Division of River Engineering
Dept. of Land and Water Resources Engineering

Combined mid- and short-term operational planning of hydropower reservoir systems

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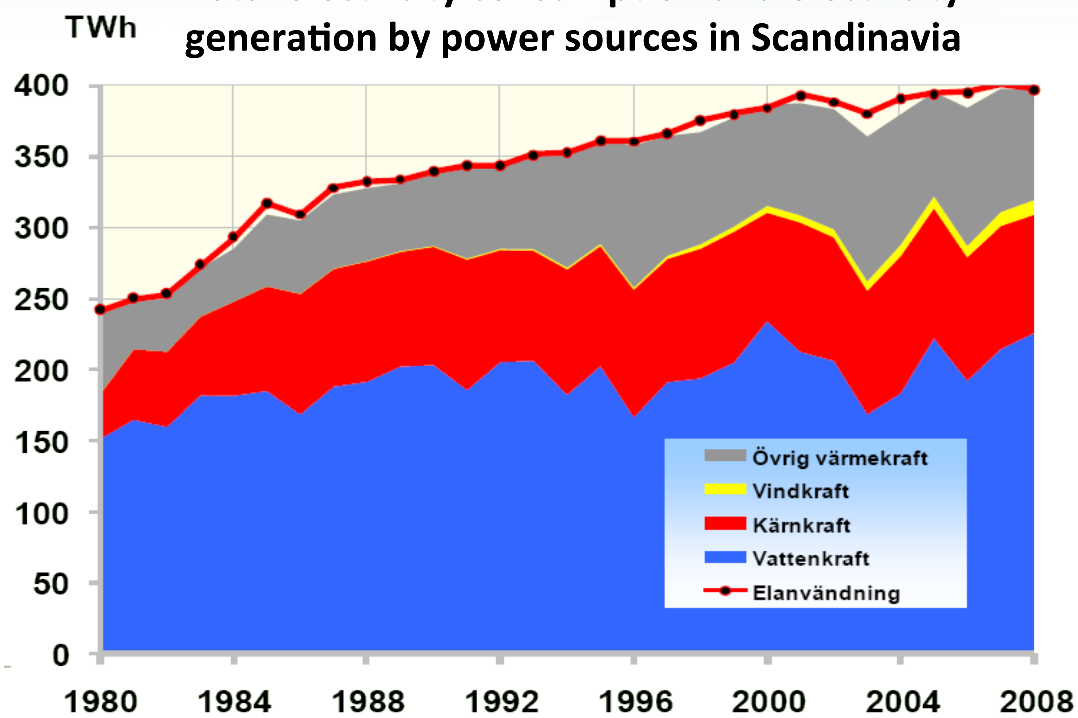
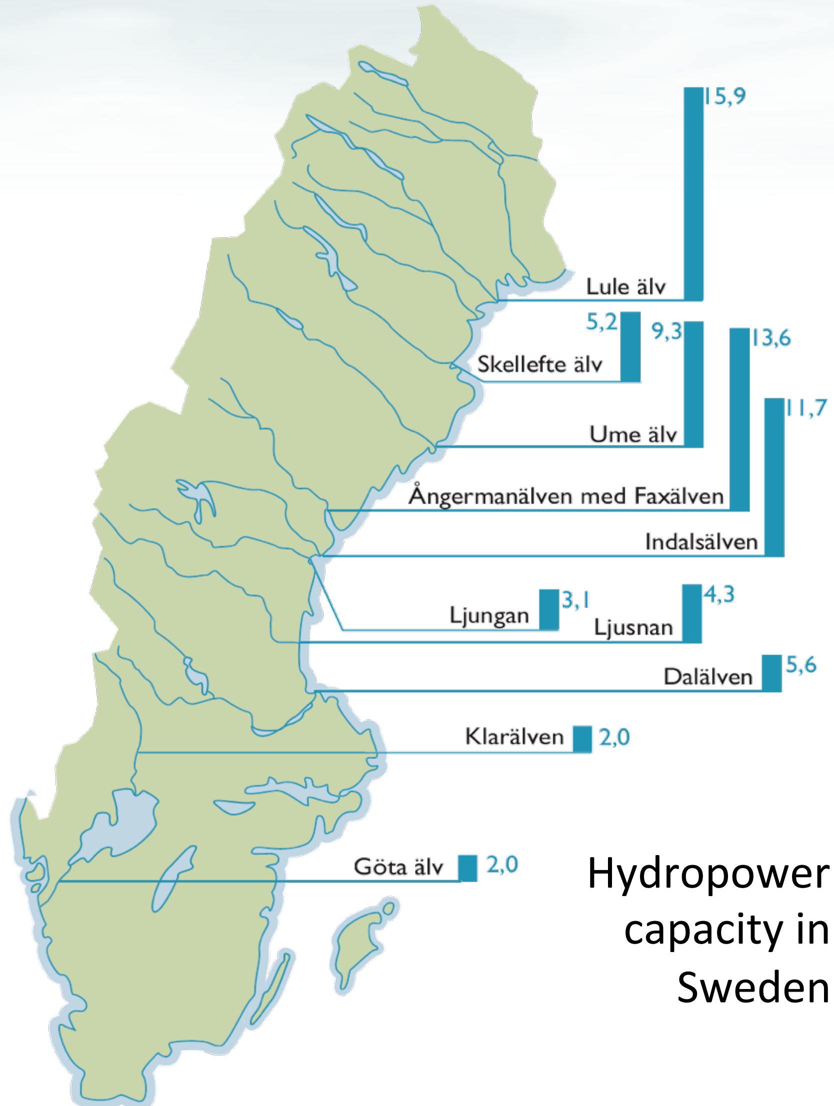
EGU Leonardo 2012

Electricity by power sources in Scandinavia

Total electricity consumption and electricity generation by power sources in Scandinavia



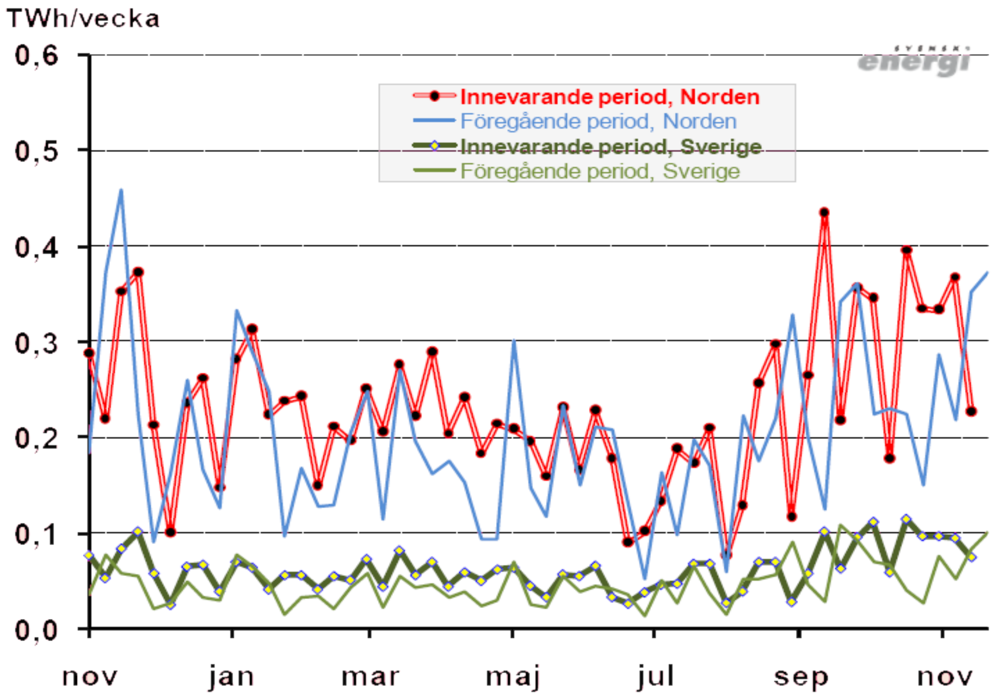
- Hydropower
- Nuclear power
- Thermal power
- Wind power

