

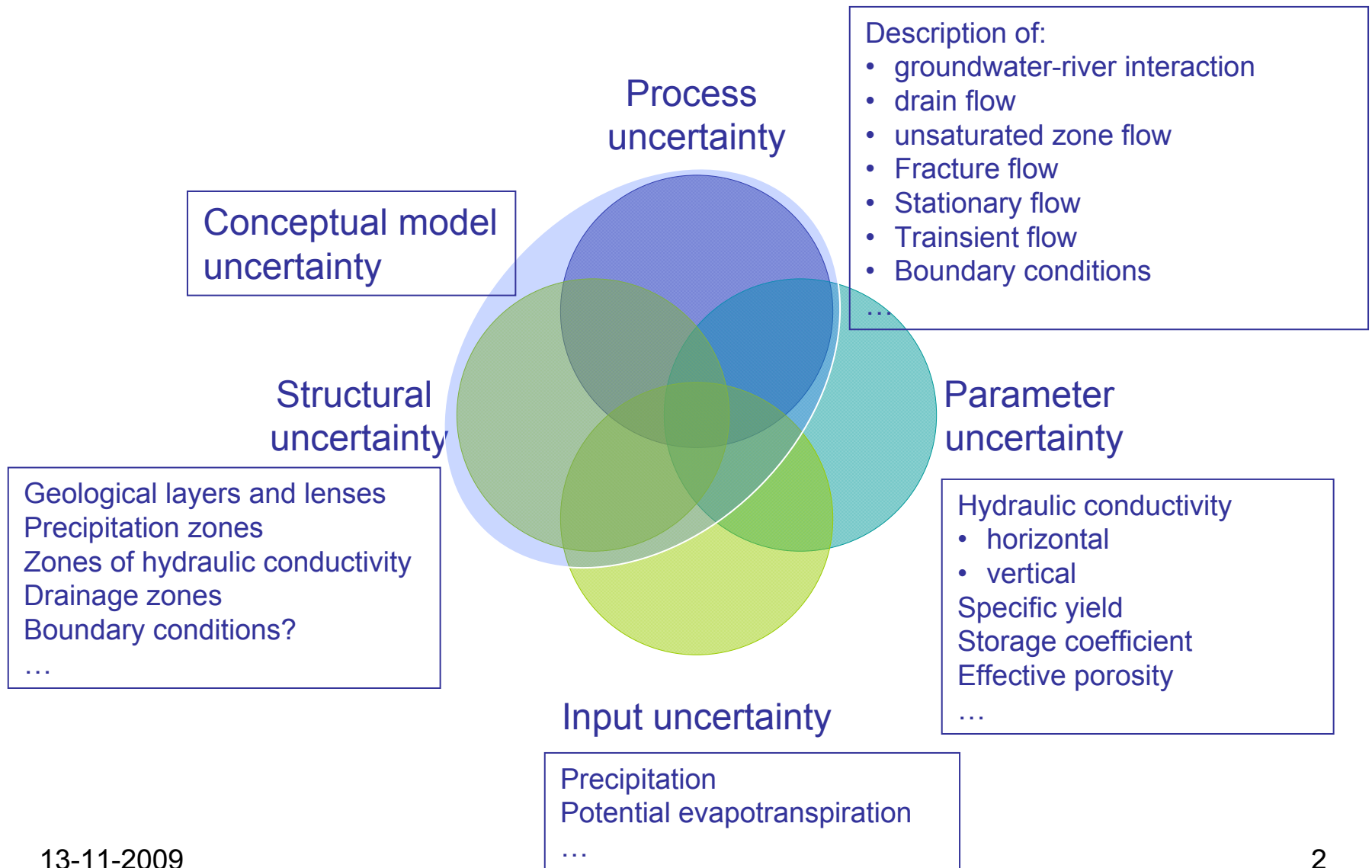
Questions:

What is calibration?

Why do we have to calibrate a groundwater model?

How would you calibrate your groundwater model?

Uncertainties in groundwater models



Calibration



Simulated state variables →
Observed state variables

which parameter should be calibrated?

In principle:

- all parameters that are uncertain

In practice:

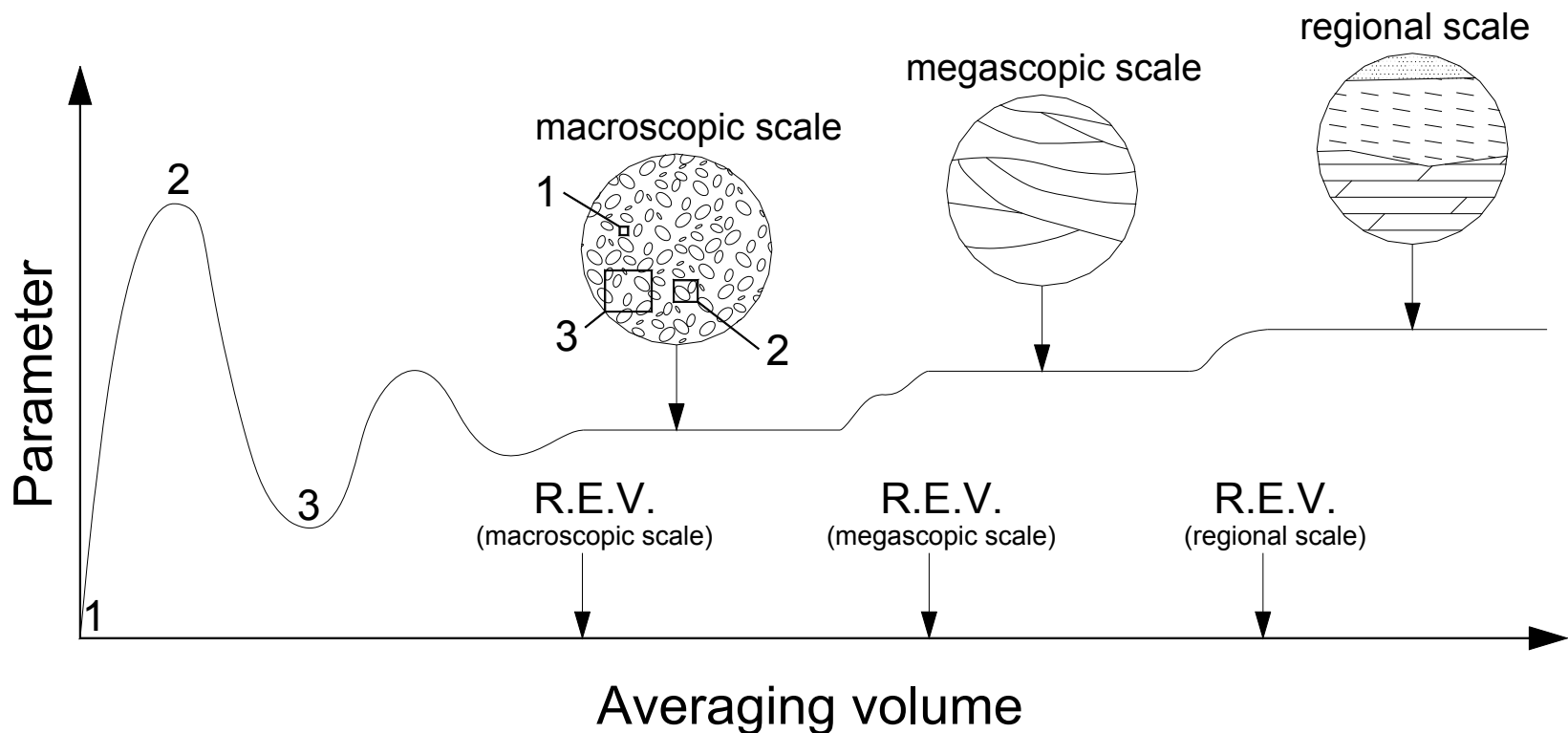
- the most uncertain parameters
- Parameters that can be identified from the observed state variables



