# Stochastic runoff forecasting and real time control of urban drainage systems

**Ude af øje, ude af sind, ude af kontrol, 13/03/2013**

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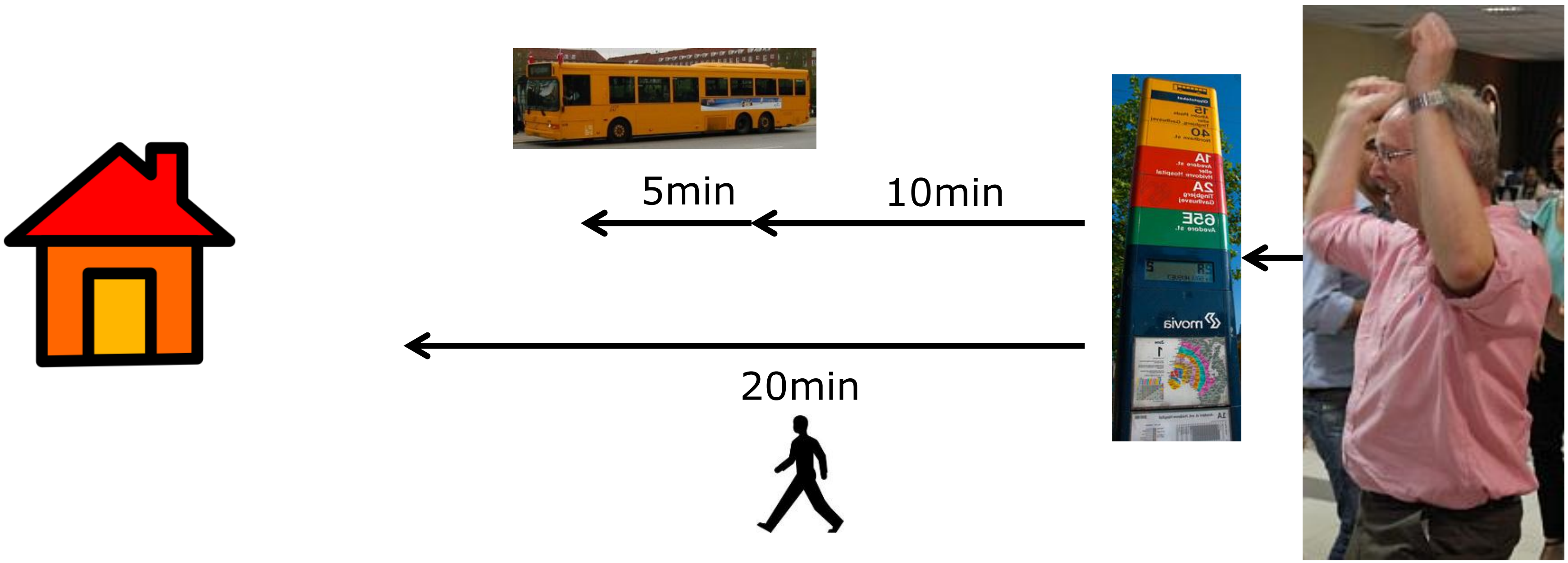
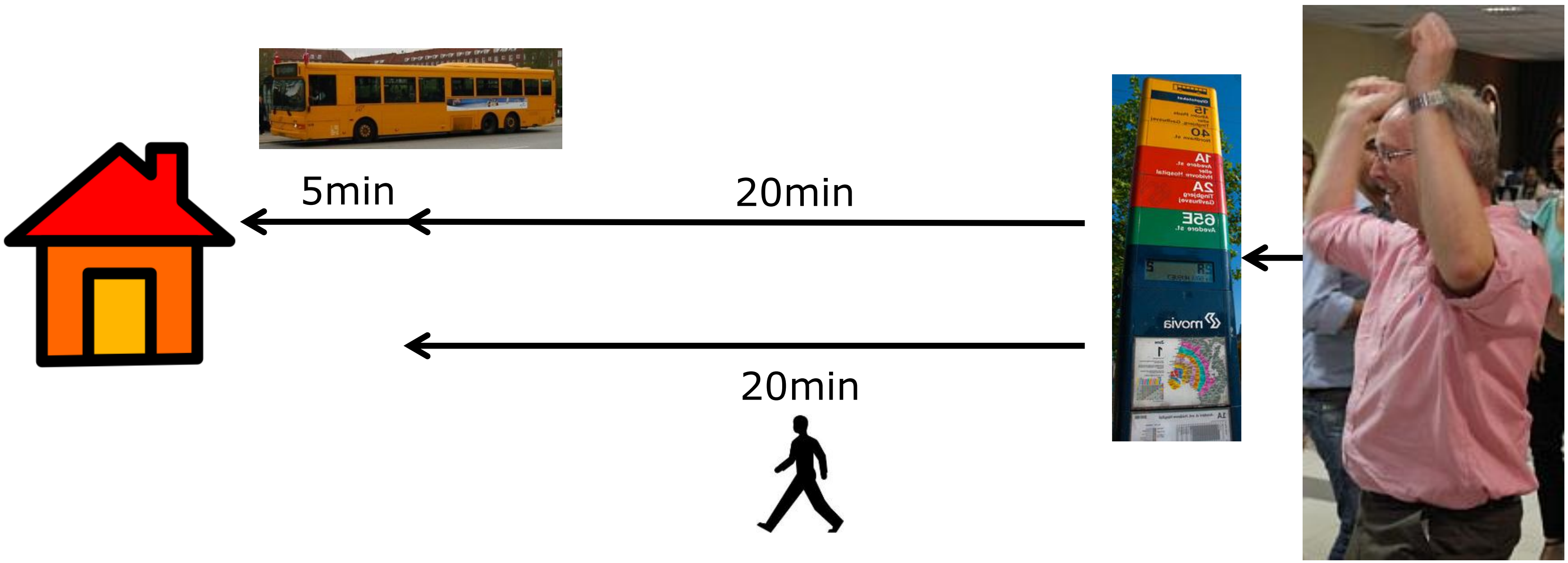
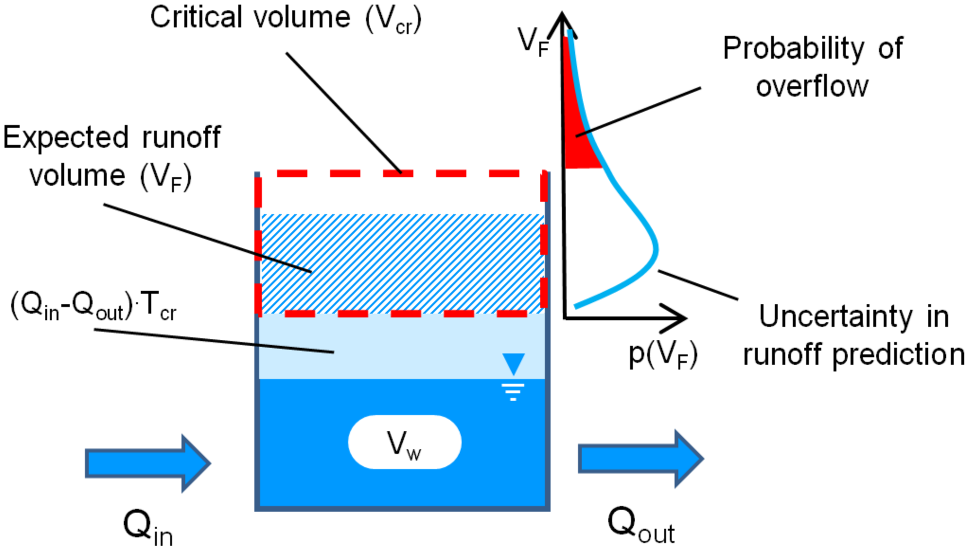
# Why do we need probabilistic forecasts? - The way home