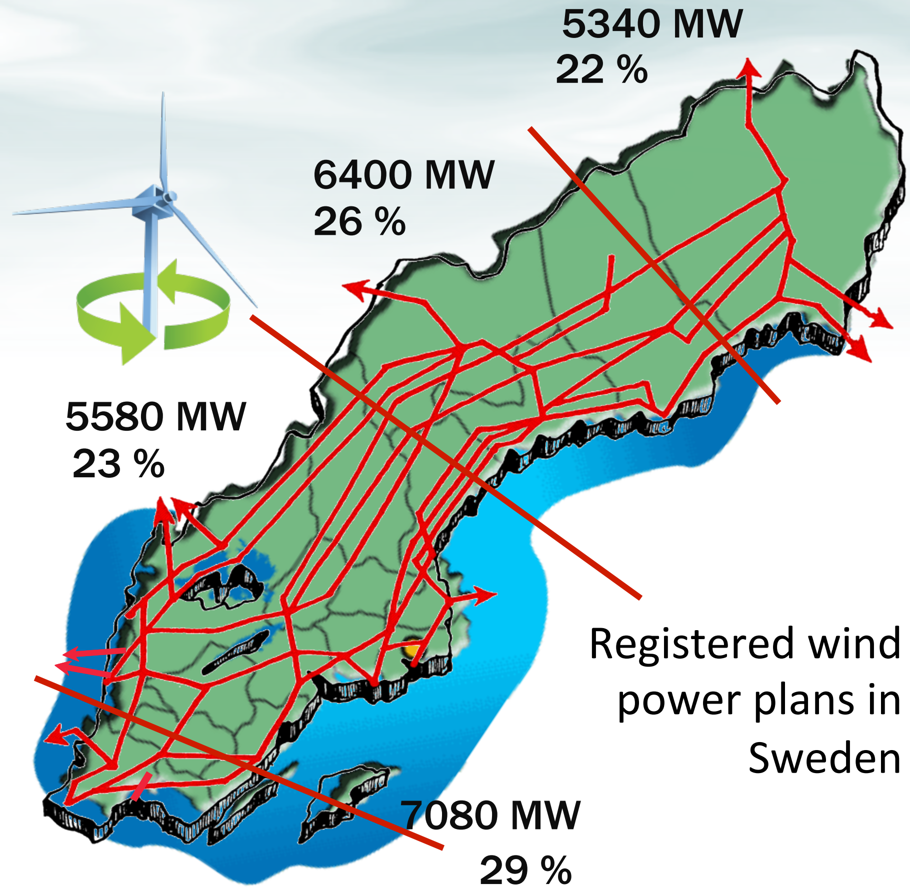


Hydropower capacity in Sweden

Towards a green energy system

Wind power production per week in Scandinavia and in Sweden, 2010





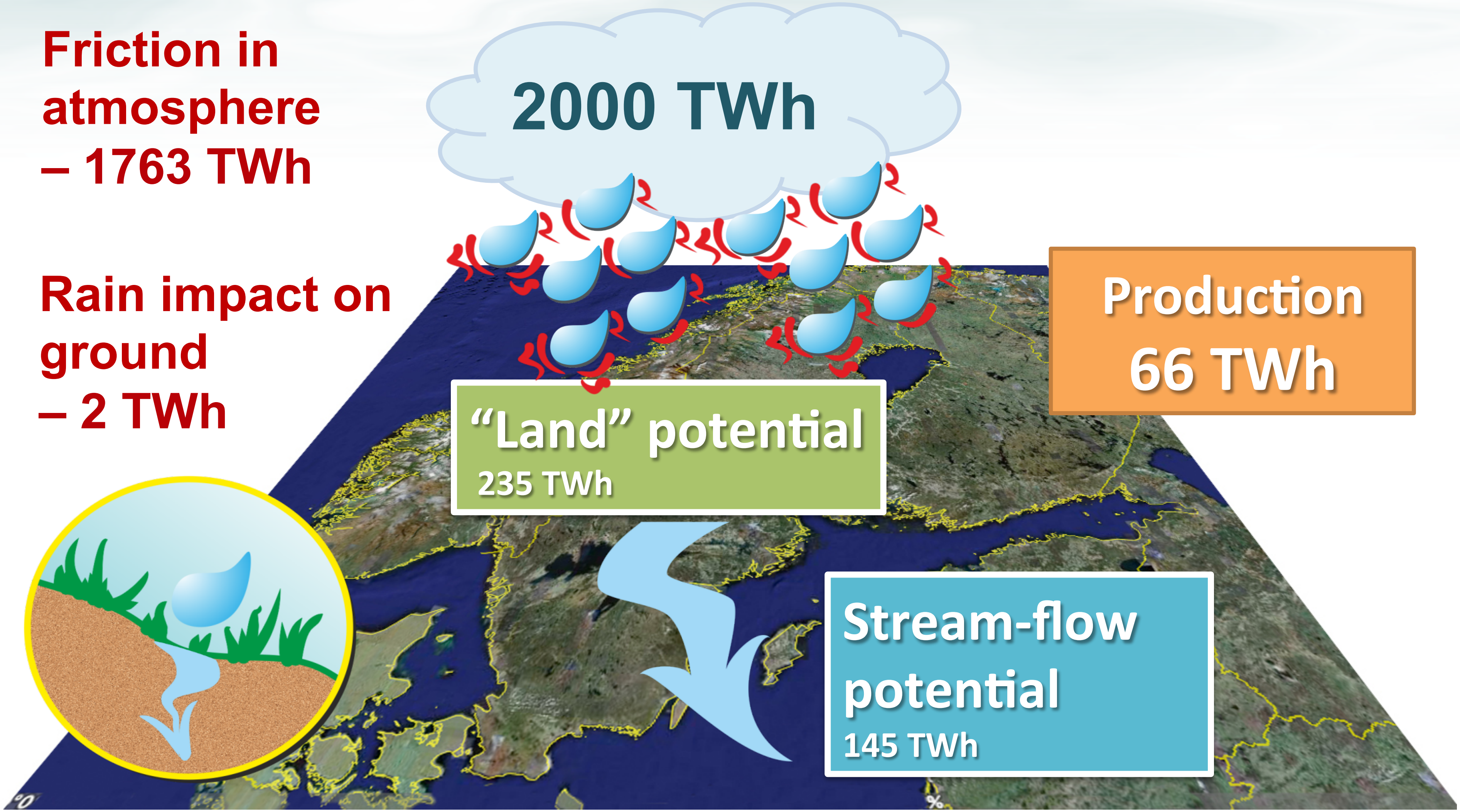
Intermittent Electricity Production

New quality demands