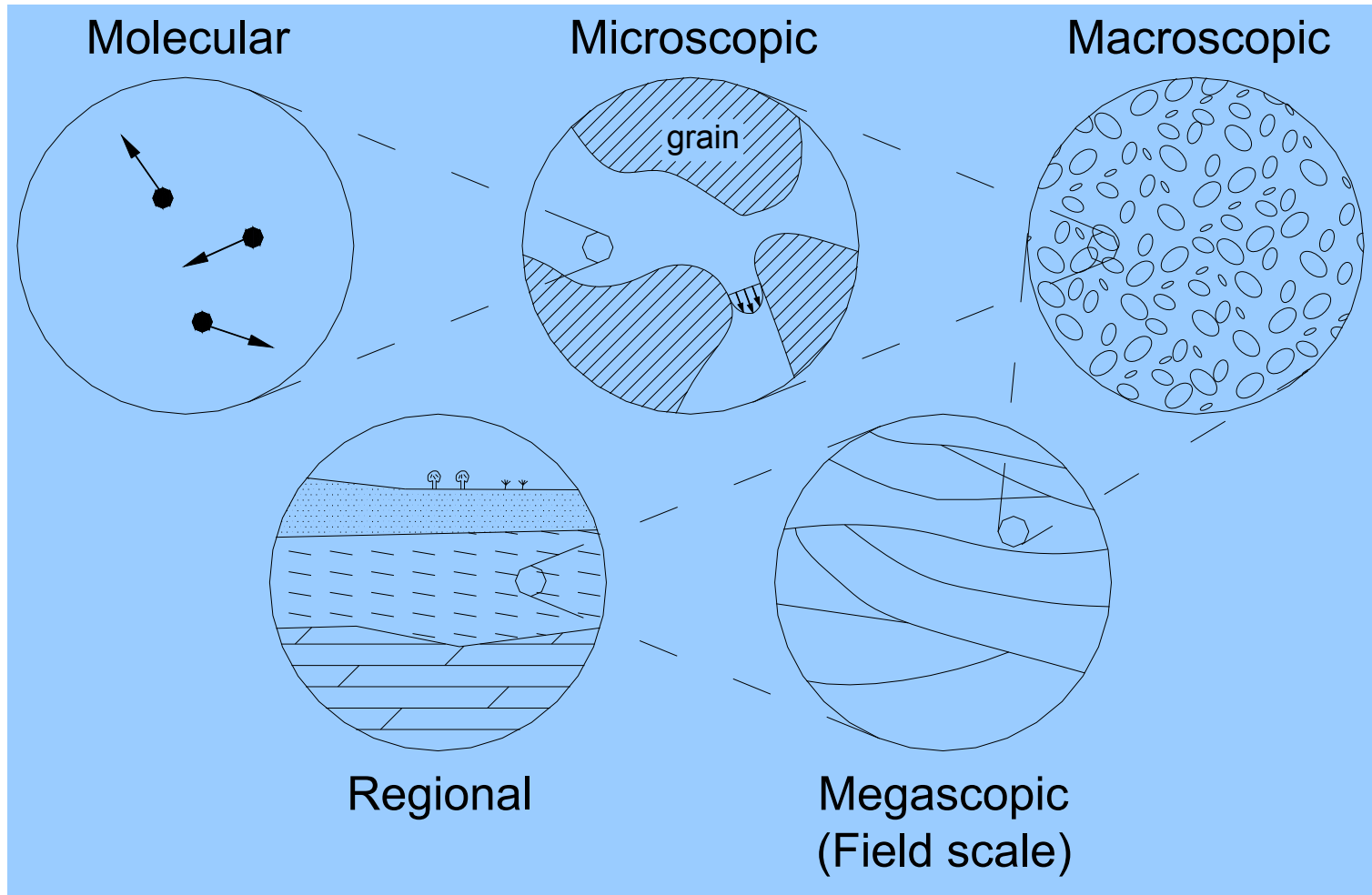
Hydrogeological parameters and especially hydraulic conductivity are target for calibrations

Why don't we just measure the uncertain parameters?

