PROCESSING WEATHER FORECASTS FOR HYDROLOGICAL ENSEMBLE FORECASTING AND DECISION MAKING IN HYDROPOWER

Seasonal Hydrological Forecasting Workshop

21-23rd September 2015, Norrköping, Sweden

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Facts about Statkraft

TOTAL NUMBER OF POWER PLANTS / FACILITIES		STATKRAFT'S CAPACITY		Symbols:
Power generation	403	Power generation	18 159 MW	☼ – Hydropower
District heating	29	District heating	714 MW	Y – Wind power
				◊ – Gas power
				🌿 – Bio power
				🔥 – District heating

SWEDEN

NORWAY

UK

GERMANY

TURKEY

NEPAL

LAOS

INDIA

PHILLIPINES

SRI LANKA

PERU

BRAZIL

ZAMBIA

CHILE

- European leader within renewable energy

- Norway's largest and the Nordic region's third largest power producer

- Core business areas within hydropower, wind power, gas power and district heating

- A significant player in the European energy exchanges with cutting-edge expertise in physical and financial energy trading and origination

- 403 power and district heating plants with a total installed capacity more than 18 000 MW, and 29 district heating plants with an installed capacity more than 700 MW.

- Total annual power production of 56 TWh, renewable percentage of 99%

- 71,5% of the installed capacity is in Norway, then Europe outside the Nordics with 16 3 % , the Nordics excluding Norway with 8,3 and the rest of the world with 3,9 %.

- Delivers more power to Norwegian industry than ever before. About 21 TWh annually

- Develops hydropower in emerging markets outside Europe.

- Significant wind power developer. Has completed Sheringham Shoal offshore wind farm off the coast of the UK together with Statoil. (315 MW)

- The Group's gross sales amounted to NOK 52,2 billion in 2014

- 4200 employees and active in more than 20 countries

- Wholly owned by the Norwegian state

Nordic Operations
Power plants are spread out over a vast region

2500 km

Statkraft in Scandinavia

- 🟢 Wind Turbine
- 🟢 Wind Turbine Farm
- 🔵 Hydropower Plant
- 🔵 Pumped Hydropower
- 🔵 Pumping Station
- 🟥 Modelled catchments
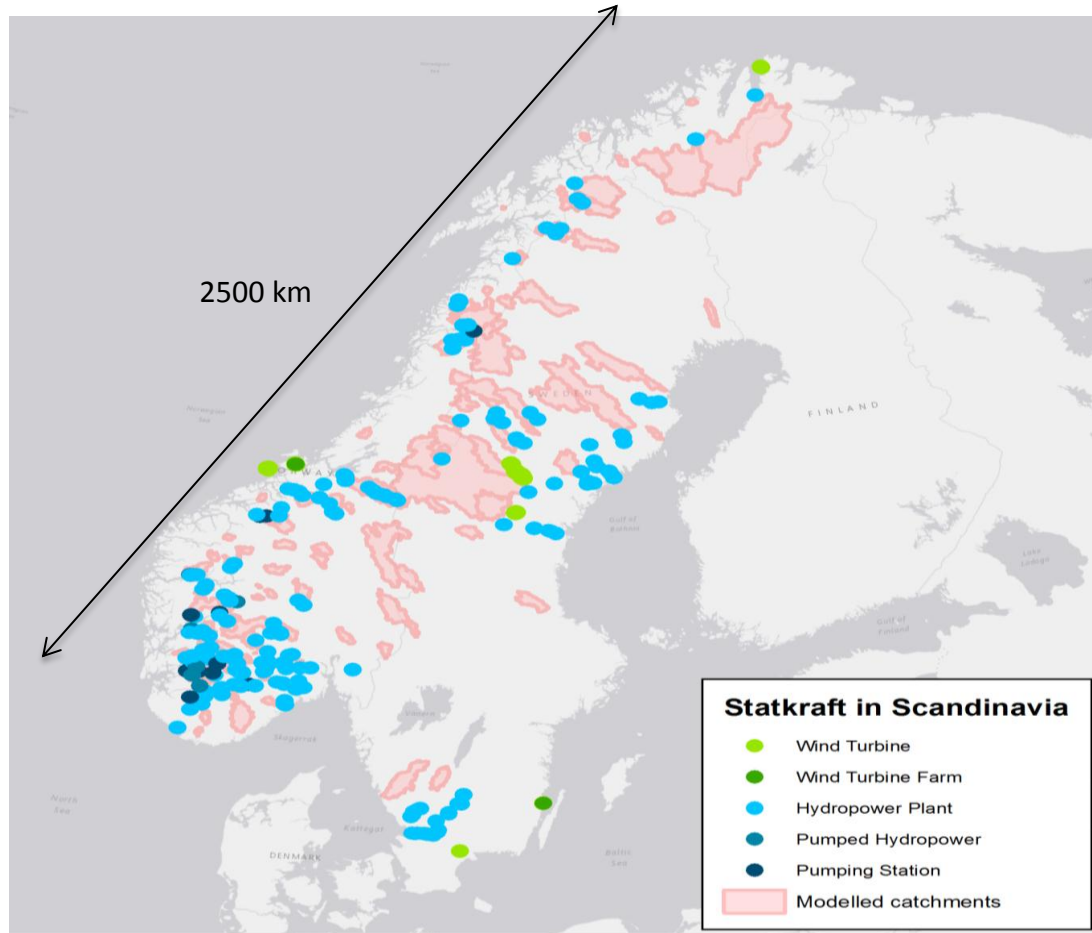
▸ **207 power plants with a total capacity of approx. 14 GW**