# Why do we need probabilistic forecasts? - The way home

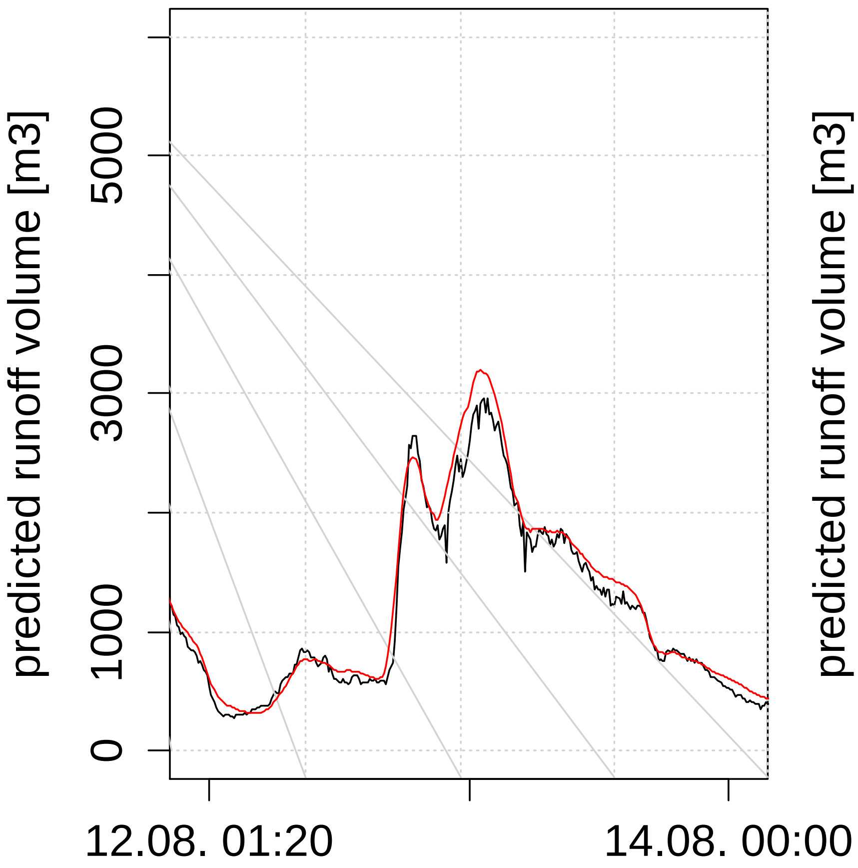


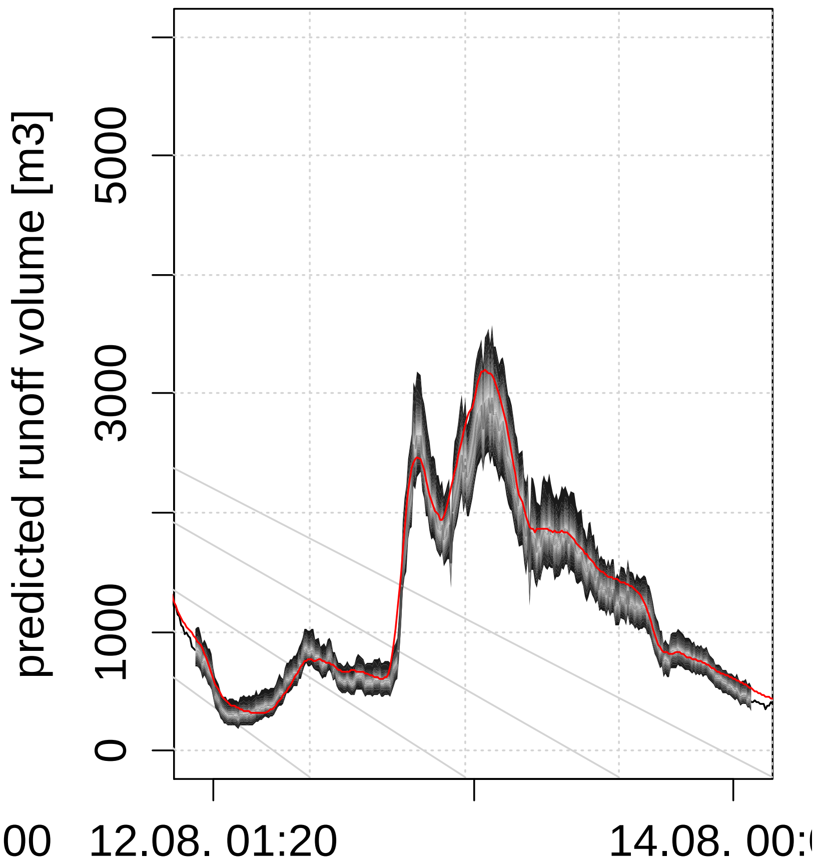
# Why do we need probabilistic forecasts? – Stormwater Storage Basins




Source: Vezzaro and Grum (2012)

# Generating probabilistic forecasts



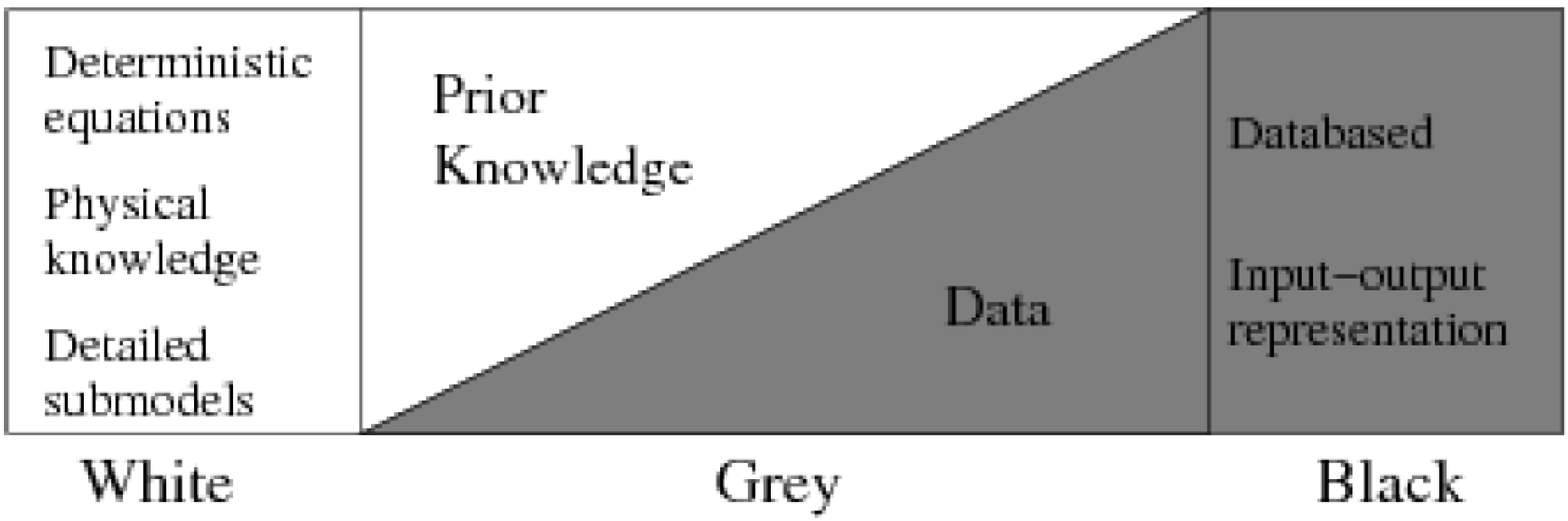
# Generating probabilistic forecasts

Output Y = Model f(X) + Stochastic term σ(X)

| Output Y | Model f(X) | Stochastic term σ(X) |
| --- | --- | --- |
| e.g. flow | e.g. reservoir cascade, simple clarifier model | describes error in model description |

# Generating probabilistic forecasts – The Greybox Modeling Approach

- combines prior physical knowledge with data
- the system is not completely described by physical equations, but equations and parameters are physically interpretable



# Generating probabilistic forecasts – Why Greybox Models

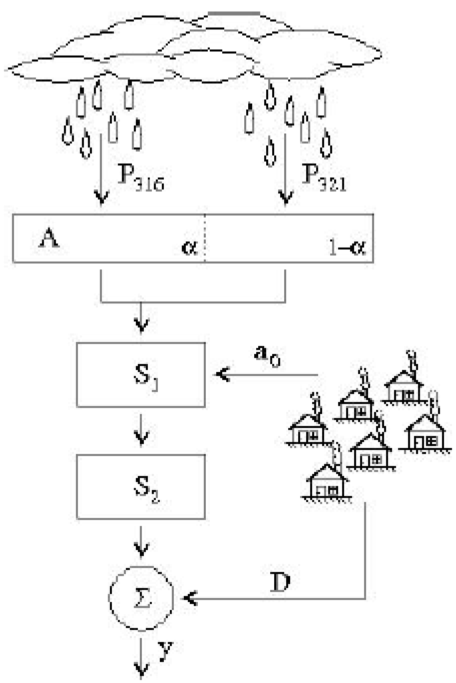
**vs. white box models**

- online applications – need simple, fast models for real time operation
- greybox models can be tuned for forecasting
- white box models typically do not account for uncertainty

**vs. black box models**

- include physical knowledge about the system in the model
- model nonlinear relationships which is not possible e.g. in ARX, ARMAX
  ...

## Generating probabilistic forecasts – Runoff Forecasting Models




Graph from Breinholt et al. (2011)

$$dS_1 = \left(A \cdot P + a_0 - \frac{1}{k} S_1\right) dt$$

$$dS_2 = \left(\frac{1}{k} S_1 - \frac{1}{k} S_2\right) dt$$

$+$

$$(\sigma_1 \cdot S_1) d\omega_1$$

$$(\sigma_2 \cdot S_2) d\omega_2$$

$$Q_t = \left(\frac{1}{k} S_3 + D\right) + \varepsilon_t$$

$A$ – area parameter

k – time constant

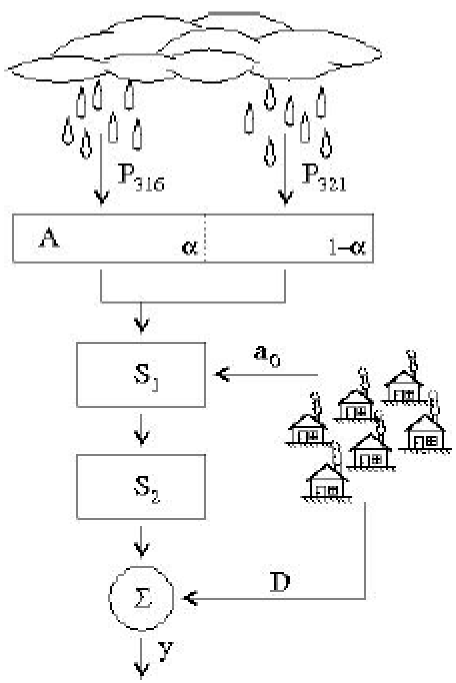
$a_0$ – mean dry weather flow

$P$ – rain input

$Q_t$ – observed flow

$D$ – dry weather variation

# Generating probabilistic forecasts – Runoff Forecasting Models

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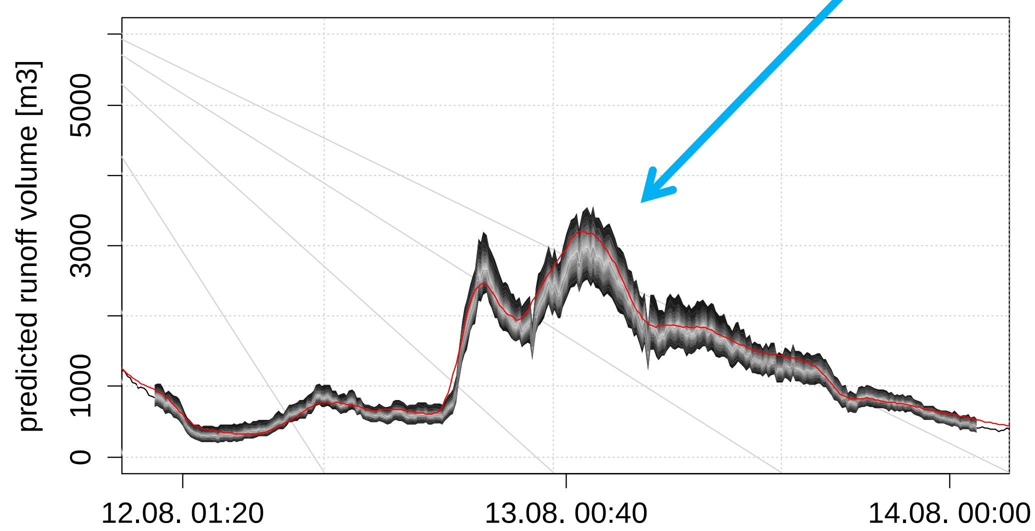
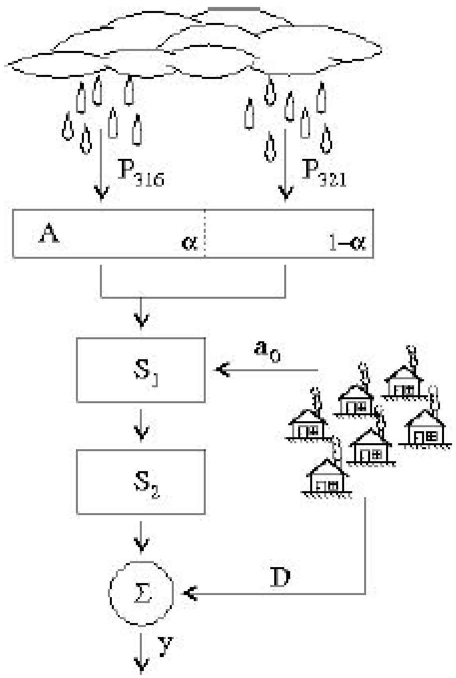