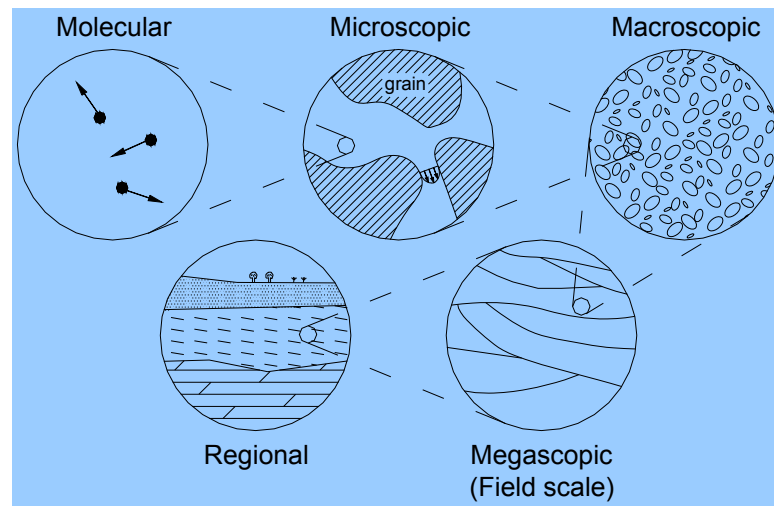
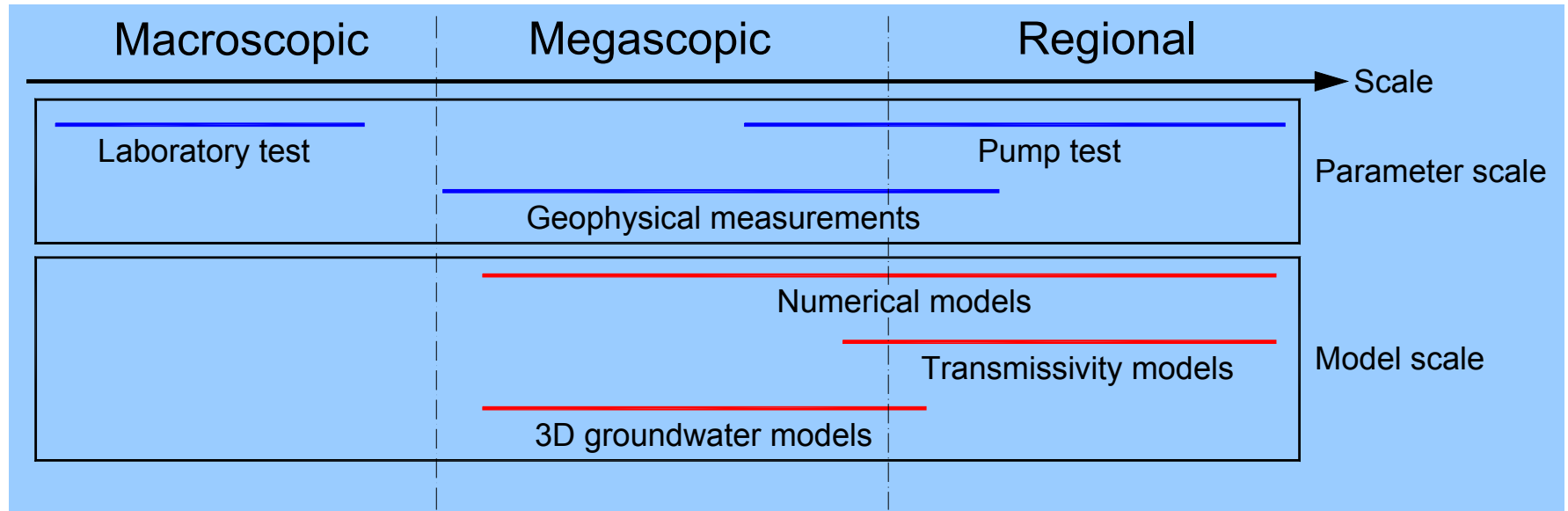
- A question of money and scale



Different scales



At what scale do we measure the parameters and at what scale do we use the parameters?



Parameterization



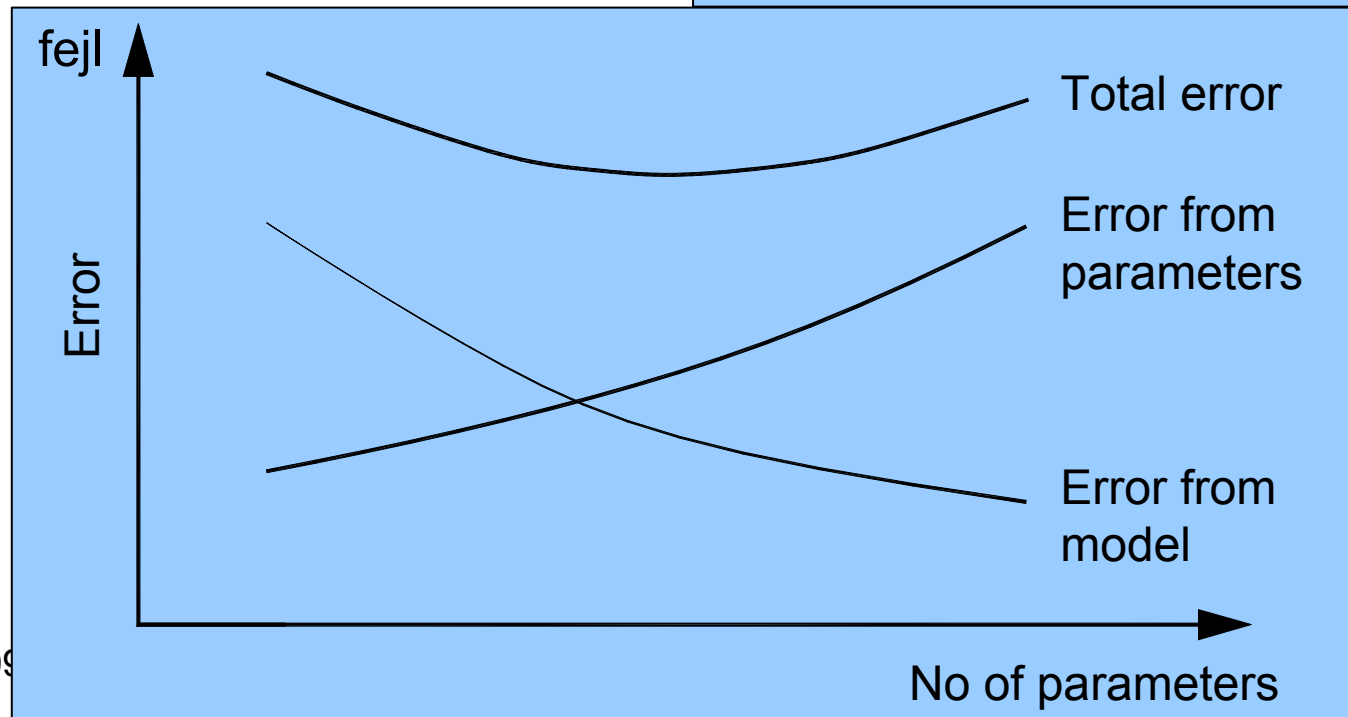
From an "infinite" number of parameters to a "finite" number of parameters.