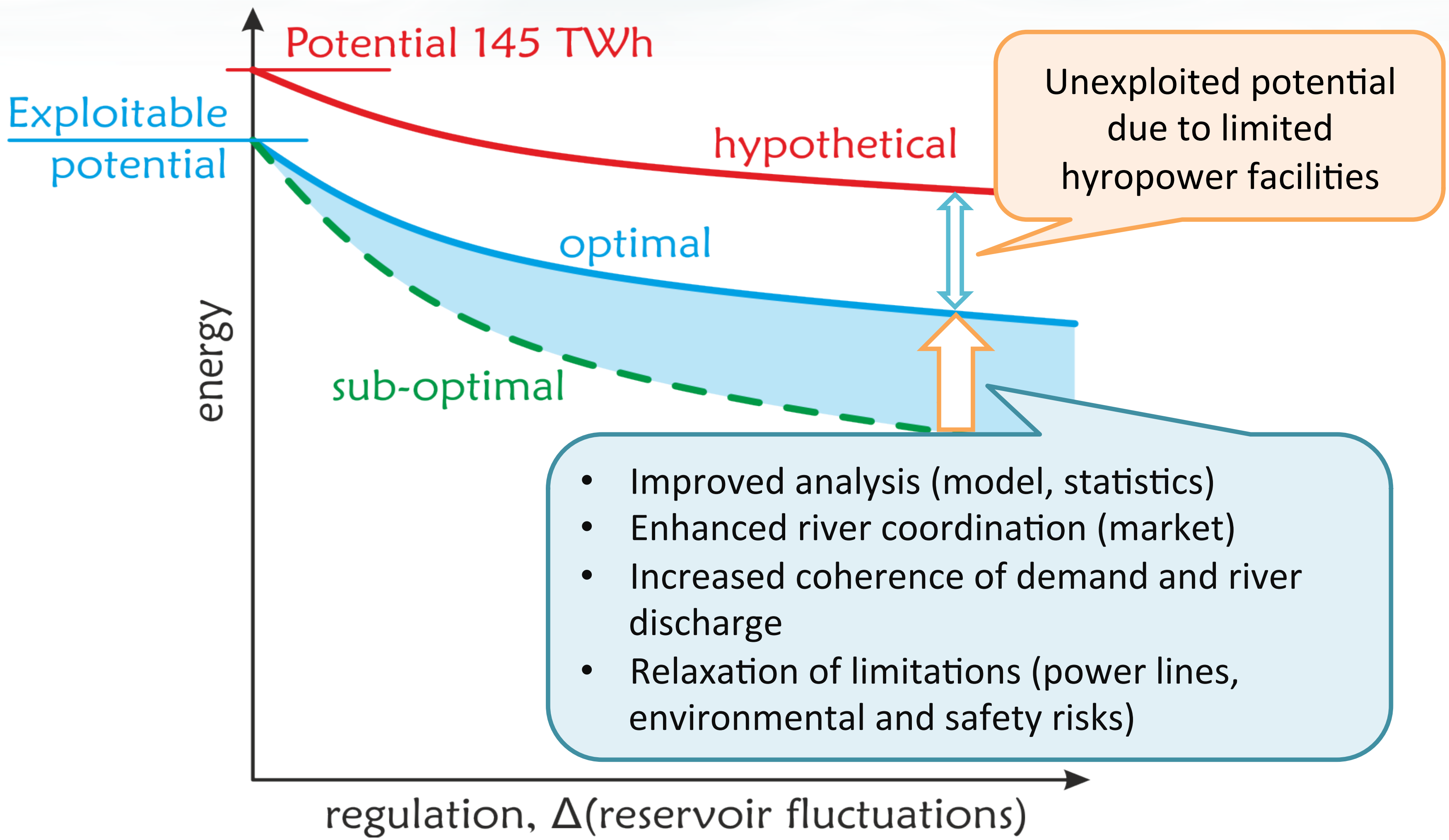
- Improved management of water resources
- Sharper tools for river runoff predictions
- Improved optimization models

Hydropower potential in Sweden

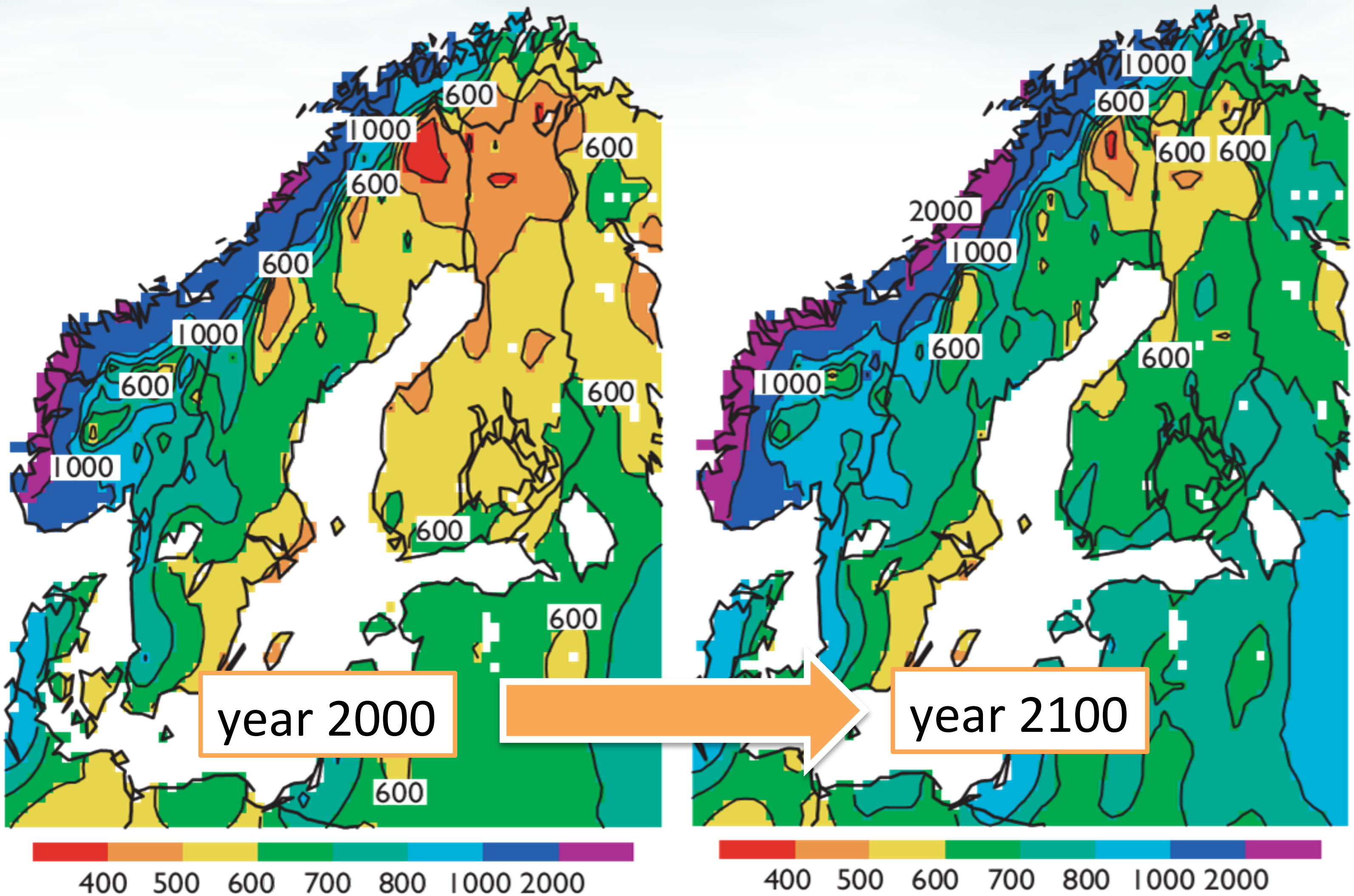
from an unpublished collaboration with Göran Lindström (SMHI)