# Generating probabilistic forecasts – Runoff Forecasting Models - Updating




Graph from Breinholt et al. (2011)

Input

Reconstructed states

predict

Predicted states
(Basin storage)

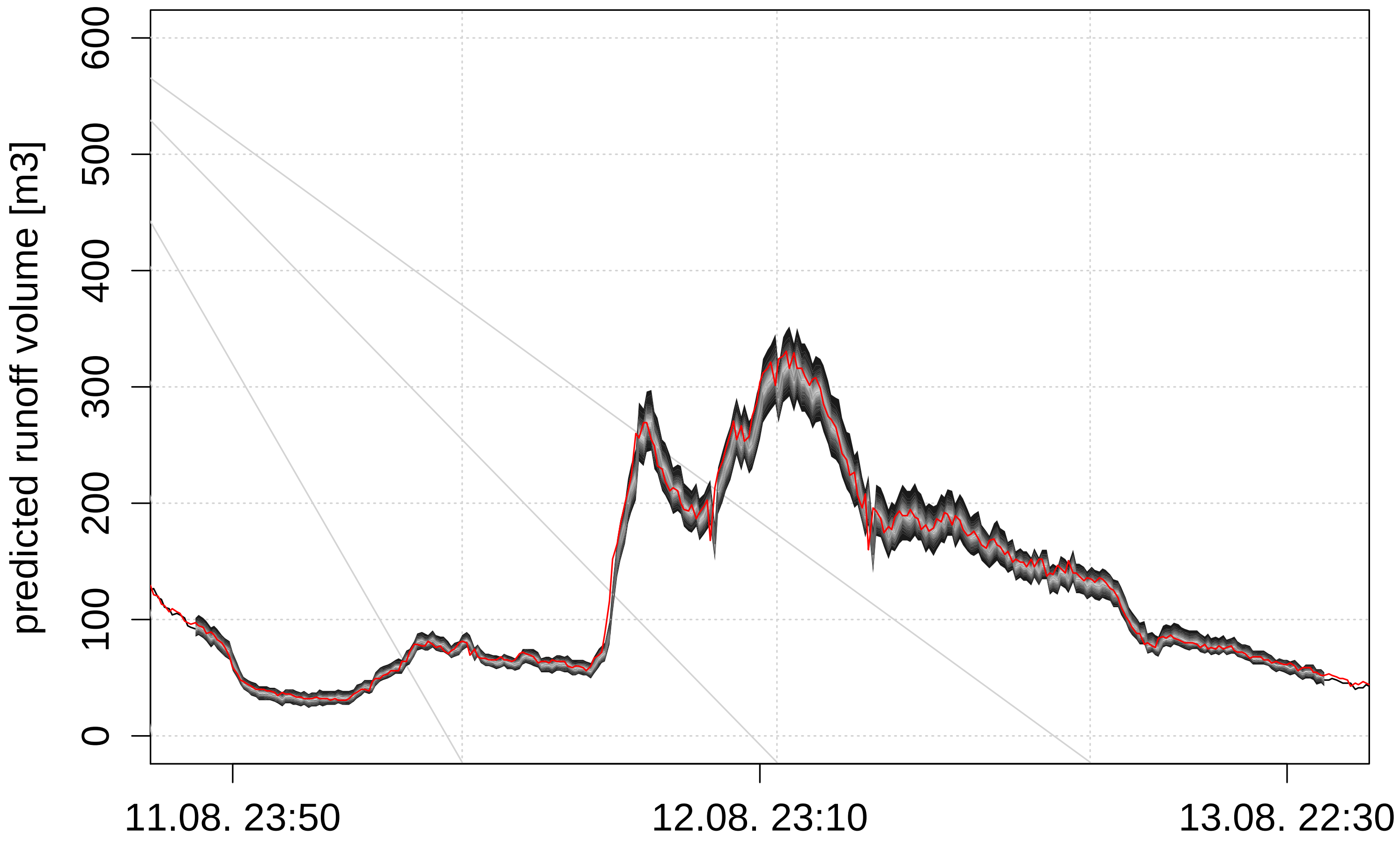
update
weighting by state and
observation uncertainty

predict

Flow

Difference predicted -
measured flow

# Generating probabilistic forecasts – Runoff Forecasting Models - Updating



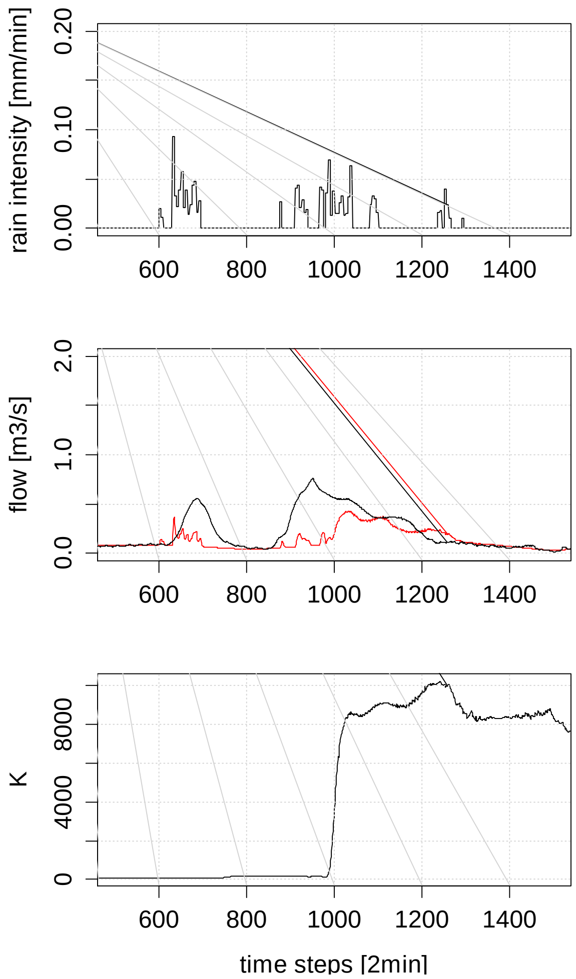
# Generating probabilistic forecasts – Runoff Forecasting Models - Adaptivity

$$dS_1 = \left(A \cdot P + a_0 - \frac{1}{k} S_1\right) dt + (\sigma_1 \cdot S_1) d\omega_1$$

$$dS_2 = \left(\frac{1}{k} S_1 - \frac{1}{k} S_2\right) dt + (\sigma_2 \cdot S_2) d\omega_2$$

$$\mathbf{dk = 0\ dt + \ (\sigma_4) d\omega_4}$$

$$Q_t = \left(\frac{1}{k} S_3 + D\right) + \varepsilon_t$$



# Stochastic Greybox Models – Pros and Cons

**<u>application range for greybox models</u>**

- online applications and forecasting
- quantifying simulation / forecast uncertainty

**<u>advantages</u>**

- simple, fast models
- state updating – models adapt to observations
- flexible framework for modeling forecast uncertainty
- typically better predictions than deterministic model
- adaptivity can be implemented

**<u>limitation</u>**

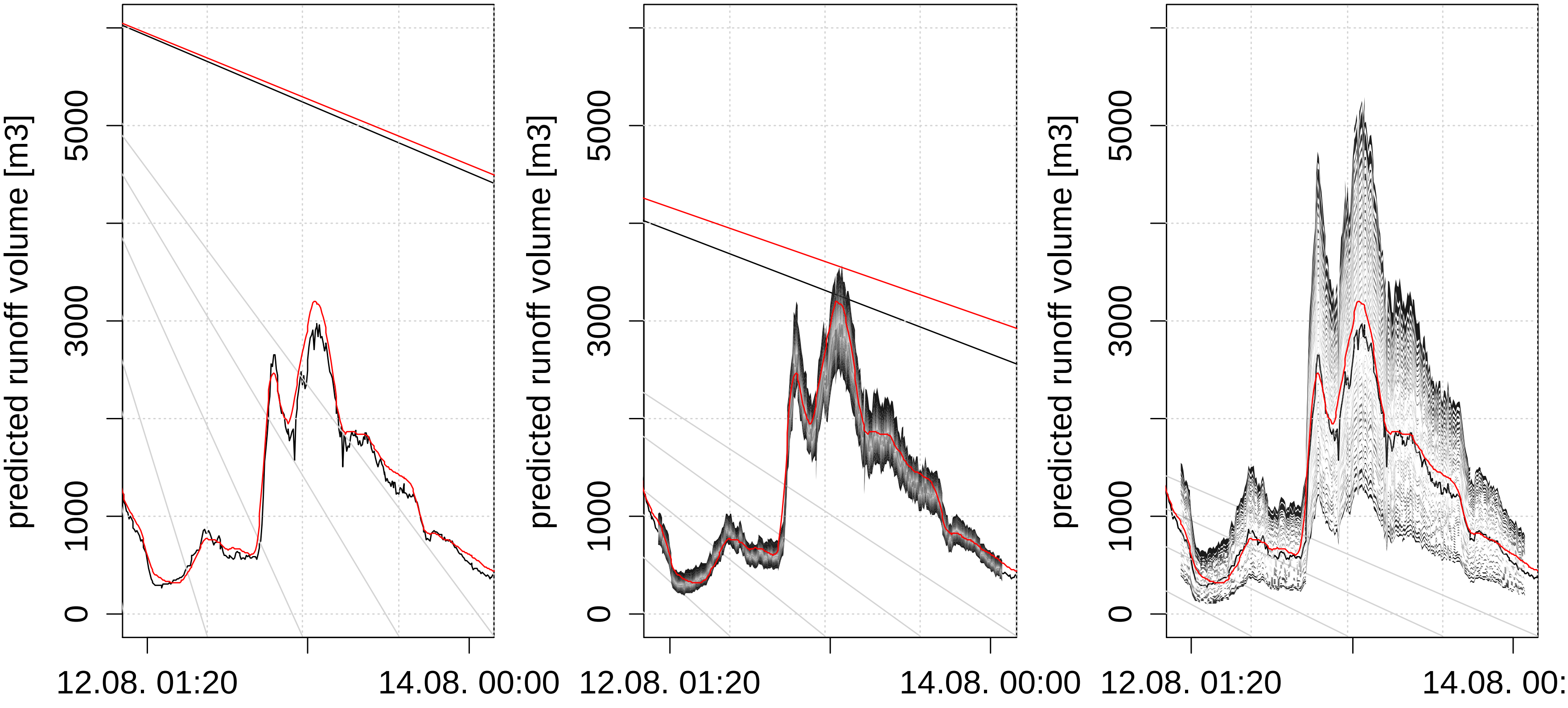
- complex, physical models cannot be handled in the current framework