The highest number of parameters?

- K_x , K_y , K_z , S_y , S_s i each cell!

The smallest number of parameters?

- one value K_x , K_y , K_z , S_y , S_s in the entire model area!



Parameter estimation

Why can't we find a parameter set that gives a perfect match to the real world (observations)?

- Comparing simulated head and observed head

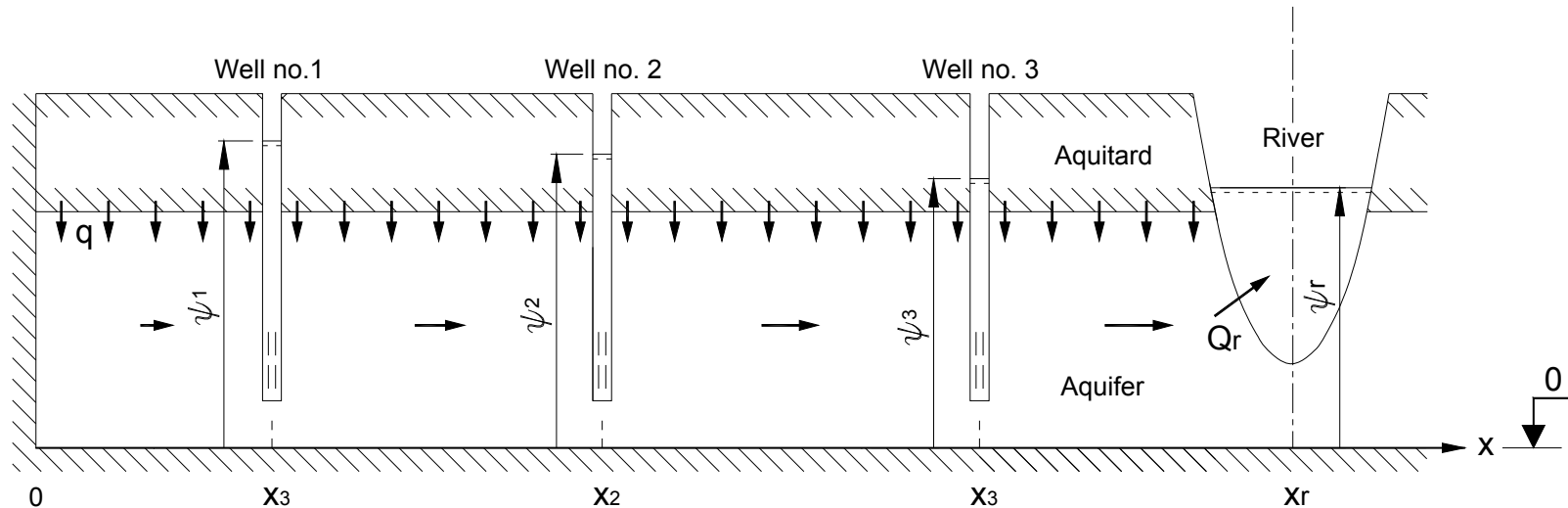
	Obs. error	Scale errors				non stationarity	Total error
		Vertical	Interpolation	Terrain	Heterogeneity		
Esbjerg	0.1	0.1	0.5	0.1	1	0.5	1.2
Fyn	0.1	0.1	1.5	0.2	2.1	0.5	2.6

(Ståbi i grundvandsmodellering, 2000)

Expected errors on simulated groundwater potential:

	Error contribution	Standard deviation [m]
Observation error	Measuring equipment	0.03
	Reading and bookkeeping	0.05
	Reference level	0.05 - 2.0
	Atmospheric pressure	0.0 - 0.15
Scale error	Horizontal discretisation	$0.5 D_x J$
	Vertical discretisation	$0.5 J_v D_z - 2.0$
	Topographical variations	s_{topo}/d
	Heterogeneity	$\sqrt{\frac{1}{3} J^2 \sigma_{\ln K}^2 \alpha_l^2}$
Time effects	Non-stationarity	$DH/2$
Total error		$\sqrt{\sum \sigma^2}$

Uniqueness



Unknown parameters:

q : Infiltration

T : Transmissivity

Governing equation:

$$\psi(x) = \frac{q}{2T} (x_r^2 - x^2) + \psi_r$$

Observations:

Case 1: potential, ψ_1, ψ_2, ψ_3

Case 2: potential, ψ_1, ψ_2, ψ_3

Stream discharge, Q_r

Case 1: Non-unique determination of q and T

Case 2: Unique determination of q and T

Requirements for inverse modelling (automatic calibration)

- Unique solution
 - Only one solution can be found
 - Many observation (evenly distributed in the model)
 - Few parameters
 - Different types of observations (head, discharge, etc.)
- Identifiable solution
 - A solution can be found
- Stable solution
 - Small error in an observed state variable leads to small changes in the parameter estimate

Regression based methods

- Search after one optimal parameter set
- Converges to locale minima
- Uniqueness, identifiability and stability is required!
- Parameter uncertainty estimates can be estimated from a gradient analyses near parameter optimum.
- Prediction uncertainty on state variables (head, stream flow, etc.)