- 149 hydropower plants in Norway
- 58 hydropower plants in Sweden
- 1 gas fired plant in Norway
- 3 wind farms in Norway
- 2 wind farms in Sweden

▸ **Model inflow to a total of 950 reservoirs**

▸ **147 HBV models**

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Agenda

1. Introduction

2. Nordic operational challenges

3. Hydrological forecasting

4. Going forward: Combining weather forecasts

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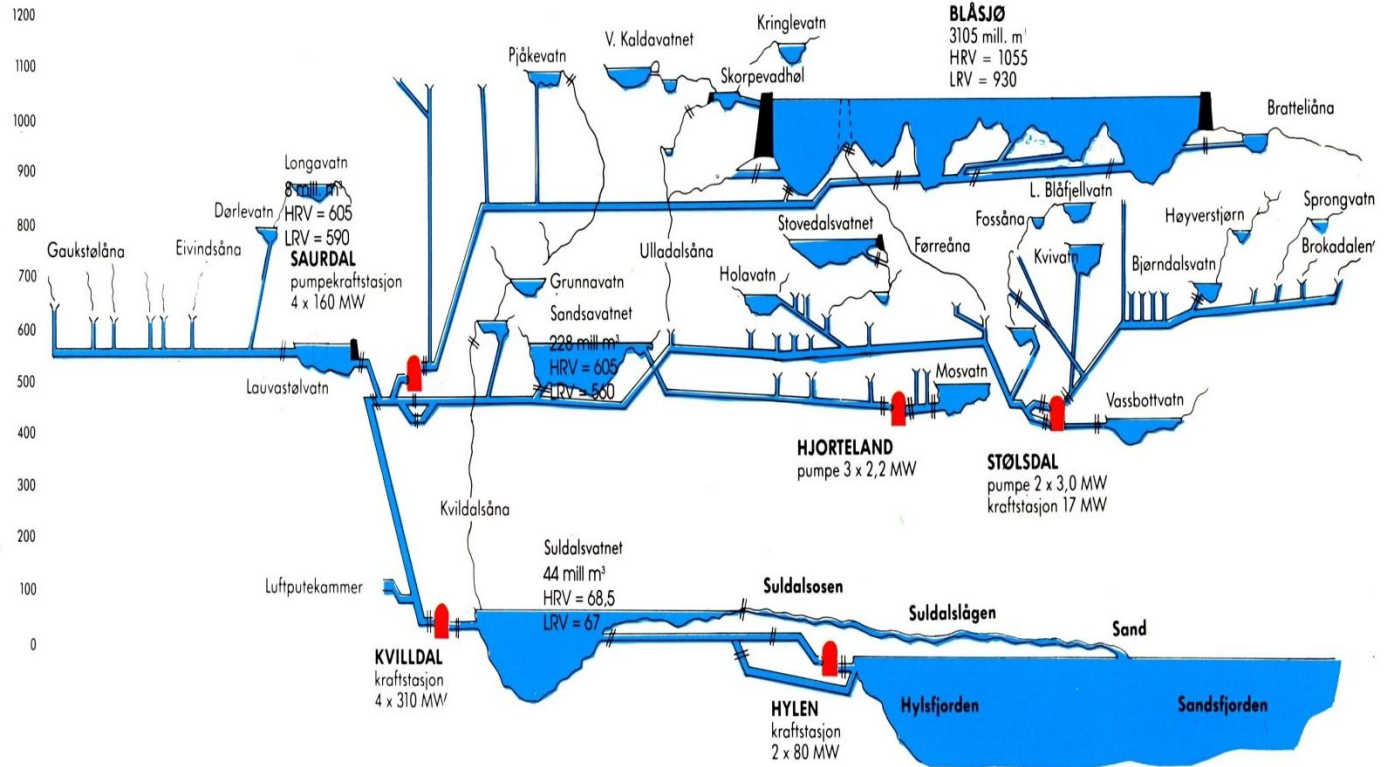
2. NORDIC OPERATIONAL CHALLENGES

