'. *Monthly Weather Review* 115, no. 7 (1987): 1330–1338.

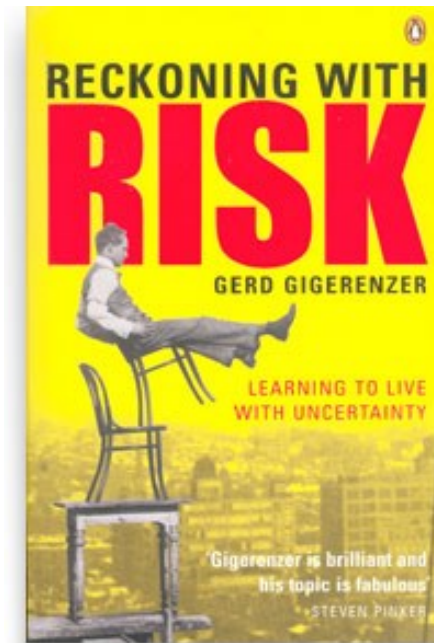
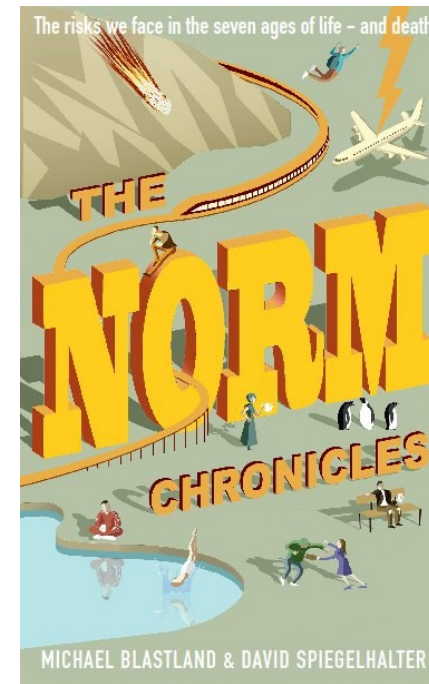
Additional reading: books



Additional, (very) accessible reading



the signal and the noise and the noise and the noise and the noise why most noise and predictions fail to but some don't n and the noise and the noise and the nate silver noise noise and the noise



HEPEX: the hydro ensemble forecasting community

scientists

practitioners

forecast users

meteorologists

hydrologists

HEPE science plans

Hydrologic Ensemble Prediction EXperiment

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Posted on [December 18, 2013](#) by [hepex](#)

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More and updated information about the organization of this special occasion for HEPEX is now available by the workshop and its provisional programme. Specific **mission deadline: 31 January 2014**. Bookmark the [workshop website](#) so you can keep yourself updated with the latest information.

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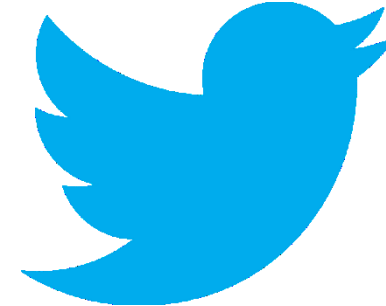
Contributors (first author)

 Select Author...

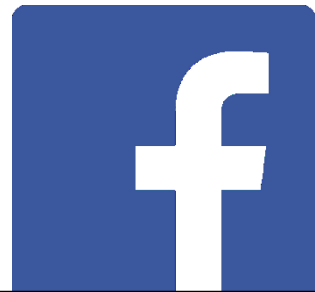
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Thank you for your attention!

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