Linear model with Gaussian distributed errors



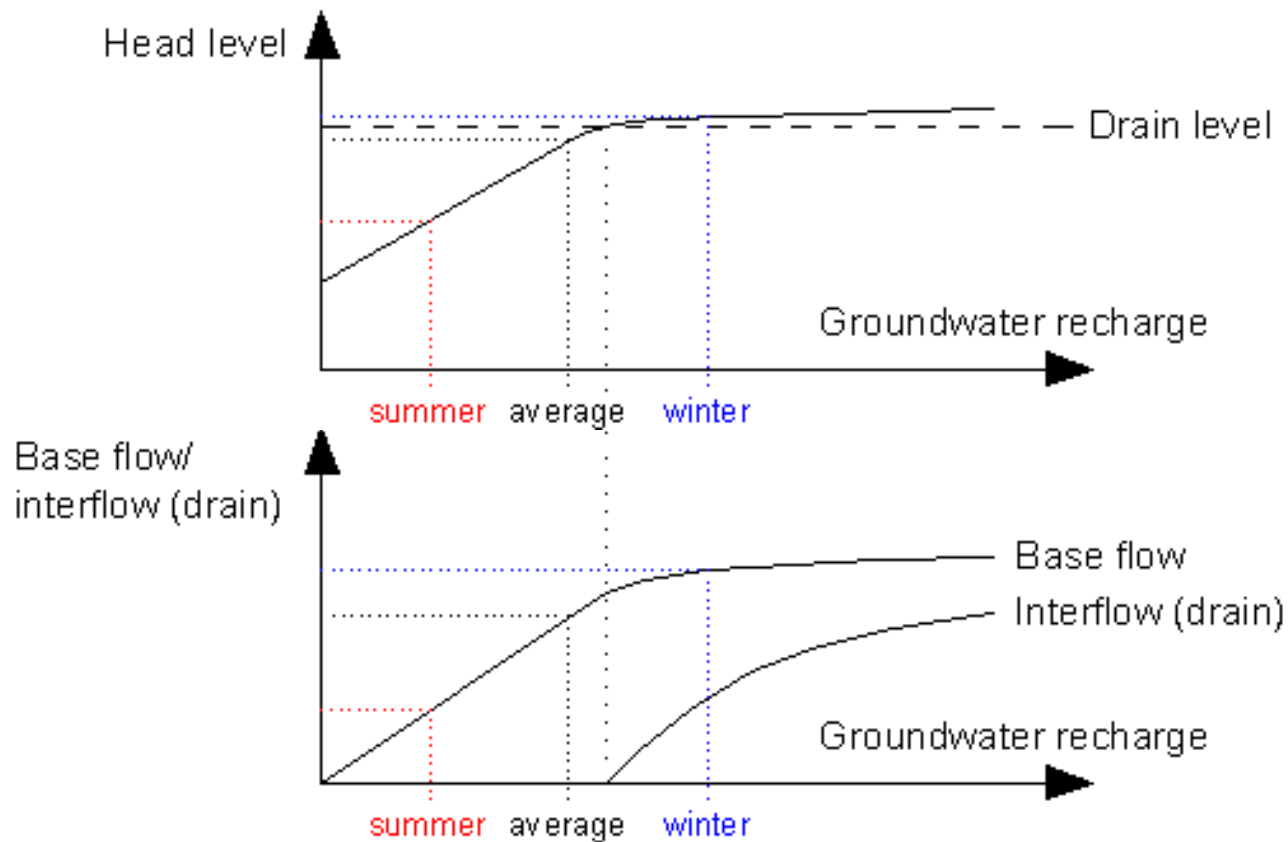
In high dimensional parameter space we have:

- Local minima, valleys and plateaus in the objective function

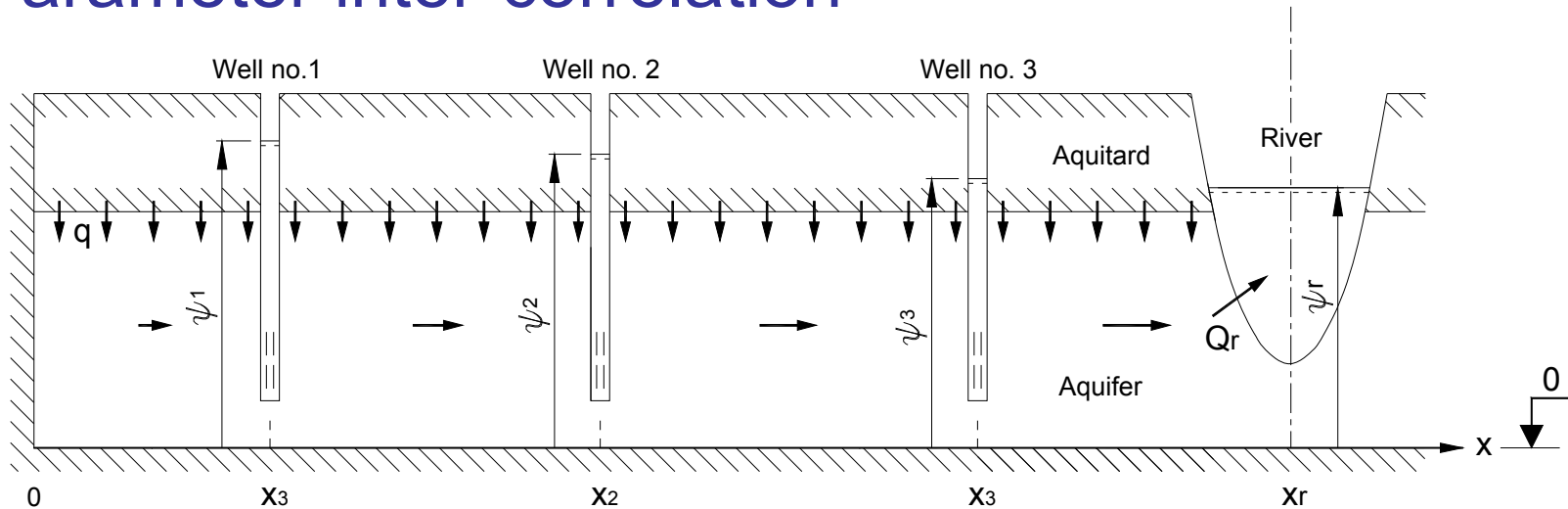
Why?:

- Insensitive parameters (e.g. hydraulic conductivity in a secondary aquifer).
- Threshold processes
- Parameter inter-correlation