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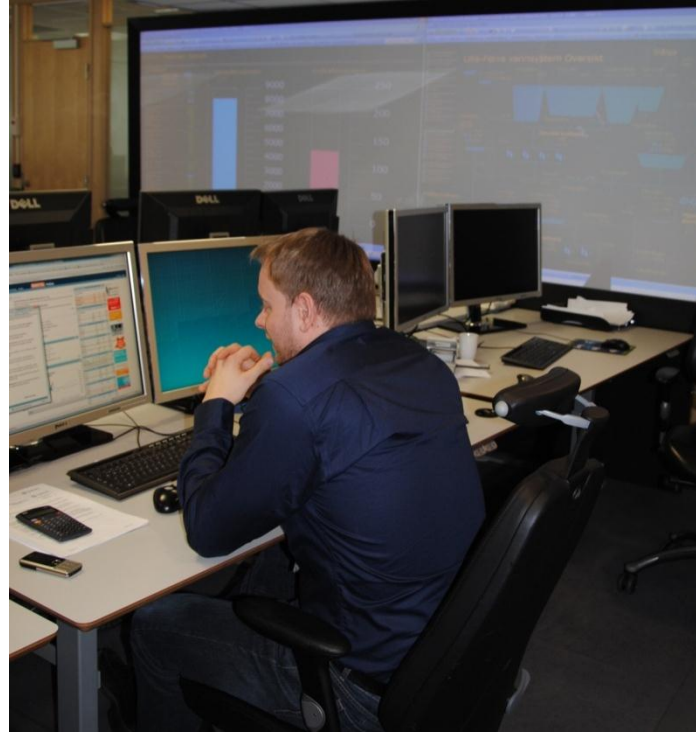# Reservoir Management:
The basic hydropower challenge
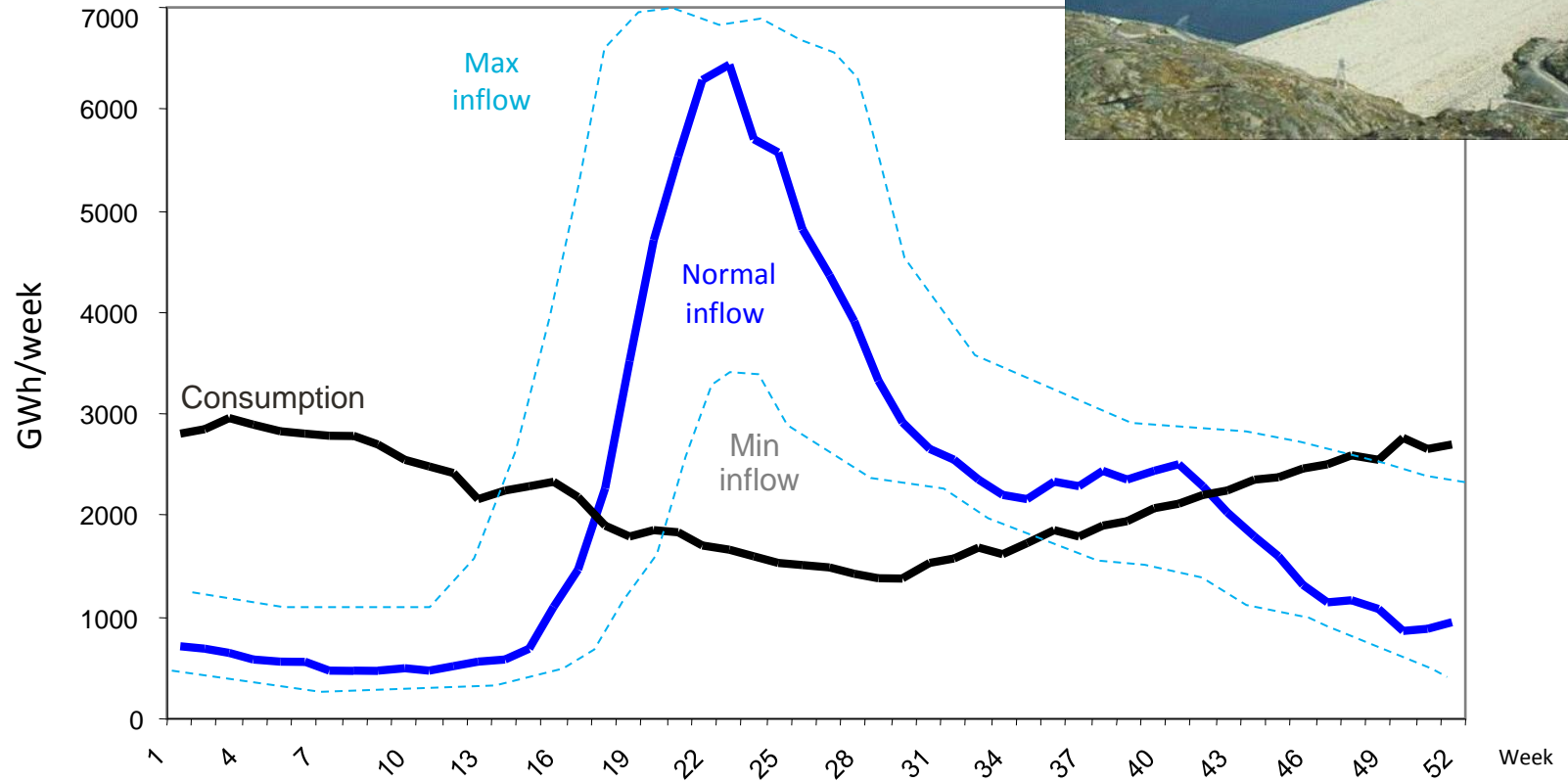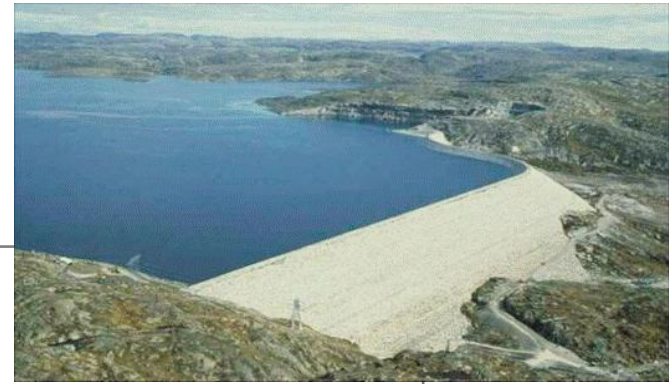
The systems can be rather complicated…
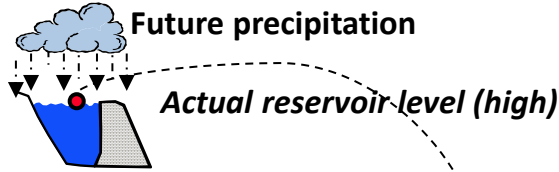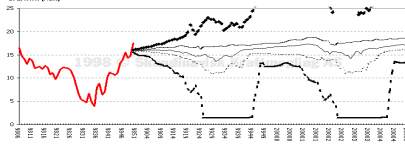## Example: ULLA-FØRRE

To produce or not to produce?