Potential versus suboptimal energy production



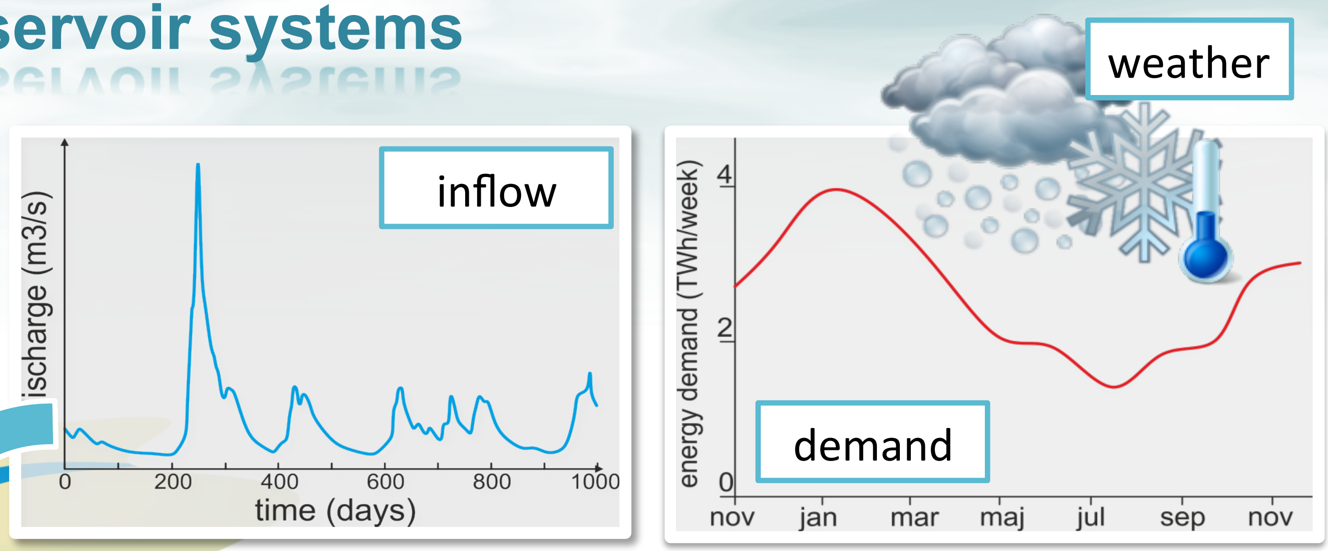
Impacts of climate change

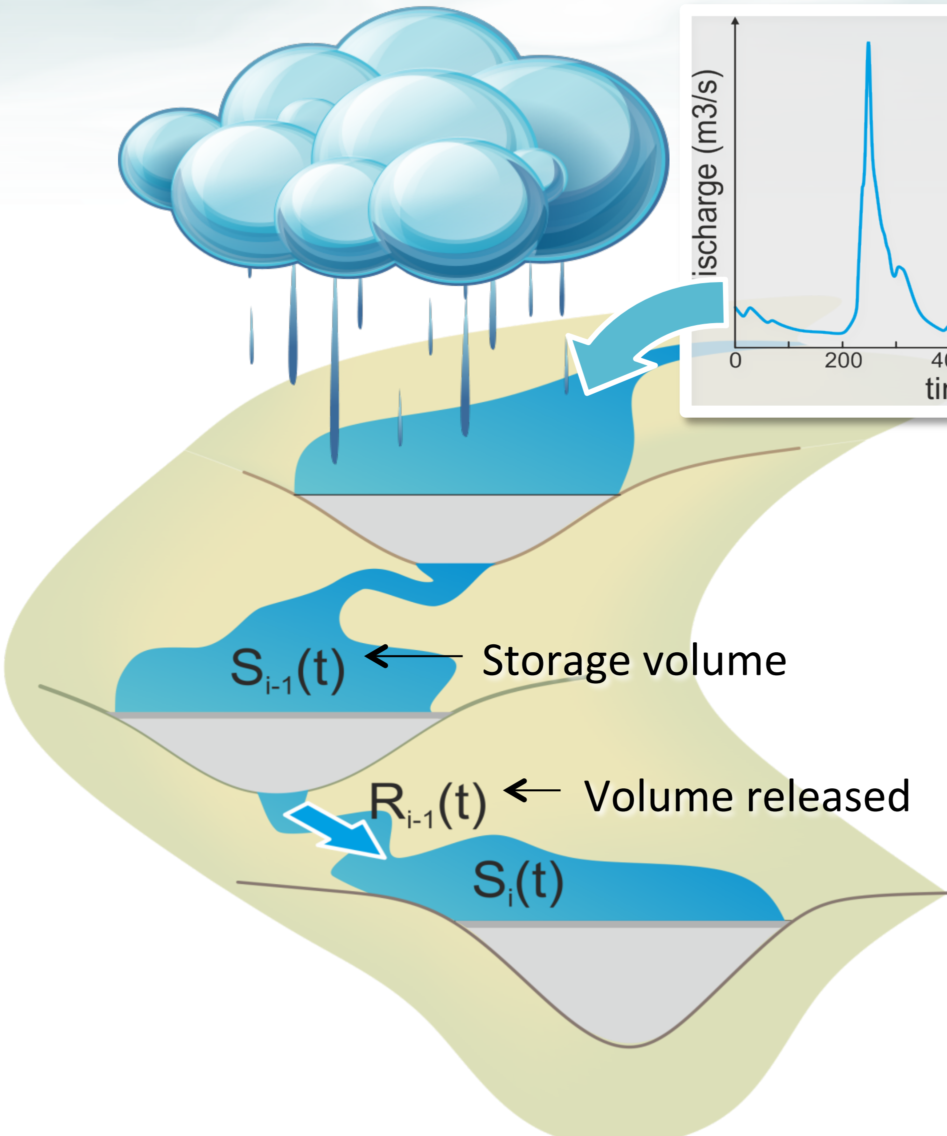


Expected increase of surface runoff: +20-40%

from SMHI/SWECLIM

Operation of multi-reservoir systems





Objective Function

Max. Energy output
Min. Flood risk
etc.

Restrictions

Power transmission constraints
Environmental risks
Other constraints

Operation of multi-reservoir systems

The optimization problem

- ✓ Water balance constraints (system dynamics)

$$S_1^t = S_1^{t-1} + Q_1^t - R_1^t - R_{S,1}^t$$

$$S_i^t = S_i^{t-1} + Q_i^t + R_{i-1}^{t-\tau_{i-1}} + R_{S,i-1}^{t-\tau_{i-1}} - R_i^t - R_{S,i}^t$$

- ✓ Plant active output constraints

$$P_{i,\min}^t \le P_i^t \le P_{i,\max}^t$$

- ✓ Plant generation discharge constraints

$$R_{i,\min}^t \le R_i^t \le R_{i,\max}^t$$

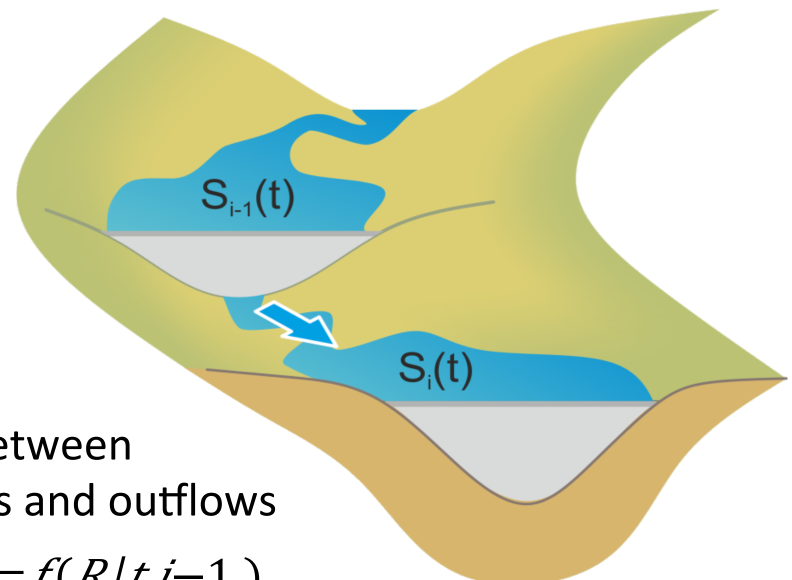
- ✓ Reservoir water-holding capacity constraints