# Stochastic Greybox Models –Software CTSM

CTSM = Continuous Time Stochastic Modeling

- model development, parameter estimation, simulation and forecasting
- developed at DTU Compute
- implement as a package in R (‘open source MATLAB’)
- download from www.ctsm.info (and www.r-project.org + www.rstudio.com)

# Generating Probabilistic Forecasts – What is a good forecast???



# Generating Probabilistic Forecasts – What is a good forecast???

**reliability**

% of observations not included in a 'x %' prediction interval

**→Requirement**

**sharpness**

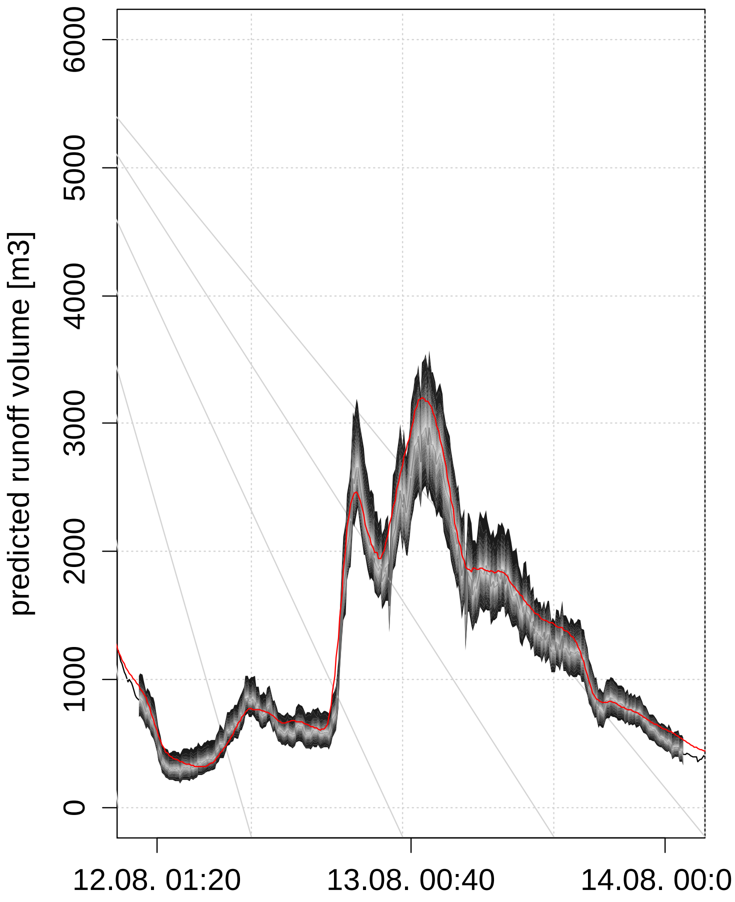
width of a 'x %' prediction interval

**→Minimize**

**skillscores**

(e.g. CRPS – continuous ranked probability score)

**→Minimize**

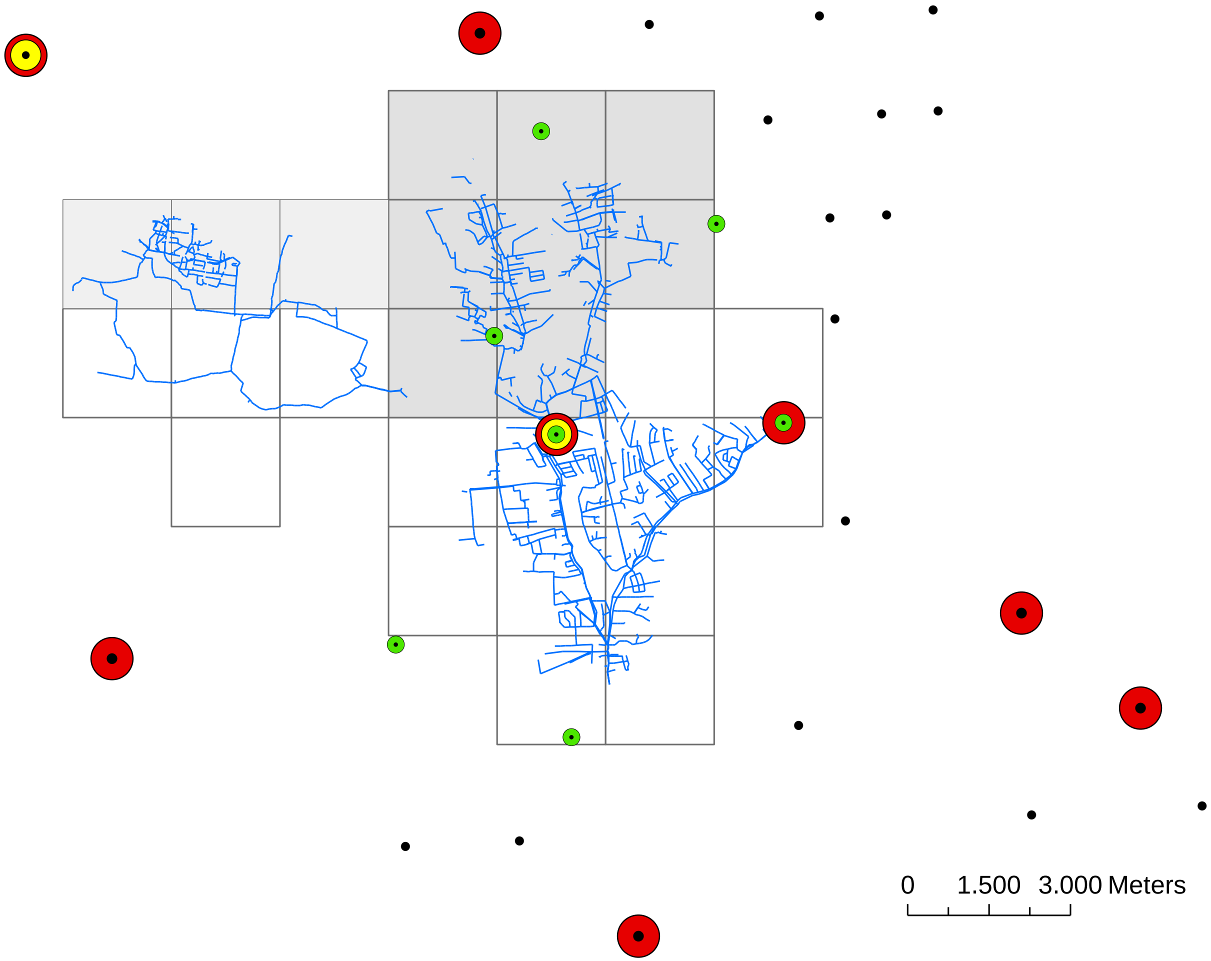


# Case Study 1

# Value of radar rainfall observations and forecasts for online runoff forecasting

(thank you to Aalborg University and DMI for providing radar data)

# Radar rainfall and online runoff forecasting




- Ballerup and Damhusåen catchments
- 5min rain gauge observations
- 10min C-band radar data from Stevns (DMI / AAU)
- Period 25/06-06/09/2010