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WATER VALUES DETERMINE THE 'RESERVATION PRICE' FOR THE INDIVIDUAL RESERVOIR

Reservoir 1 (small)

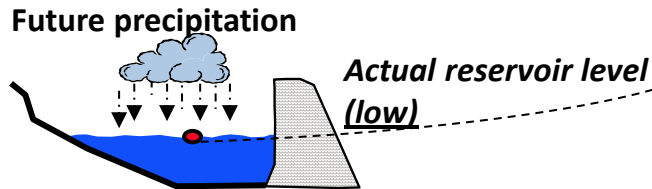**Future precipitation**
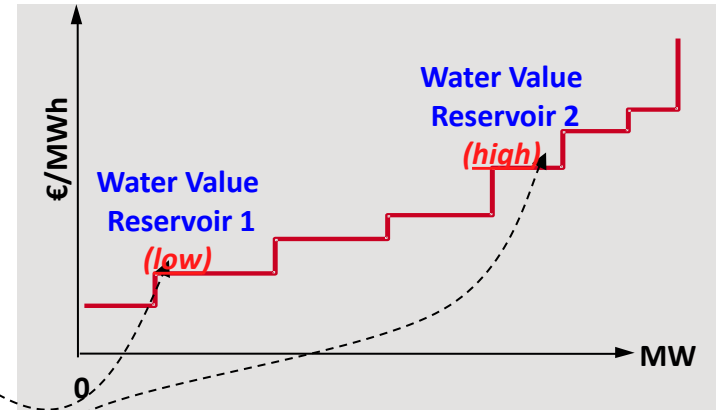
Actual reservoir level (high)

Price forecast

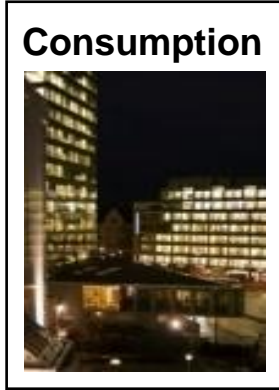**Future spotprices depending on total inflow to Norway/Sweden**

Reservoir 2 (big)

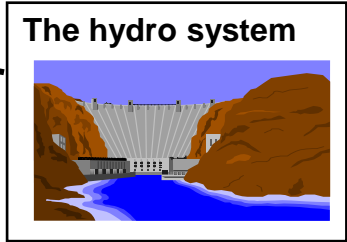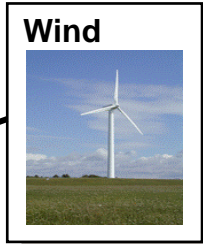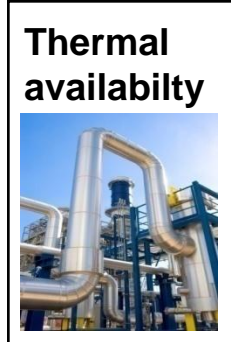**Future precipitation**

Actual reservoir level (low)

Our "supply curve" is based on water values for every reservoir

Water Value Reservoir 2 *(high)*

Water Value Reservoir 1 *(low)*

Water value = alternative cost of producing one extra MWh from the reservoir.

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EMPS: Simulations of the Nordic power market

Wind

Thermal units' marginal costs

Thermal availabilty

Simulations of the Nordic power market

The hydro system

Consumption

Trade
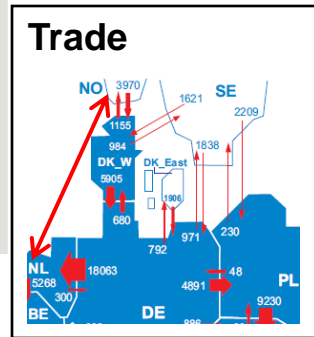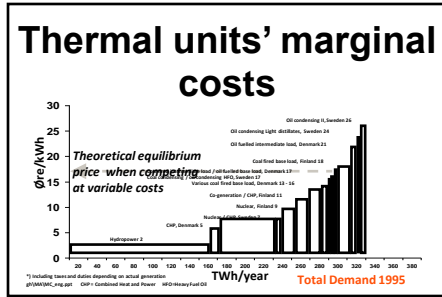
ANALYSIS AND RESULTS

- Water values
- Optimal production plans
- Price forecasts with sample space

Hydrological data

Transmission

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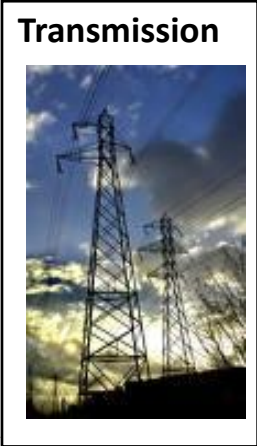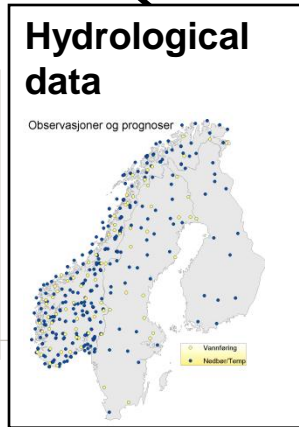
HYDROLOGICAL INPUT TO EMPS