$$S_{i,\min}^t \le S_i^t \le S_{i,\max}^t$$

- ✓ Objective function

$$J = \mathrm{Max} \sum_{t=1}^{T} \sum_{i}^{N} E(H_i^t, R_i^t)$$

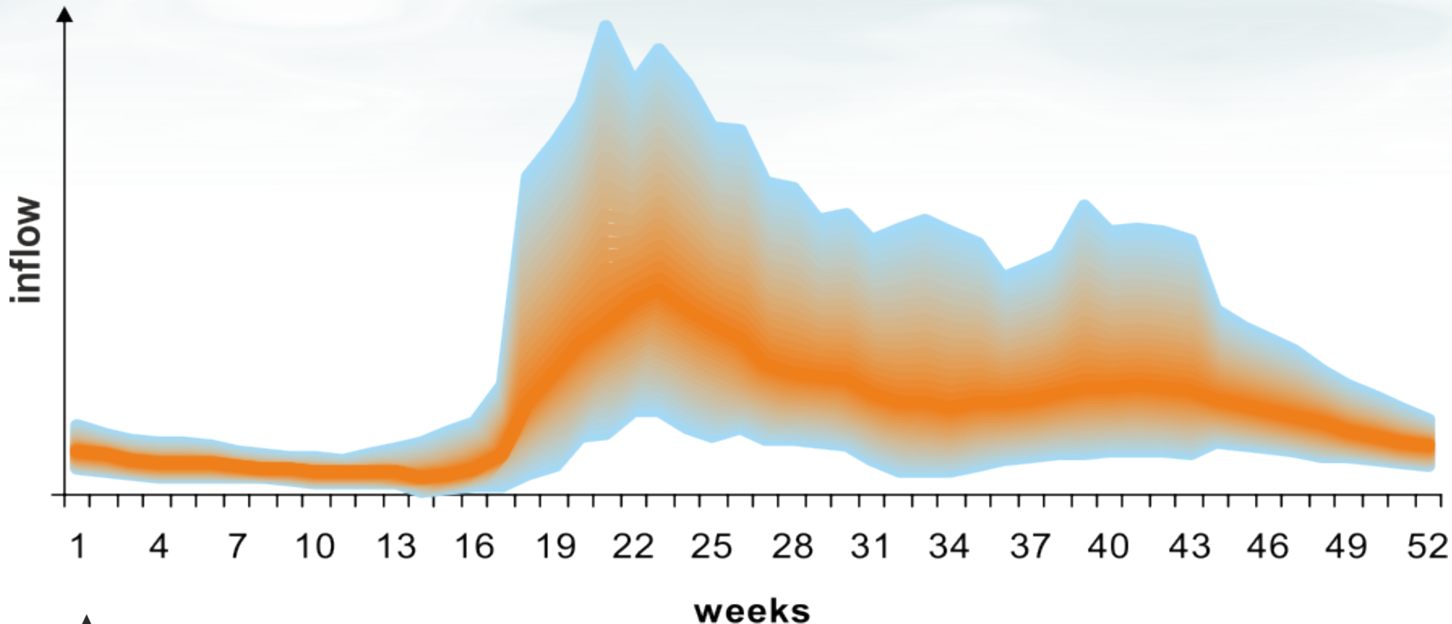
Flow routing between reservoirs

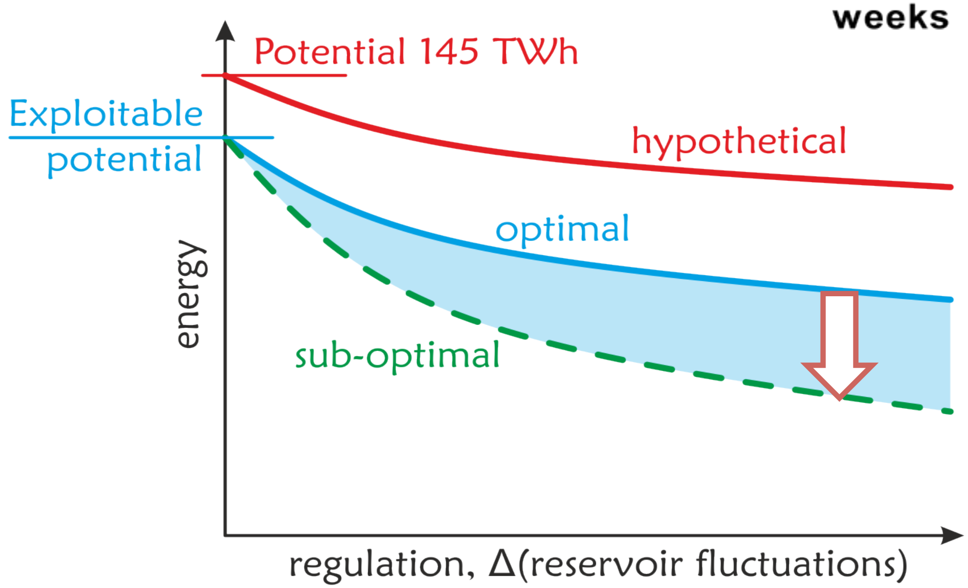


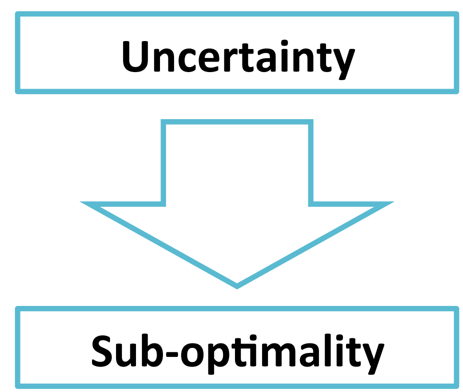
Link between
Inflows and outflows

$$R_{t,i} = f(R_{t.i-1})$$

Reservoir operation under forecast uncertainty

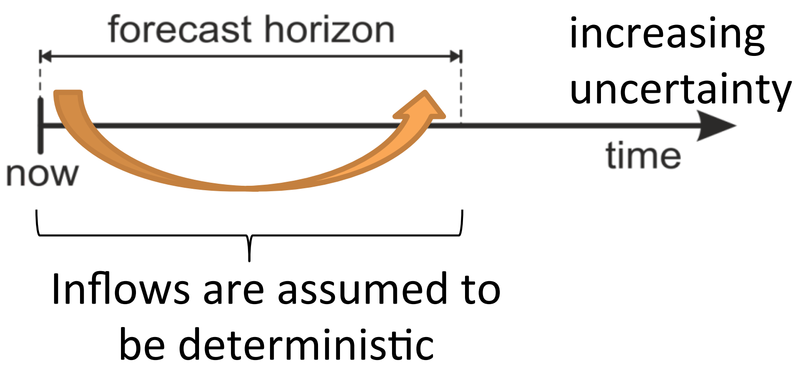




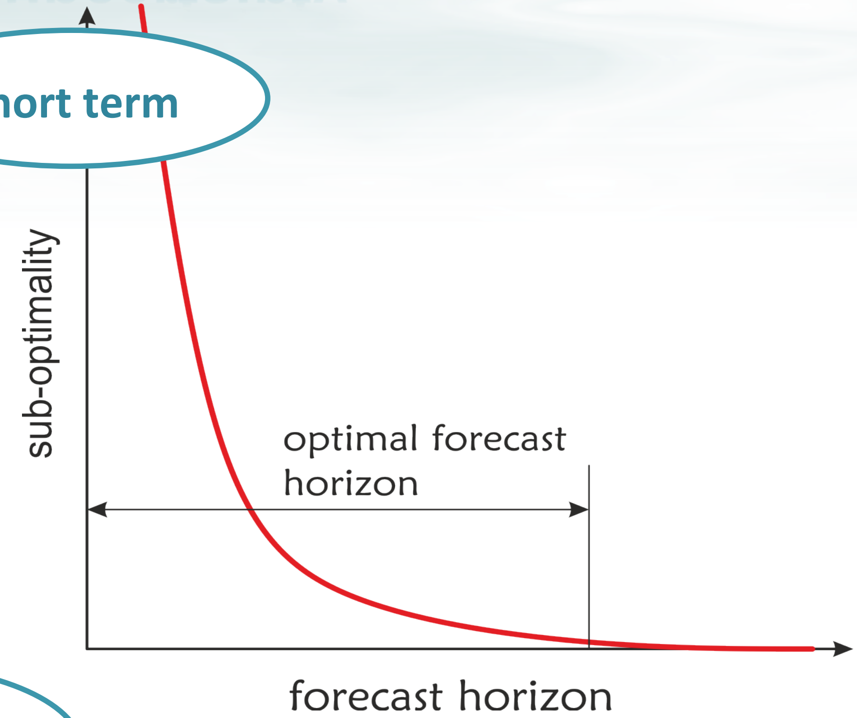


Reservoir operation under forecast uncertainty

Deterministic optimization methods
(Myopic policies or rolling horizon methods)



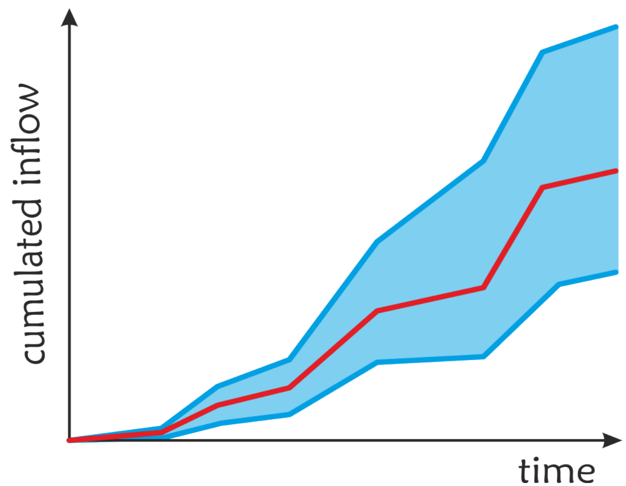
Short term



Stochastic optimization methods

Mid- and Long- term

- Assume inflows are random variables
- Account for different scenarios
- May lead to substantially different operation policies than deterministic methods
- More complex