# Radar rainfall and online runoff forecasting – comparing radar and rain gauge input

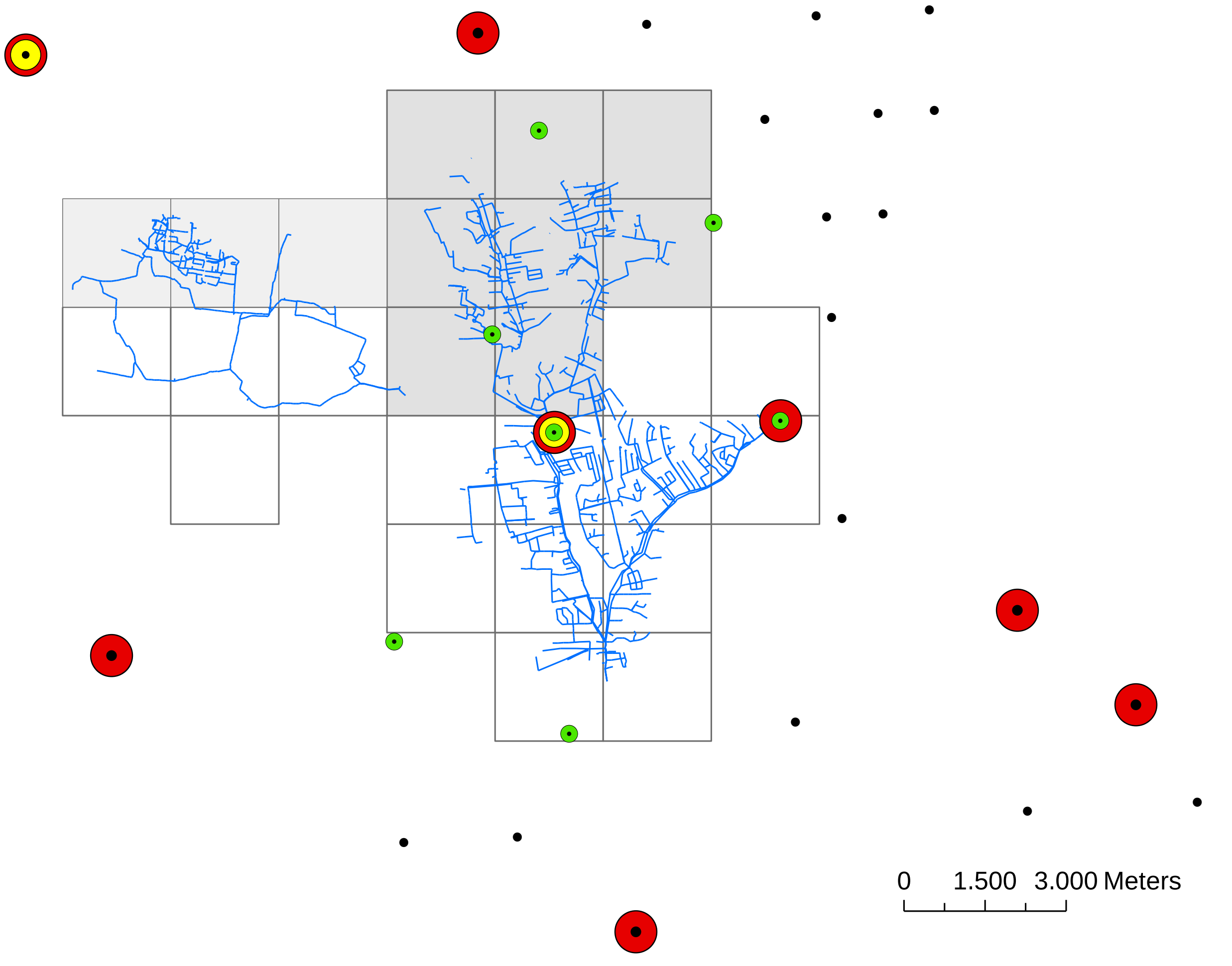
- use mean area rainfall
- 100min runoff forecasts with different rainfall inputs
- using radar rainfall measurements and forecasts reduces error of probabilistic runoff forecasts (compared to input from rain gauges)

| | Ballerup | Damhusåen |
|---|---|---|
| RMSE Raingauge | 276.8 | 3464.1 |
| RMSE Radar | 260.3 | 2624.7 |
| CRPS Raingauge | 152.3 | 1463.3 |
| CRPS Radar | 144.9 | 1399.1 |

**RMSE** (root mean square error) – average error of 100min point forecast [$m^3$]

**CRPS** (continuous ranked probability score) – average error of probabilistic forecast

# Radar rainfall and online runoff forecasting – comparing model complexity



# Radar rainfall and online runoff forecasting – comparing model complexity

- use rain gauge input

- model 1 – mean area rainfall
- model 2 – subcatchment model

- 100min runoff forecasts with different model structures

- accounting for spatial distribution of rainfall in the model improves forecasts

| | **Ballerup** | **Damhusåen** |
|---|---|---|
| RMSE model 1 | 276.8 | 3464.1 |
| RMSE model 2 | 262.4 | 2631.3 |
| CRPS model 1 | 152.3 | 1463.3 |
| CRPS model 2 | 146.0 | 1352.2 |

**RMSE** (root mean square error) – average error of 100min point forecast [$m^3$]

**CRPS** (continuous ranked probability score) – average error of probabilistic forecast

## Case Study 2

## Value of probabilistic runoff forecasts in real time control

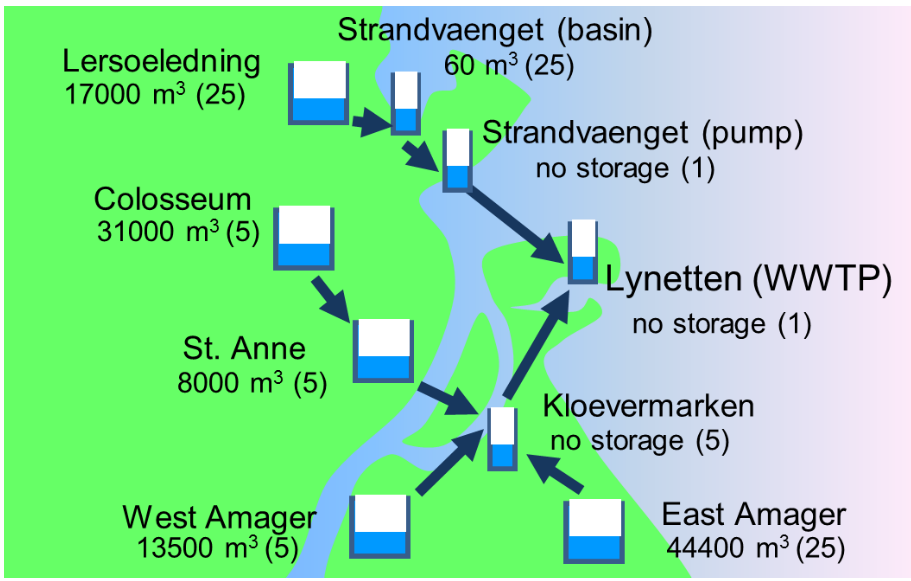
(in cooperation with Krüger AS)

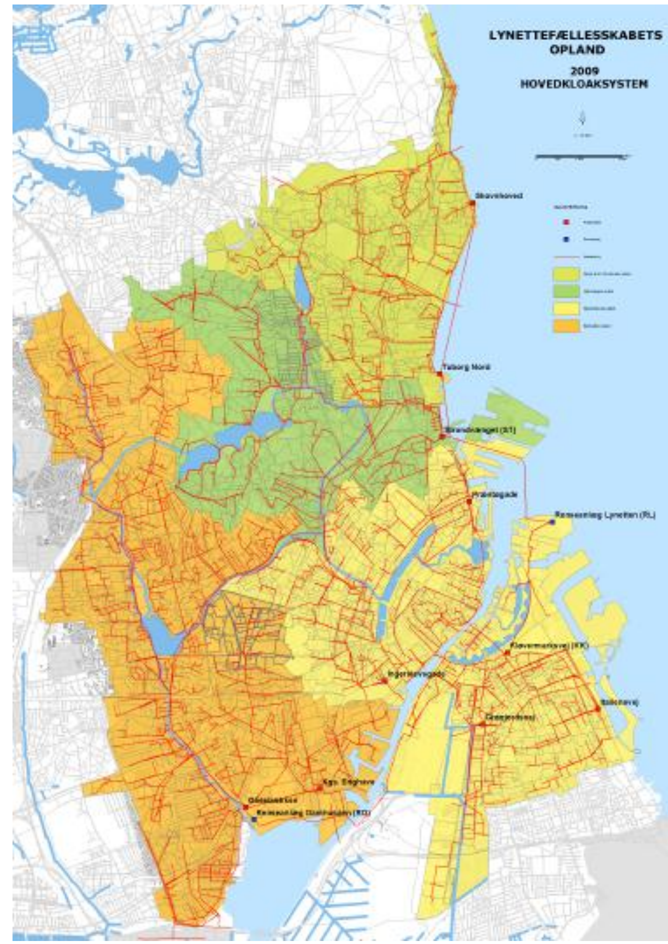
# Real Time Control of Stormwater Flows

- dynamic operation of drainage system
- objectives:
  - reduction of combined sewer overflows
  - avoiding flooding
  - ...
- actuators: pumps, valves
- operational examples: Québec, Paris, Dresden