Updated water levels for 950 reservoirs

EMPS
Nordic countries

83 scenarios for consumption temperatures and wind, coupled with inflow

83 consistent scenarioes for inflow and snow for 950 reservoirs; daily resolution, five years horizon

Historical precipitation and temperature

HBV
a precipitation-runoff model

Calibrated against 1980-2010 data

Snow measurements

Weather forecasts

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3. HYDROLOGICAL FORECASTING USING HBV

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Current operational set-up for simulation of future inflow (and snow levels) using HBV-models

Historically observed and HBV-simulated inflow
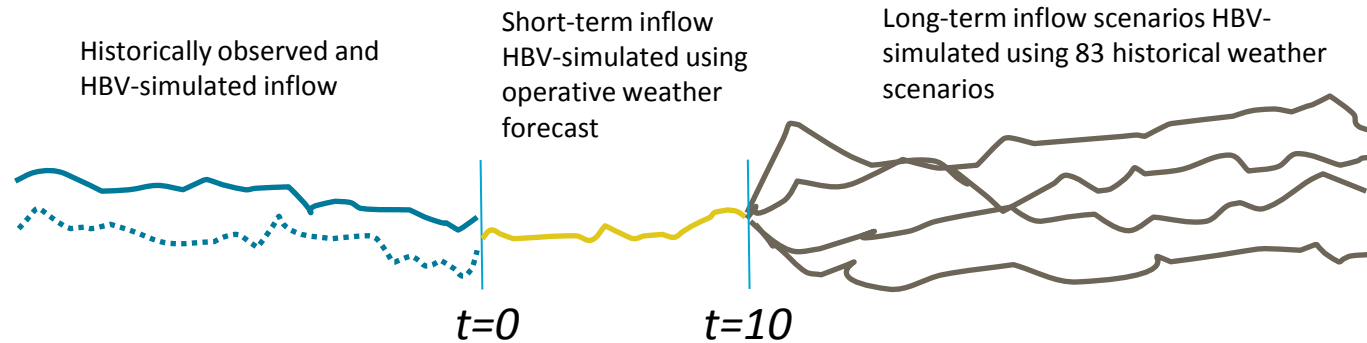
Short-term inflow HBV-simulated using operative weather forecast

Long-term inflow scenarios HBV-simulated using 83 historical weather scenarios

t=0   *t=10*

- ▸ <u>Start-state</u> estimated using observed precipitation and temperature up until today (*t=0*)
  - Updated with snow measurements
  - Manual updating of observed temperatures if significant deviation between simulated and observed inflow

- ▸ <u>Forecast</u> horizon simulated using 10-day operational EC forecast
  - Manually corrected by meteorologist

- ▸ Scenarios for <u>long-term</u> horizon simulated from day 10 using end-state from forecast horizon as start state and 83 historical weather years (1931-2013)
  - Series back-filled to 1931
  - Wind corrected precipitation
  - Climate corrected to 1980-2010 mean

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…in addition we can in principle process other weather forecast through HBV…

▸ ECMonthly:
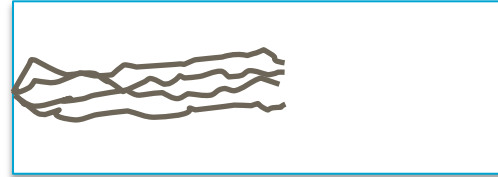
▸ ECENS:
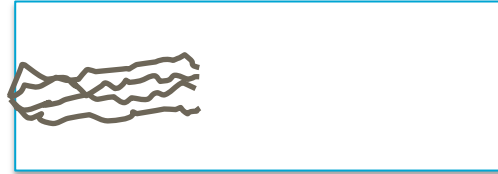
▸ Short-term forecast:

▸ …but this information is often lost in decision making as we are not able to process it further through the optimisation models

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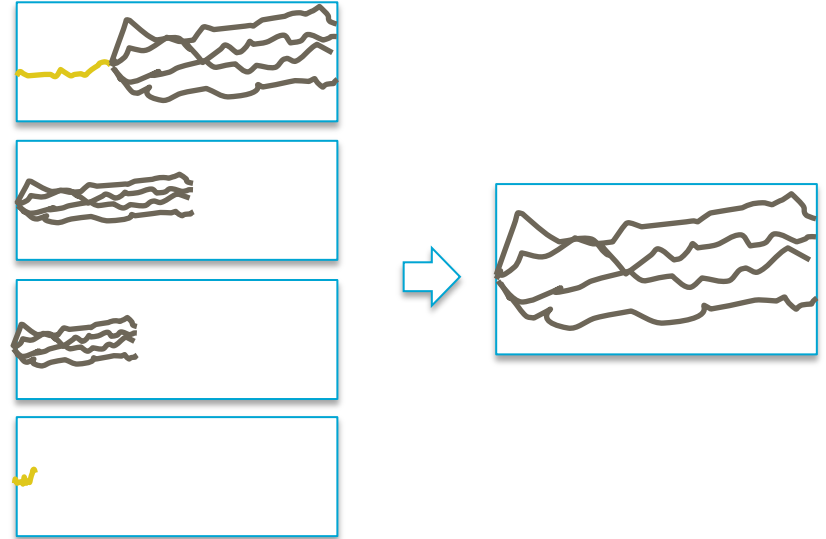# 4. GOING FORWARD

Missing uncertainty

Combining various forecast sources into one dataset

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# Goal: Improve forecast by addressing missing uncertainty

▸ Capture missing uncertainty
  - Weather uncertainty first 10 days

▸ Improve forecast by combining various weather forecast:
  - EC-Monthly
  - ECENS: captures uncertainty
  - Arome or other short-term forecasts

Question: Can we create 83 weather scenarios from day 0 that are consistent with short- and mid-term forecasted probability distributions and match historical scenarios in the long-term?