Operation of multi-reservoir systems

- Optimality equation (Bellman 1957)

$$V_t(S_t) = \max_{R_t} \left(P_t(S_t, R_t) + \gamma E\{V_{t+1}(S_{t+1}) | S_t\} \right)$$

Discount factor

Expectation

Value function

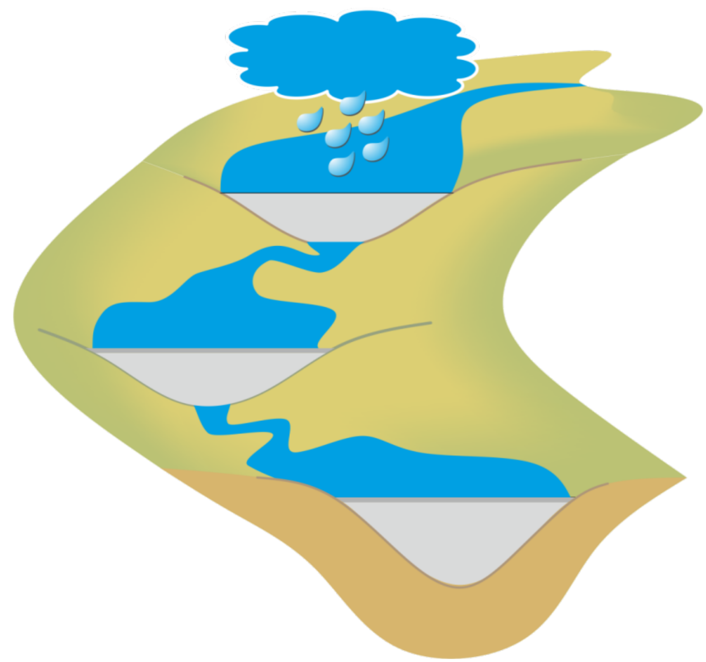
Storage

Utility function

Controllable releases

- The computational requirements increase exponentially with the number of reservoirs ("curse of dimensionality")

- Possible solutions:
  - ❑ Approximate dynamic programming (ADP) and reinforcement learning techniques



Approximate dynamic programming (ADP) using function approximators

- The value function is expressed as a sum of basis functions

$$\bar{V}_t(S_t)=\sum_f \theta_{ft}\,\phi_f(S_t)$$

- The optimality equation is solved forward in time starting from an initial estimate of the value function

- The coefficients of the value function approximation are determined iteratively via an offline learning process considering a number of inflows scenarios

- Once the value function has been determined, the optimal operating policy is obtained directly from the optimality equation:

$$V_t(S_t)=\max_{R_t}\left(P_t(S_t,R_t)+\gamma\, V_{t+1}(S_{t+1})\right)$$

Generation of stochastic inflow series

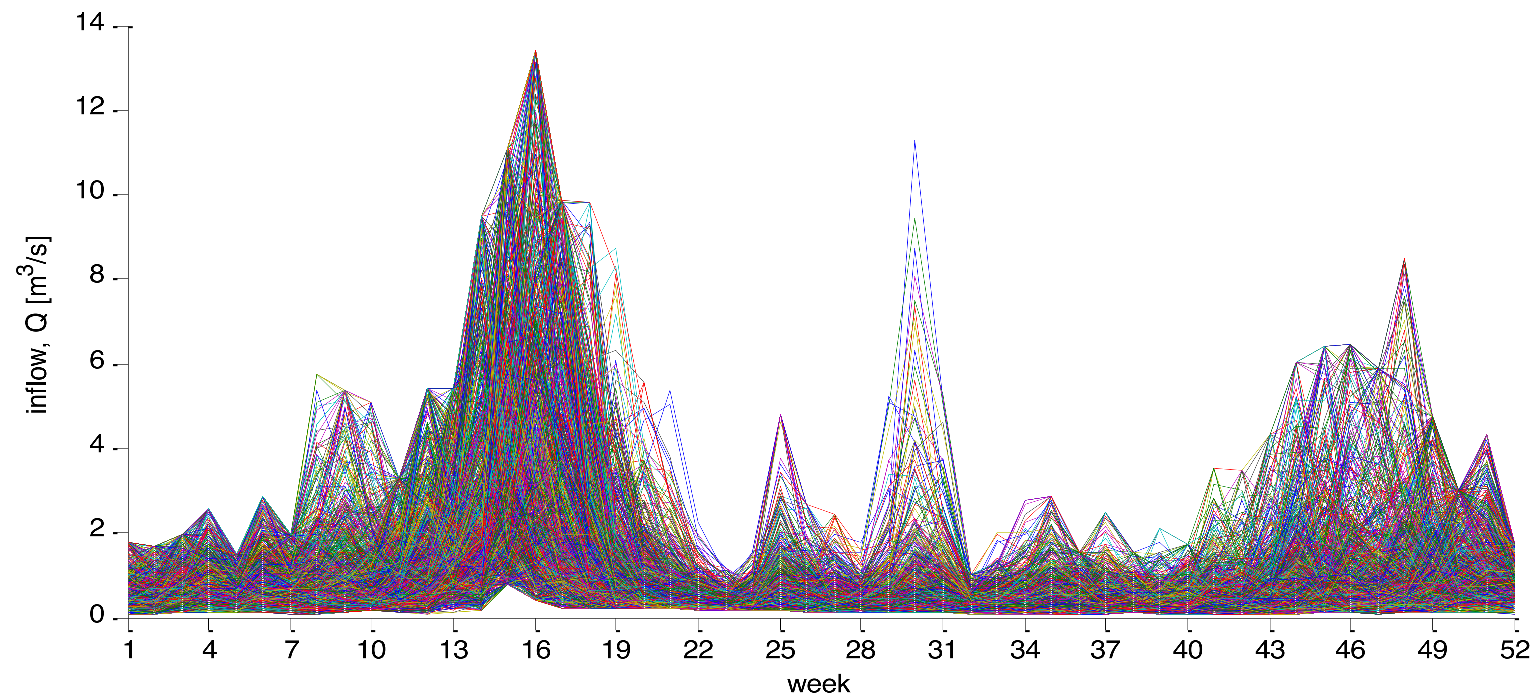
- Periodic Autoregressive Model

Standard normal random variable

$$Q_t^N = a_{0,t} + a_{1,t} Q_{t-1}^N + a_{2,t} \zeta_t \quad , \quad t = 1, 2, \ldots, 52$$