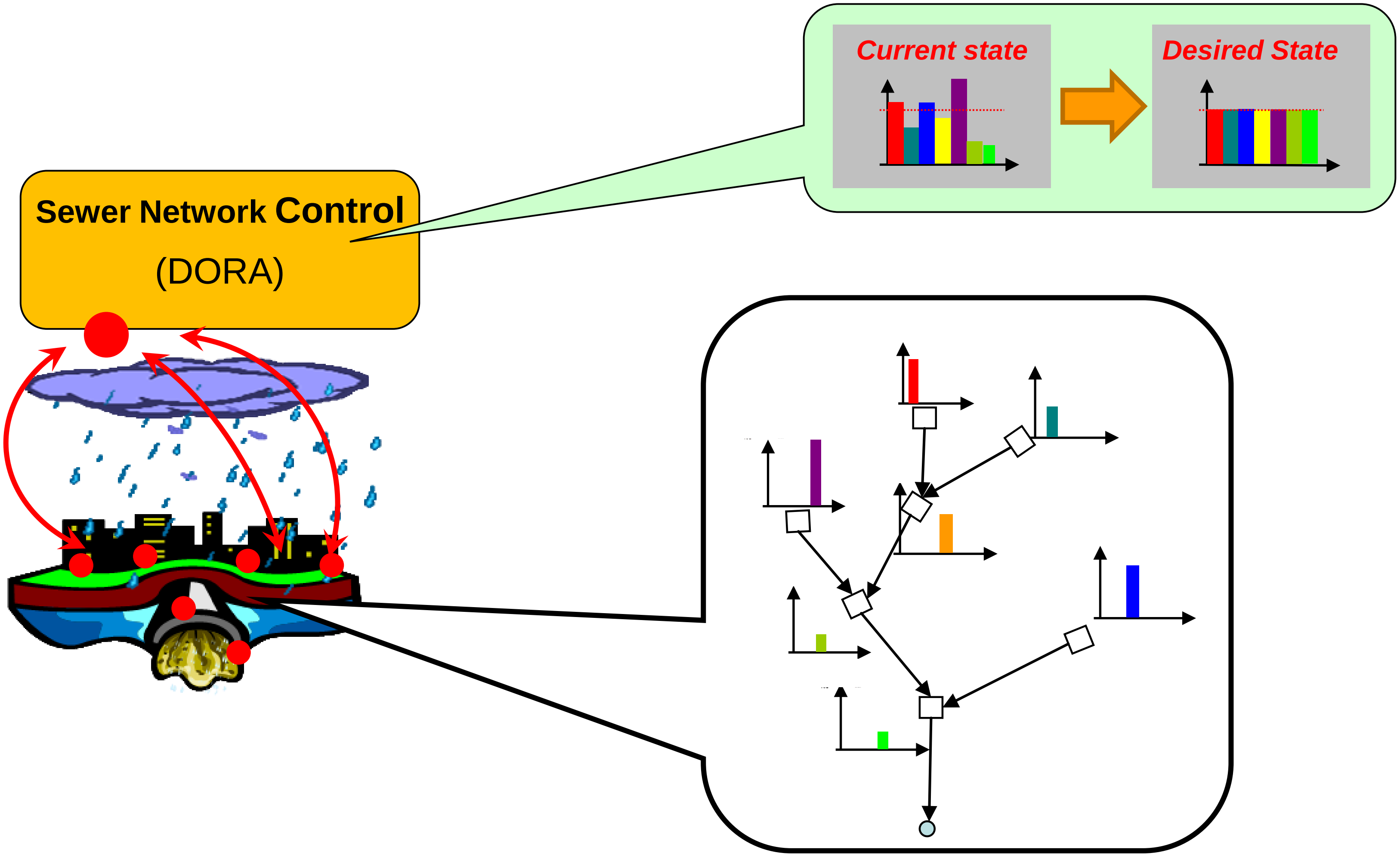
Source: Stadtentwässerung Dresden

# The Lynetten Catchment



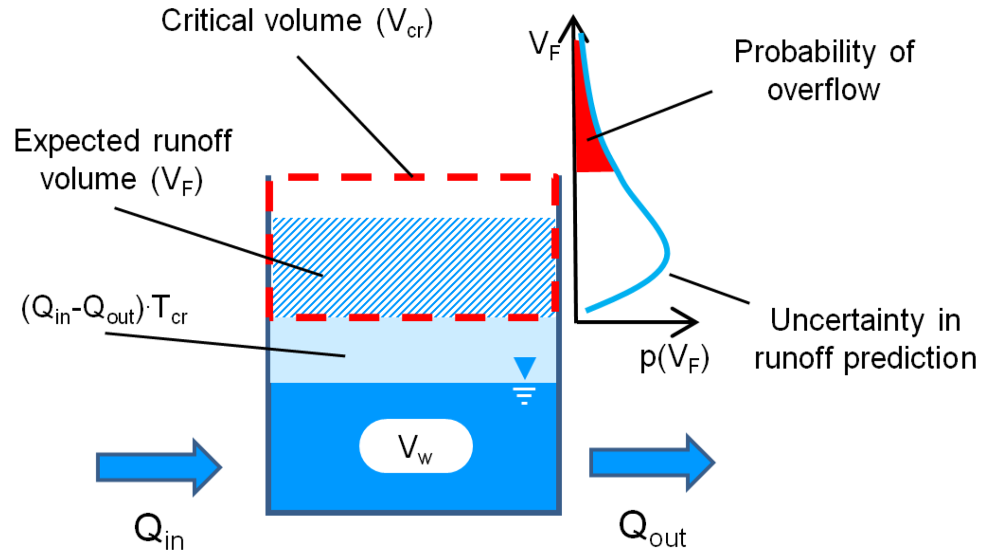
# Real Time Control Lynetten Catchment
## (METSAM project)




Source: Krüger A/S

# Integrated control strategy
## (Dynamic Overflow Risk Analysis – DORA)

- runoff forecasts are uncertain
- uncertainty varies
  - between wet and dry weather
  - in the course of events
  - from event to event
- proper decision making requires dynamic quantification of forecast uncertainty




Source: Vezzaro and Grum (2012)

# Real Time Control Lynetten Catchment
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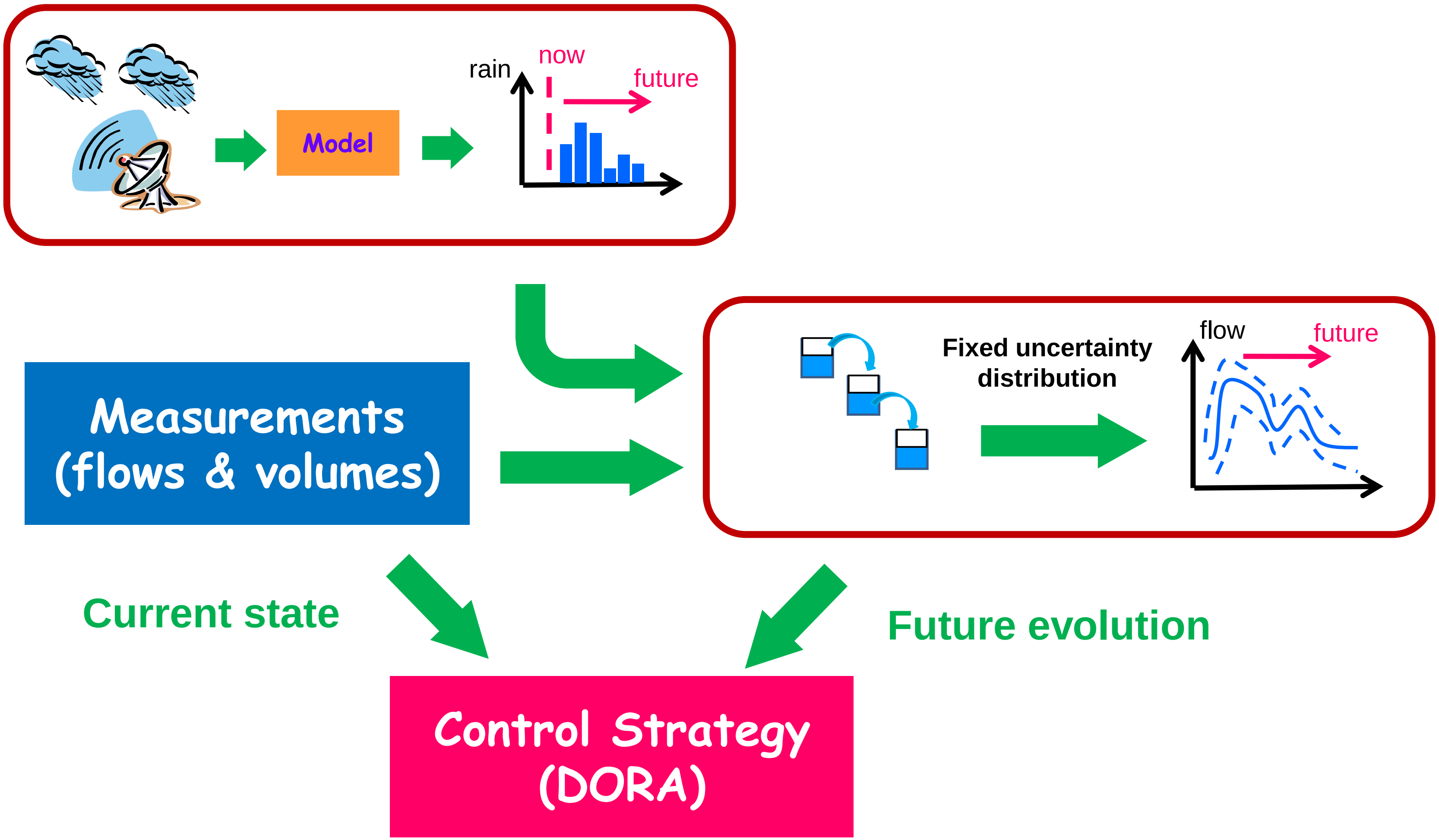
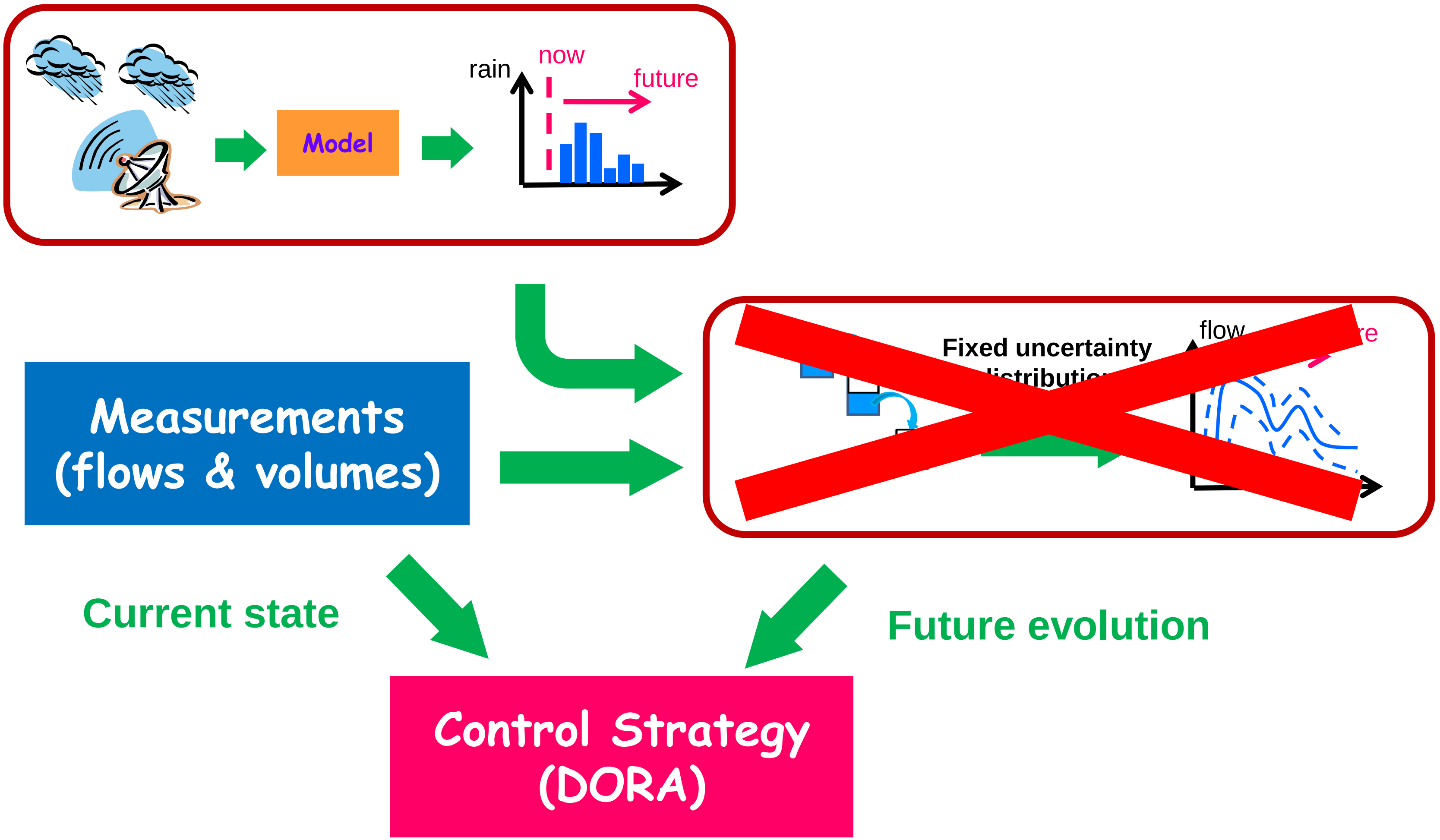