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Example:
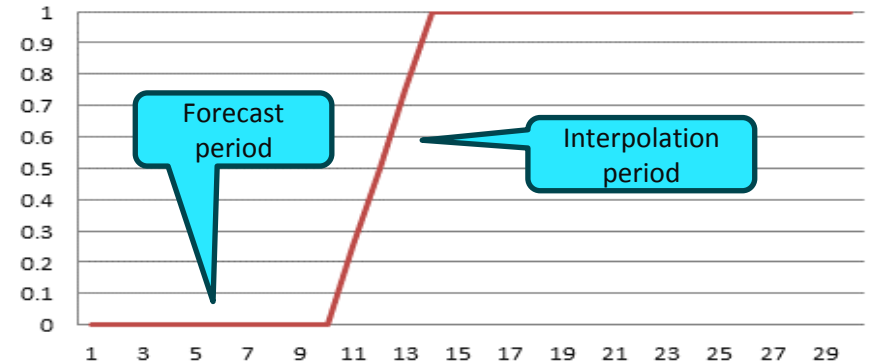**Quantile mapping 83 historical scenarios to EC-ENS with interpolation from day 10 to day 14**
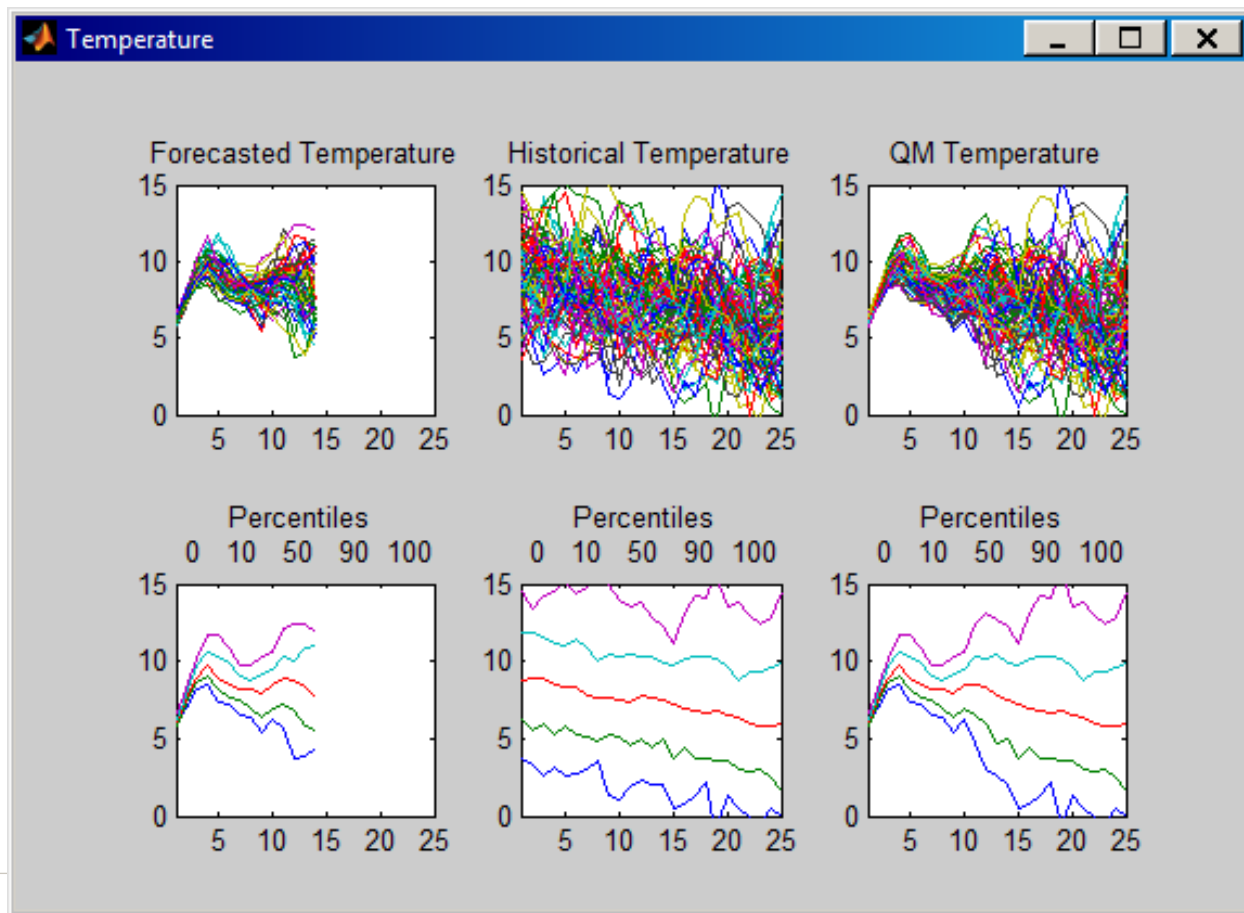
Quantile Mapping: Mathematical
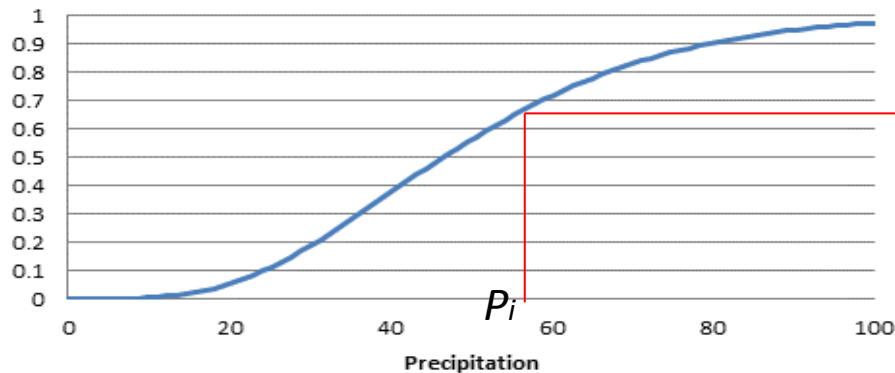
Scenario i for day d is given by