- Treshold processes



Parameter inter-correlation



Unknown parameters:
 q : Infiltration
 T : Transmissivity

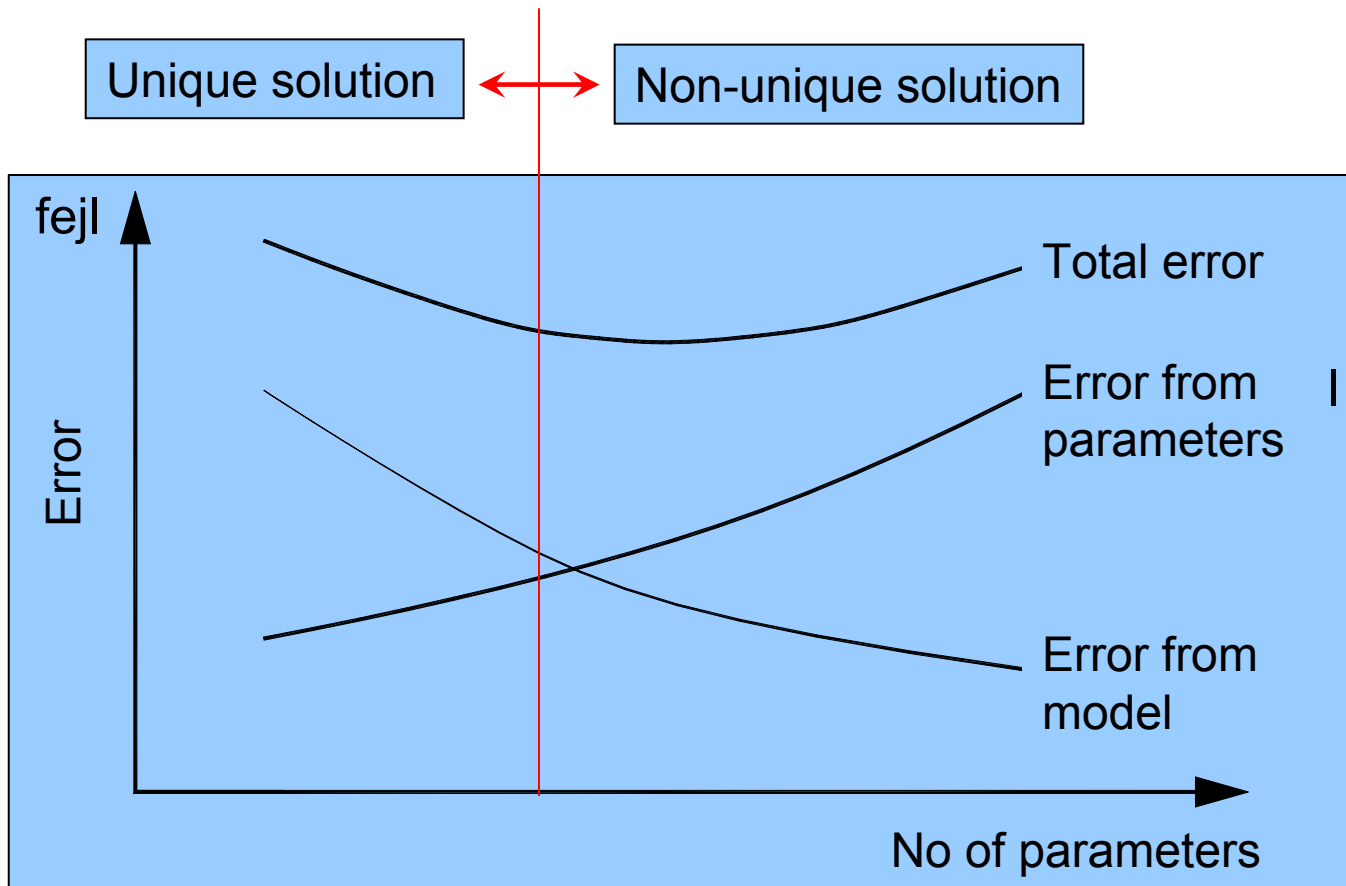
Governing equation:

$$\psi(x) = \frac{q}{2T} (x_r^2 - x^2) + \psi_r$$

$q \uparrow \rightarrow T \downarrow$

The equifinality problem

- *A large number of models, parameters and variables may be acceptable for reproduction of the considered system*