# Stochastic runoff models



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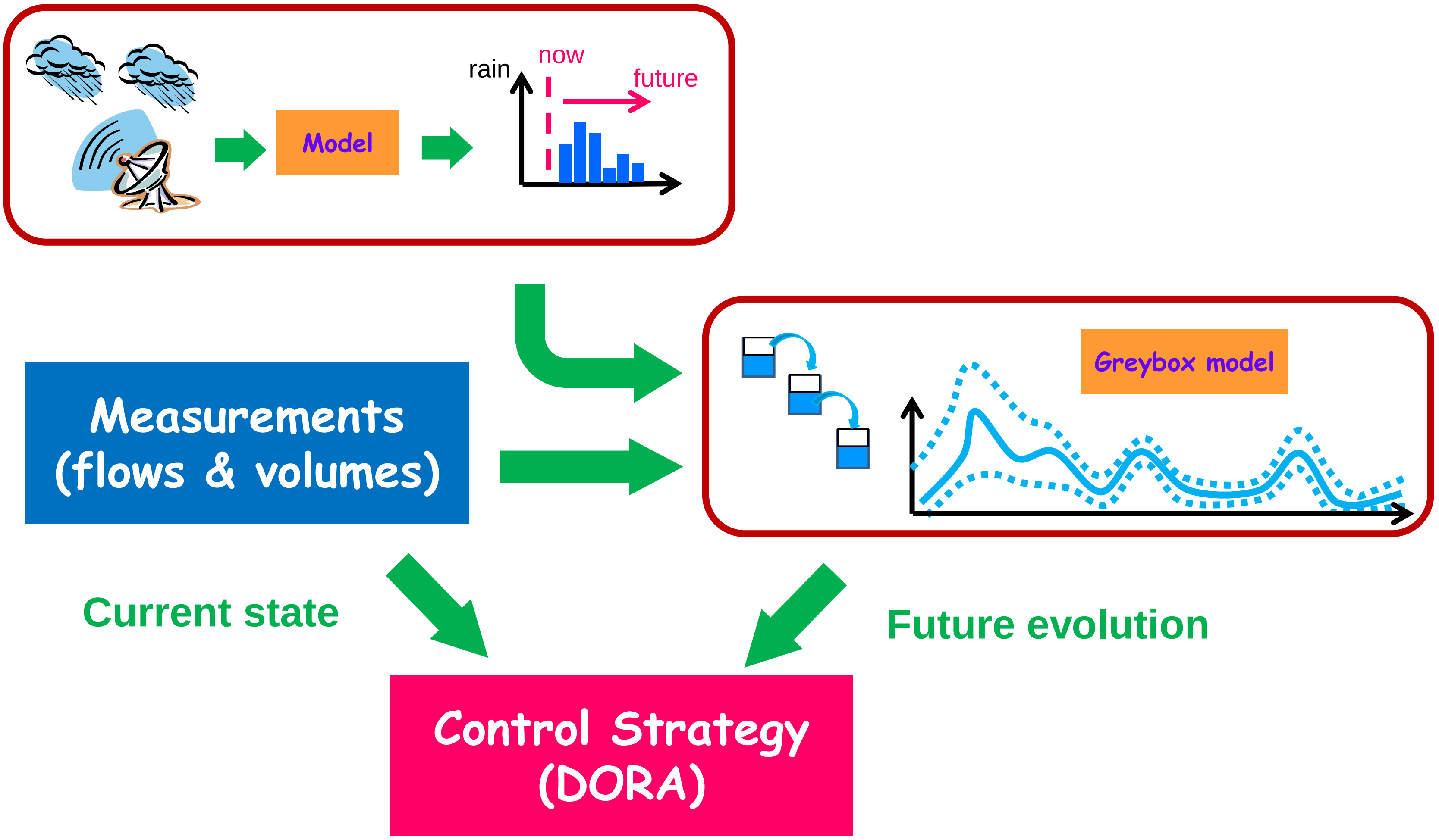
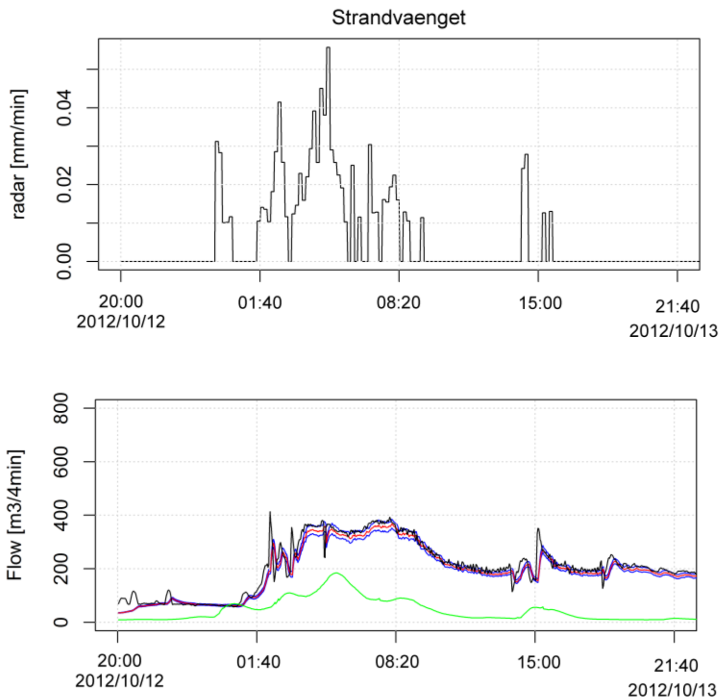
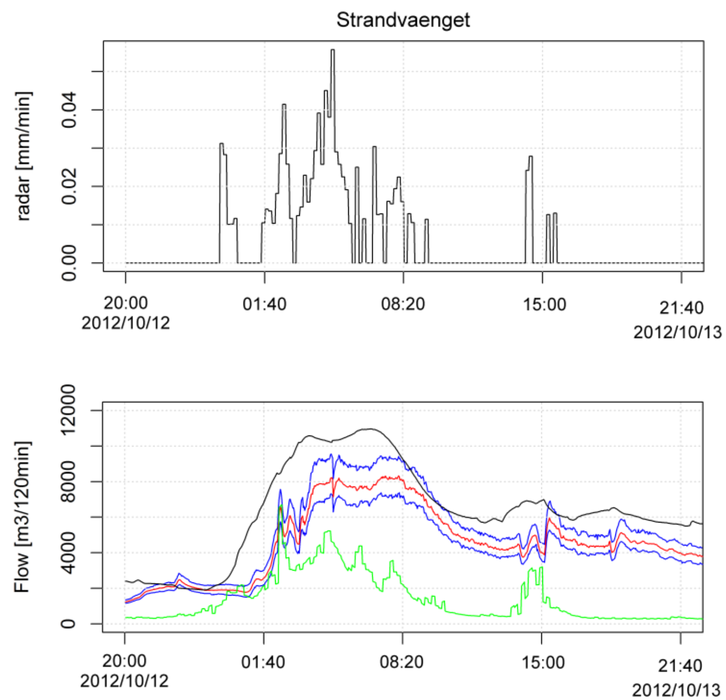