$$(1-w(d))F_d^{-1}(H_d(p_i))+w(d)p_i$$

where F_d is the forecasted CFD for day d, H_d is the historical CFD for day d, p_i is the historical precipitation value for day d in scenario i and $w(d)$ is a weight function

w: weight function

Forecast period

Interpolation period

H_d: Historical CDF for day d

P_i

Precipitation

F_d: Forecasted CDF for day d

$F_d^{-1}(H_d(p_i))$

Precipitation

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The Schaake Shuffle: A Method for Reconstructing Space–Time Variability in Forecasted Precipitation and Temperature Fields (Clark et al. 2004)
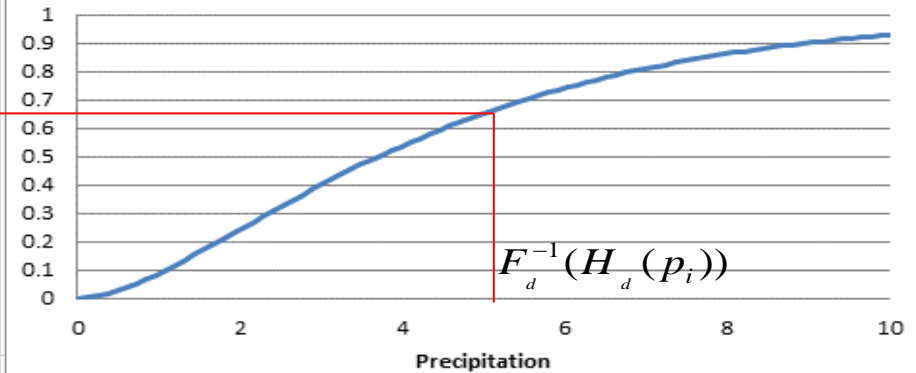
So far implemented for EC-ENS forecast…

Accumulated precipitation over regions 1 2 3 4 5 6 7 8
EC00ENS (blue) vs LTMdaily (red)
Percentiles 1 2 3 4 5 6 7 80 10 50 90 100 (blue) vs

Accumulated inflow over regions 1 2 3 4 5 6 7 8
EC00ENS (blue) vs LTMdaily (red)
Percentiles 1 2 3 4 5 6 7 80 10 50 90 100 (blue) vs
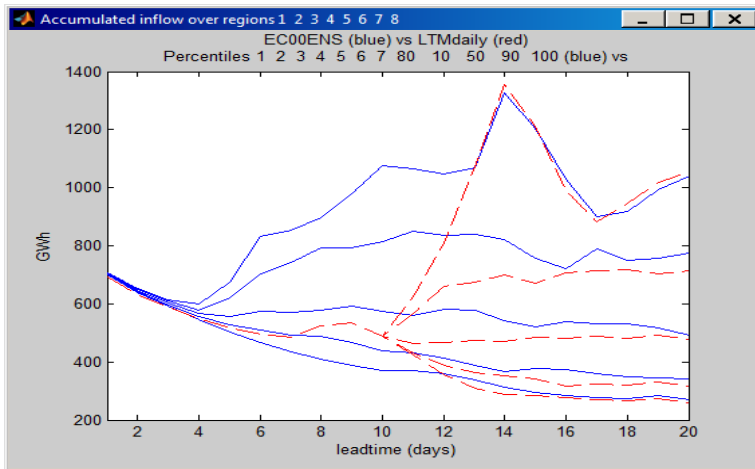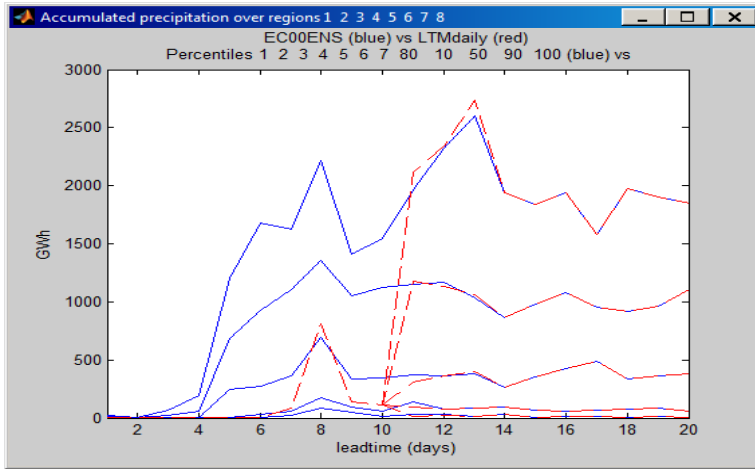
CHANGES IN AREA PRICES EMPS
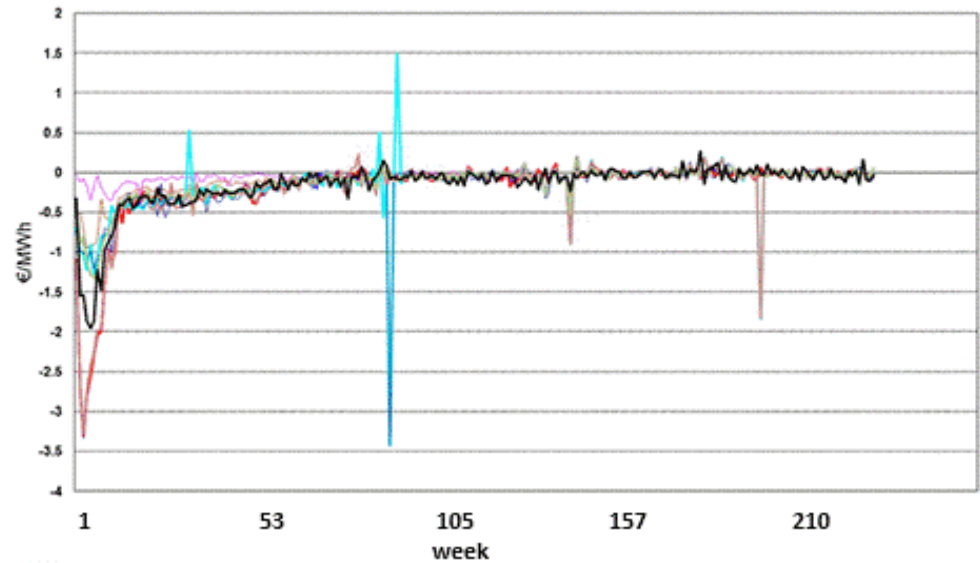
Idea: Use this method to combine several forecasts into one dataset