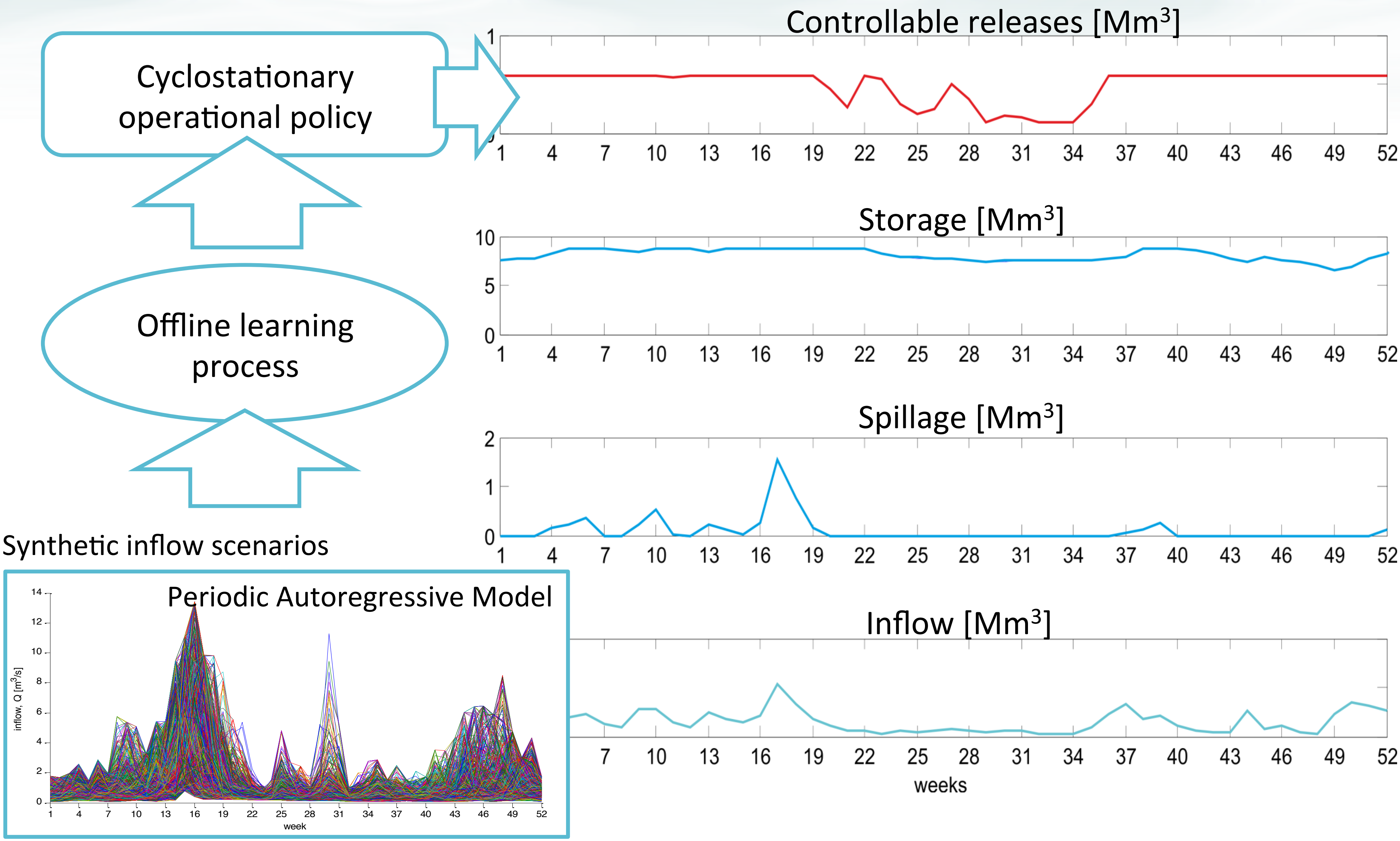
Normalized inflow

Synthetic inflow scenarios

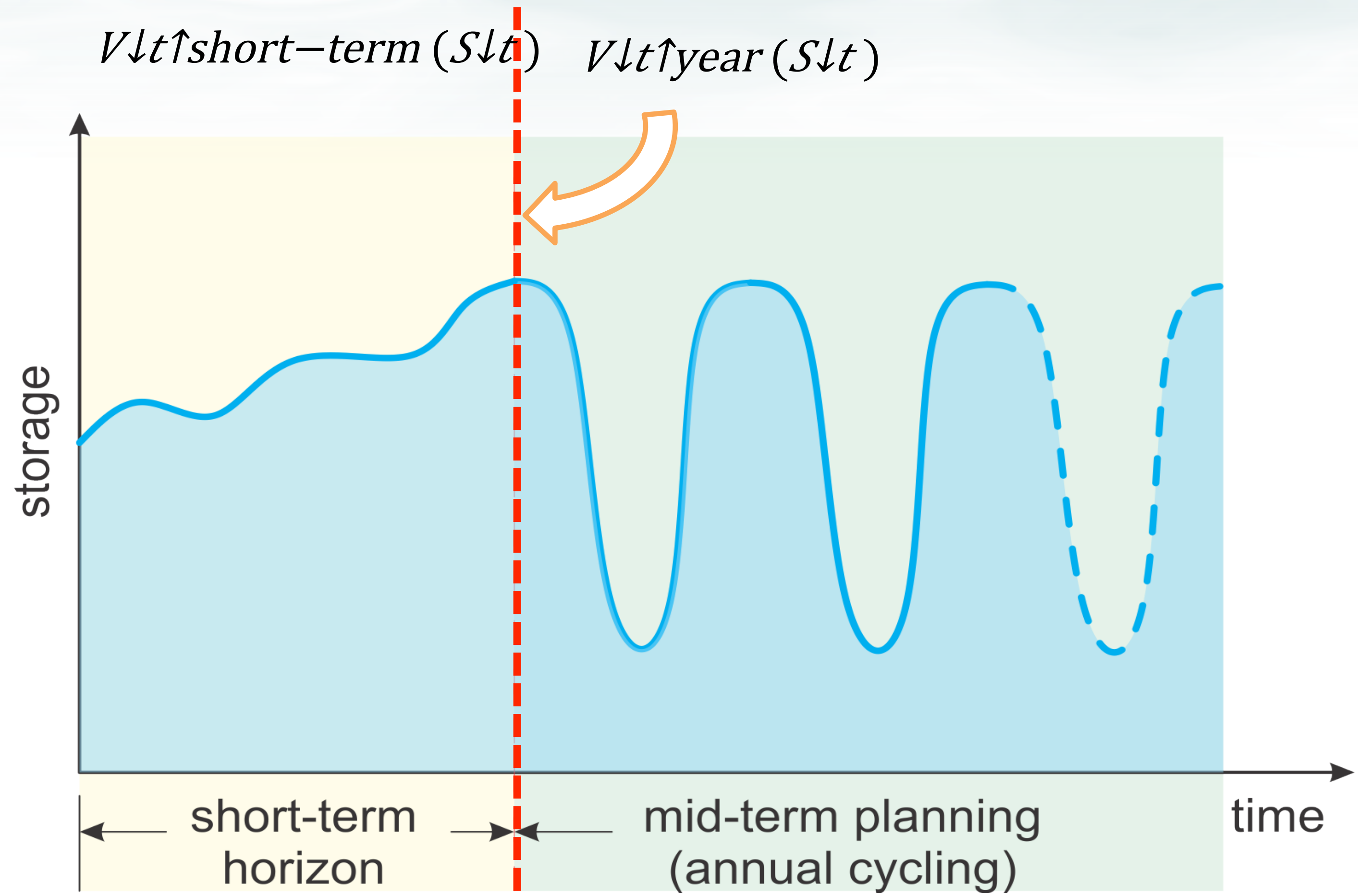


Optimization under uncertainty

An ADP algorithm for stochastic multi-reservoir operation

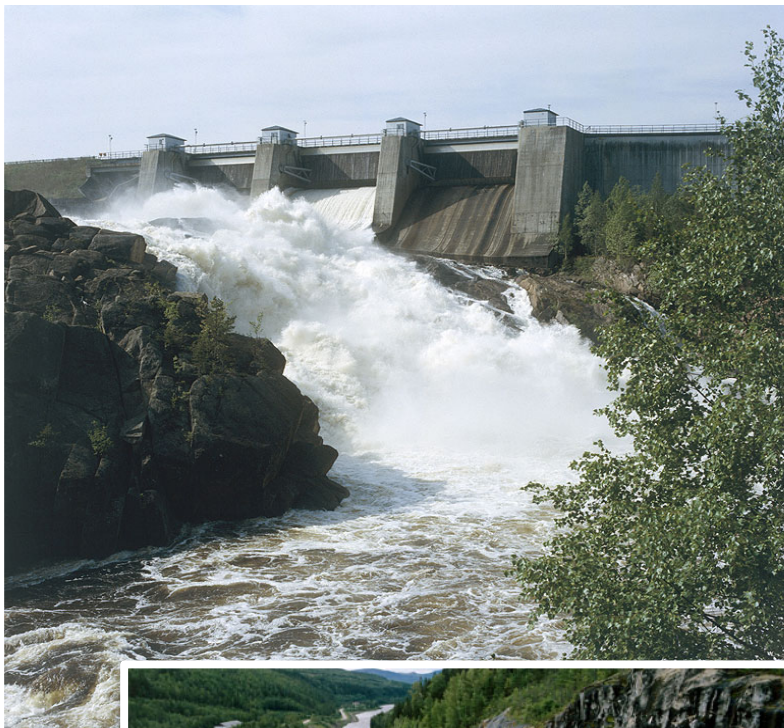


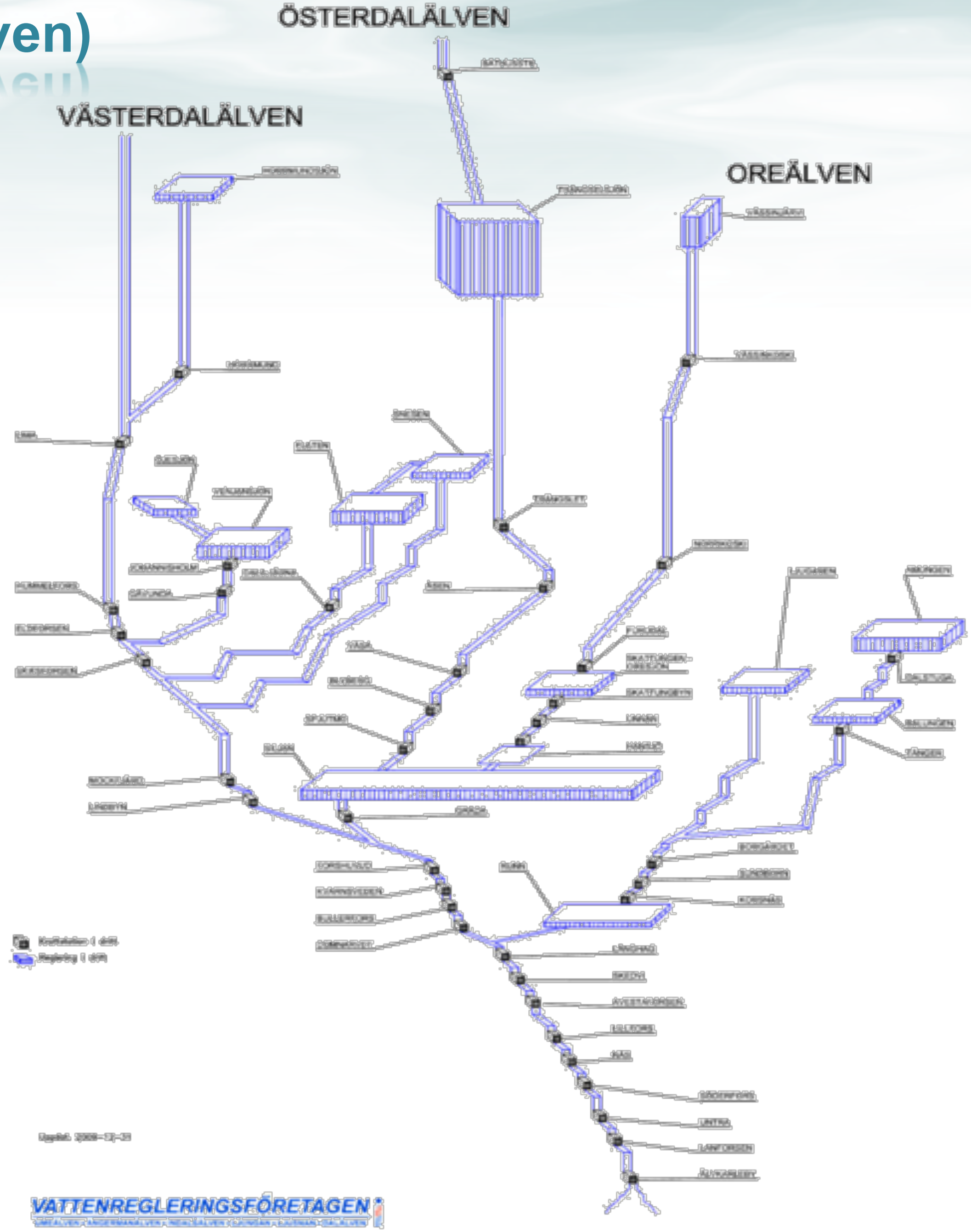
Combined short- and mid-term planning



Synthetic inflows are generated assuming the variance of the forecast error increases linearly with time

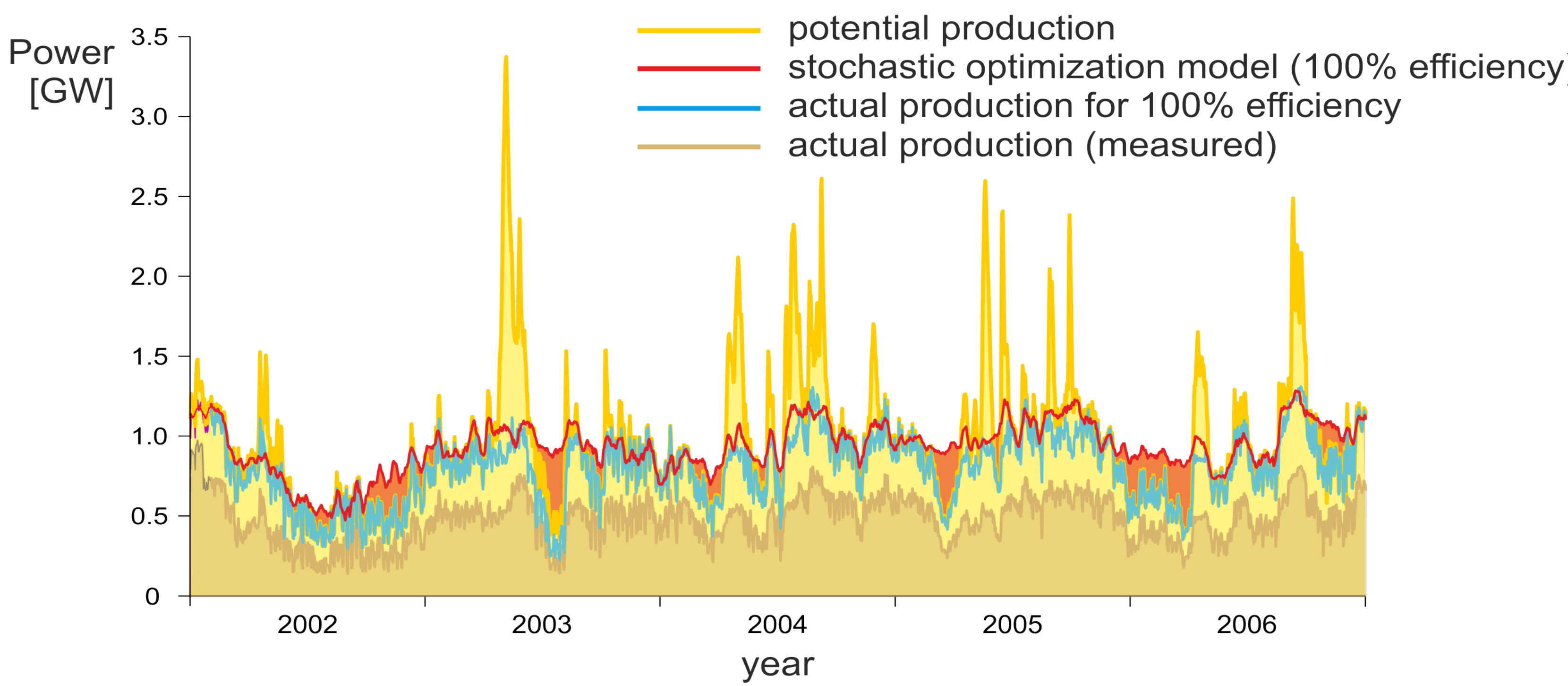
Case study: The Dal river (Dalälven)





Case study: The Dal river (Dalälven)

Potential production	8.3 TWh/year
Actual production (measured)	4.2 TWh/year
Actual production assuming 100% efficiency	6.8 TWh/year
Stochastic optimization model assuming 100% efficiency	7.7 TWh/year
Optimization with perfect information assuming 100% efficiency	8.1 TWh/year



Conclusions

- There is potential for significanlty increasing the energy production by managing water resources more efficiently

- The efficiency of water management policies is affected by uncertainty and forecast errors

- A new stochastic optimization model for multireservoir systems has been developed
  - The curse of dimensionality is solved using an approximate dynamic approach
  - The method combines mid- and short-term planning

- Further model developments will consider:
  - Different variants of the algorithm
  - Comparison with other deterministic and stochastic optimization models for small-scale problems
  - Incorporation of a flow routing model


Thank you!