# Probabilistic Runoff Forecasting – Example

Forecast horizon 4 min

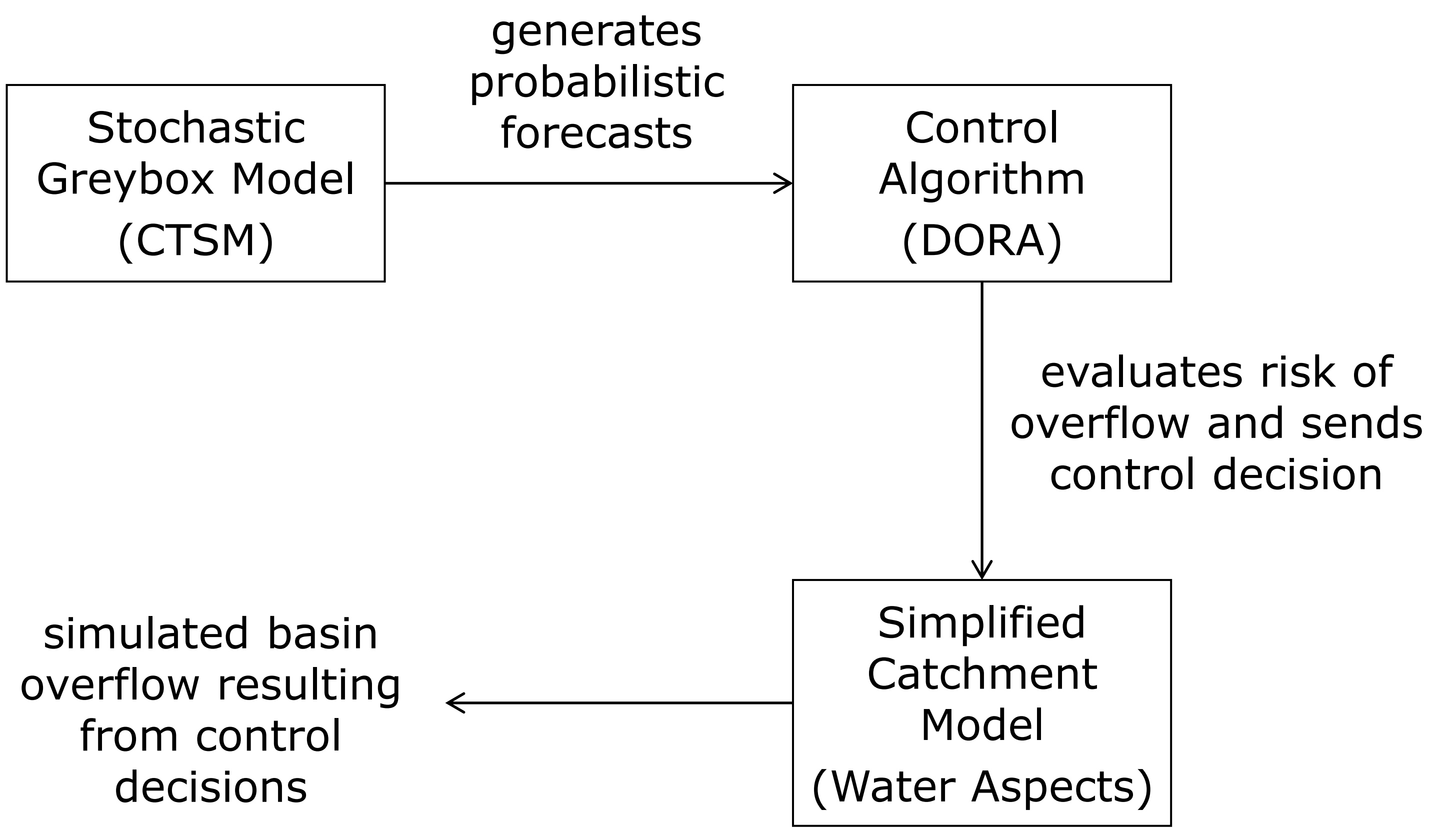



Forecast horizon 120 min

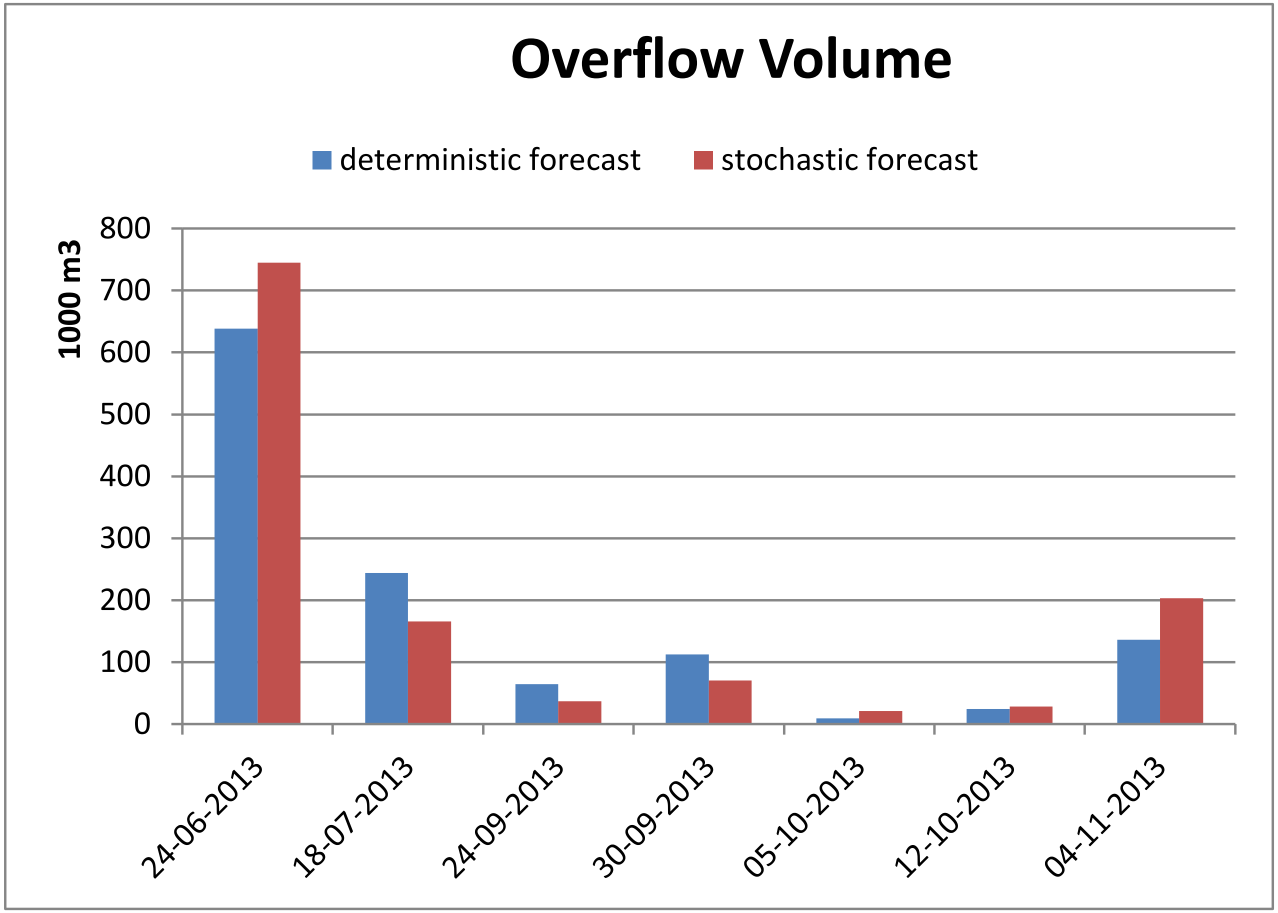



black – observation, green – state of the art deterministic forecast, red / blue – probabilistic forecast with 95% confidence bounds

# Experimental design



# Effect of Probabilistic Forecasts on Real Time Control



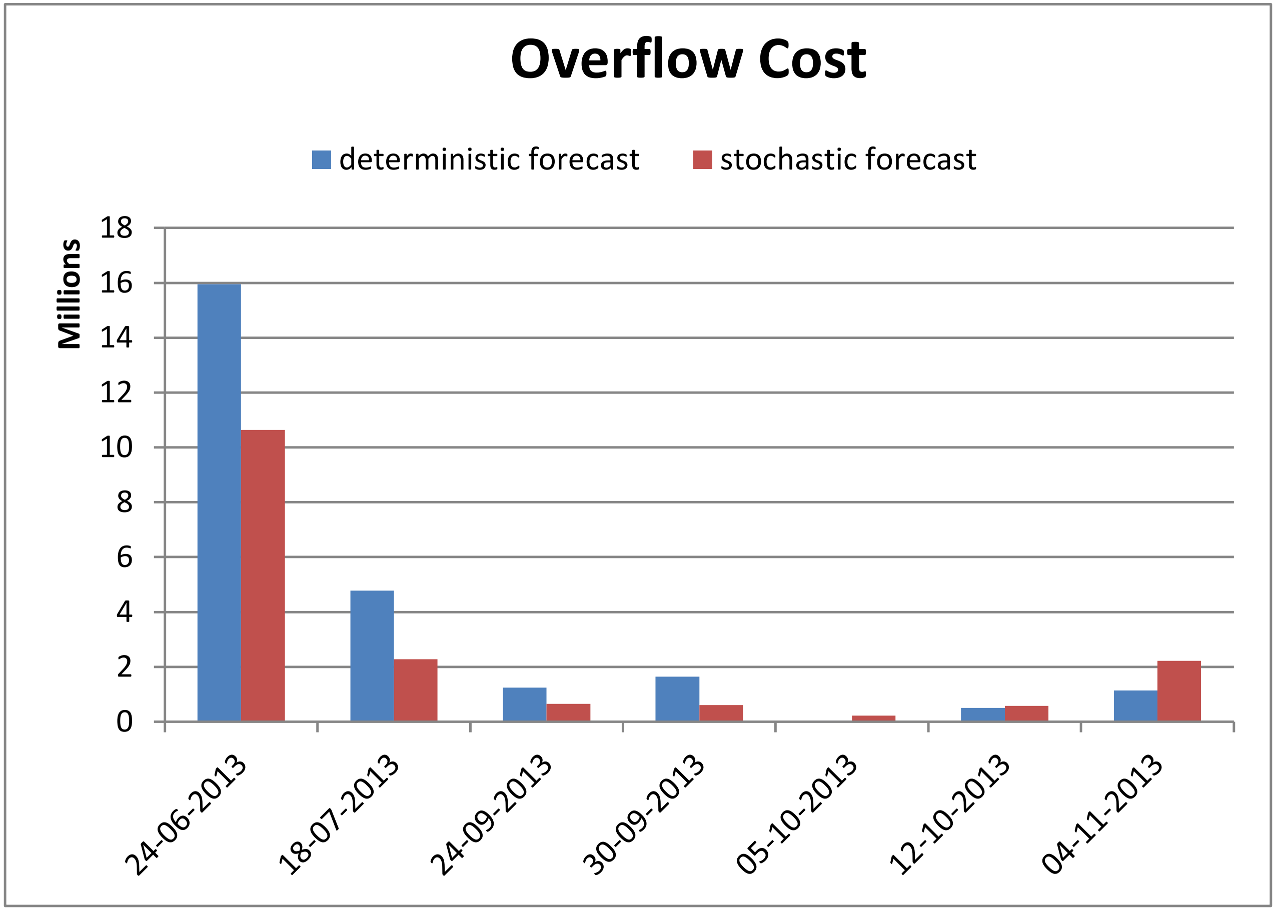

overflow volume in 7 sample events increased by **+3%**

(compared to state-of-the-art)

control objective is not overflow volume but overflow cost

(overflow volume weighted by location where it occurs)

# Effect of Probabilistic Forecasts on Real Time Control




overflow cost in 7 sample events reduced by **-32%**

(compared to state-of-the-art)

# Summary

# Summary and Outlook

**Use greybox models for**

- online applications –simple, fast models for real time operation that adapt to online measurements
- quantifying predictive uncertainties

**Applications**

- runoff forecasting – simulation studies indicate improved decisions in real time control
- other applications where forecasts and quantification of uncertainties are required (predicting capacity of secondary clarifiers, predicting TSS)

**Future work**

- study effect of probabilistic forecasts on real time control in more detail
- model runoff forecast uncertainties depending on rainfall input (rainfall patterns, weather model data)

# Thank you!

For further info: rolo@dtu.dk