▸ Quantile Map historical scenarios daily to the following forecasts:

1. EC-Monthly (long-term)
2. EC-ENS (mid-term)
3. AROME (short-term)

▸ Operational meteorologist determines interpolation periods

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Strengths

▸ Easy implementation

▸ Can be used for a wide range of indices (precipitation, temperature, wind, etc)

▸ Preserves historical correlations in time and space

▸ Allows for large flexibility in short-term and mid-term forecasting methodology

▸ Can be combined with other pre- and post-processing techniques

Weaknesses

▸ Does not utilize forecasted correlation properties
  - For instance the quantiles of the QM scenarios may not match the quantiles of the forecast when aggregated in space or time

▸ Quality of ensemble weather forecast in mountainous coastal region?
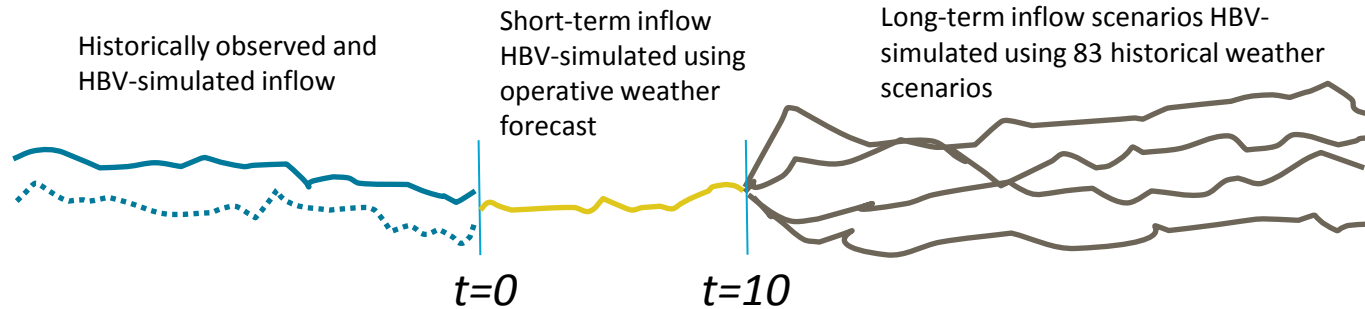 - Need for bias correction?

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THANK YOU

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Some other refinement possibilities to current set-up

Historically observed and HBV-simulated inflow

Short-term inflow HBV-simulated using operative weather forecast

Long-term inflow scenarios HBV-simulated using 83 historical weather scenarios

t=0

t=10

▸ Use filtering methods for updating start states in HBV model

 - Replacing manual updating of temperatures

▸ Improve quality of back-filed historical series?

▸ Calibration of HBV-models?

 - Which calibration data to use? Remove `bad´ periods from calibration data?

▸ Model start state uncertainty

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Next step…?
Model start state uncertainty on future inflow using similar approach?

▸ Idea:
- Simulate, for instance 10, alternative start states by updating HBV models with perturbed observed temperatures and precipitation
- For each alternative start state, run HBV models from current date using the 83 QM scenarios for temperature and precipitation
- In total, this will result in 10x83 alternative scenarios for inflow and snow
- If this is too many scenarios for the EMPS model, reduce the number of scenarios to 83 by either sampling from the alternative scenarios or by quantile mapping the original 83 scenarios to the 830 alternative scenarios

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