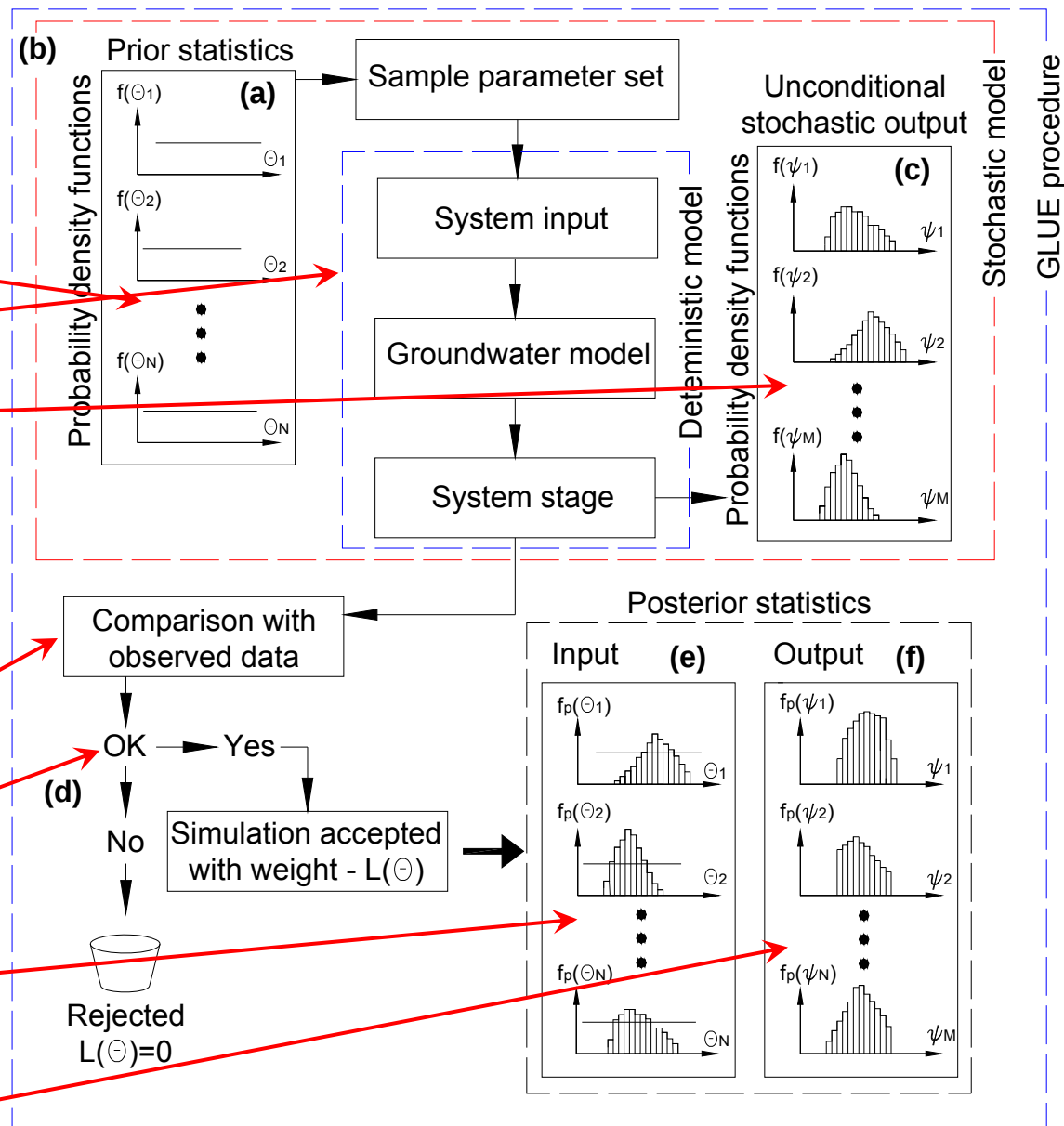
What is GLUE?

Stochastic model:

- stochastic input
- deterministic model
- stochastic output

Parameter estimation model:

- compare results from each deterministic simulation with observations
- reject or accept the simulation
- posterior parameter distribution
- density functions for output

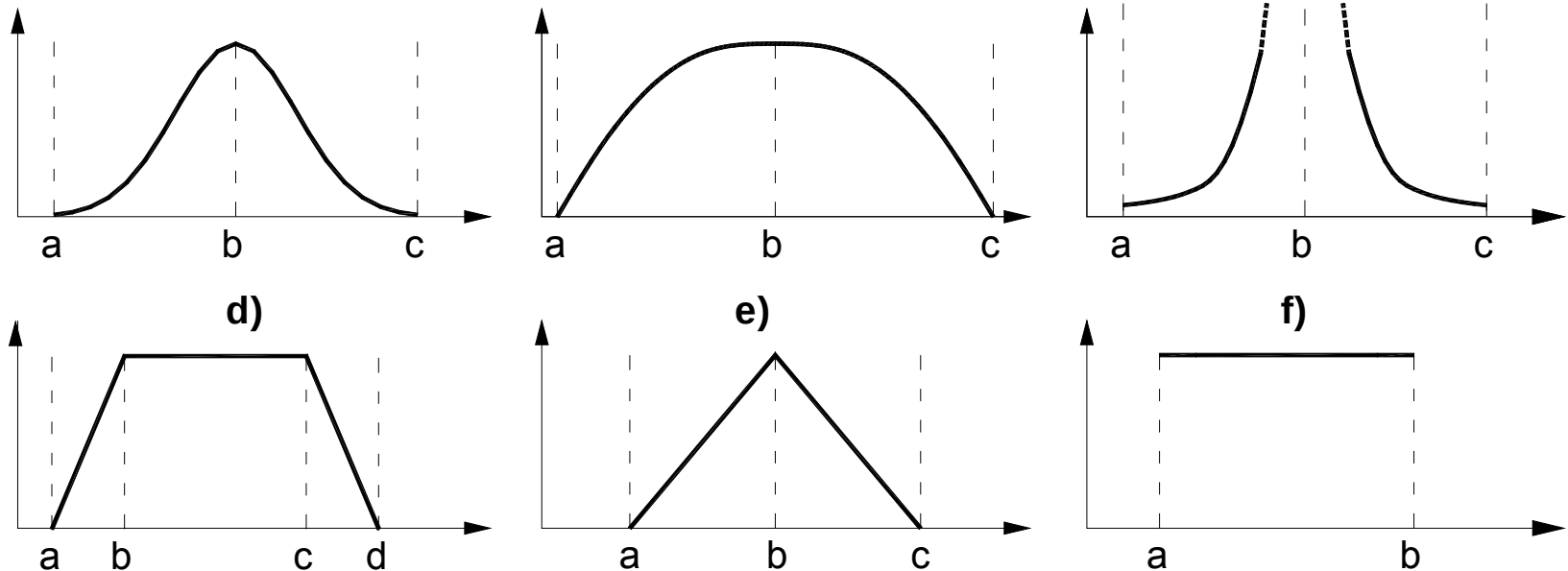


GLUE

Generalized Likelihood Uncertainty Estimation methodology

Calculate the conditional likelihood $L(\theta_i | \mathbf{y}_j^*)$

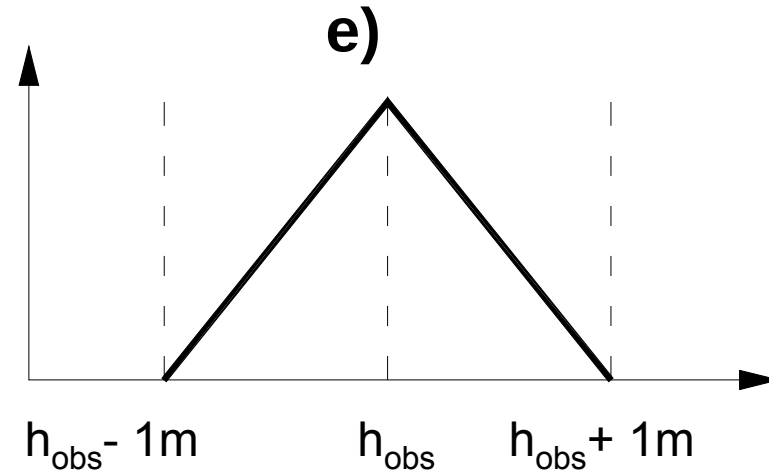
Point likelihood measure:



Likelihood measures

Observed and simulated heads:

Well no.	Sim. head	Obs. head	Point Likelihood
1	29	28.1	0.1
2	28	27.5	0.5
3	26	25.25	0.25



“Global” likelihood:

Geometric inference function

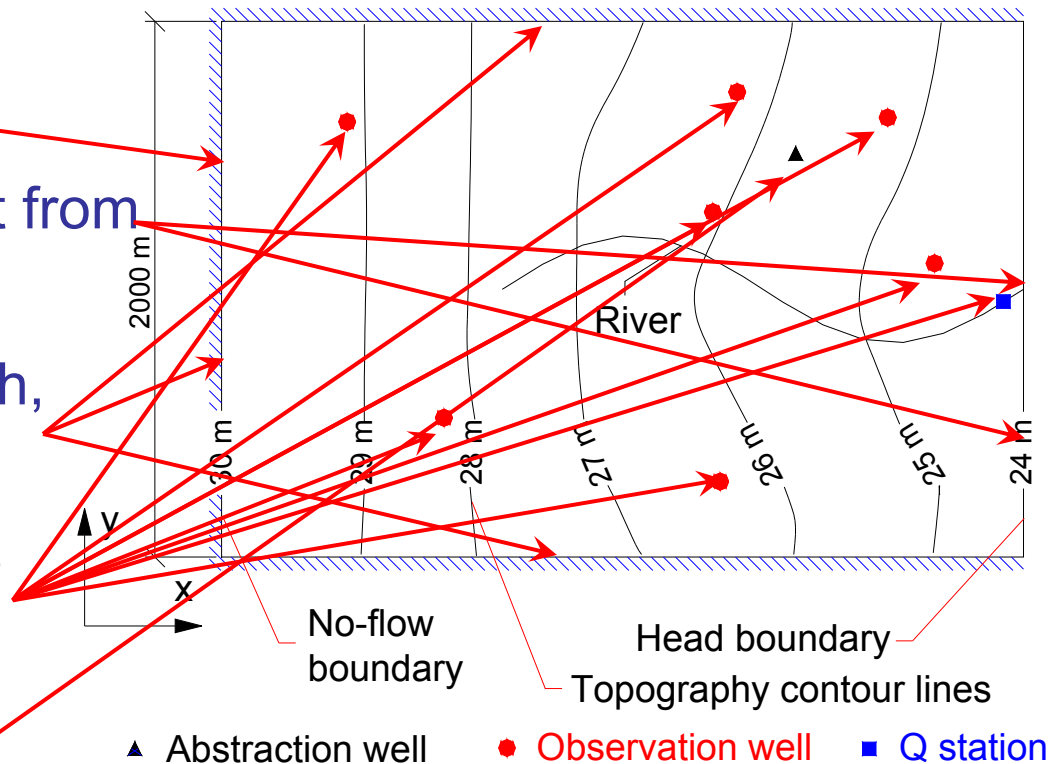
$$L(\theta_i | \mathbf{y}^*) = (L(\theta_i | \mathbf{y}_1^*) L(\theta_i | \mathbf{y}_2^*) L(\theta_i | \mathbf{y}_3^*))^{1/3}$$

$$L(\theta_i | \mathbf{y}^*) = (0.1 * 0.5 * 0.25)^{1/3} = 0.232$$

Case study – synthetic setup

Conceptual model

- River catchment
- Base flow and river outlet from catchment in East
- No-flux boundary at South, West and North
- Head and river discharge gauging points
- Groundwater abstraction



Objective of the case study: **Capture zone estimation**

Case study – synthetic setup

Conceptual model – geological model

Two alternative geological models:

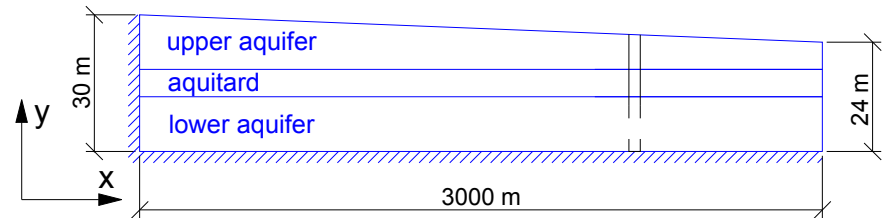
Model A:

- three continuous layers
- constant parameters within each layer

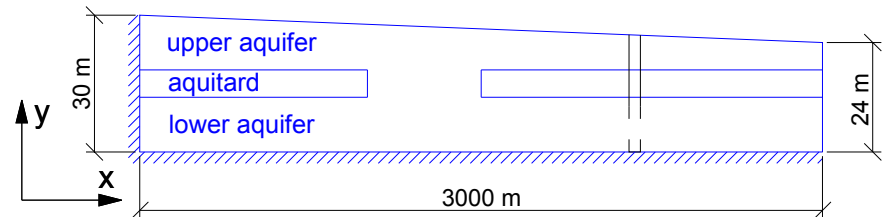
Model B:

- continuous upper and lower aquifer
- sandy window in aquitard
- constant parameters within each layer

Model A



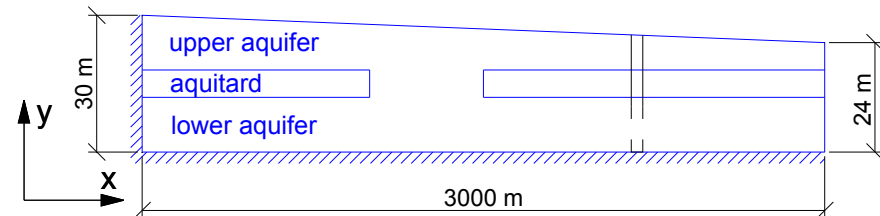
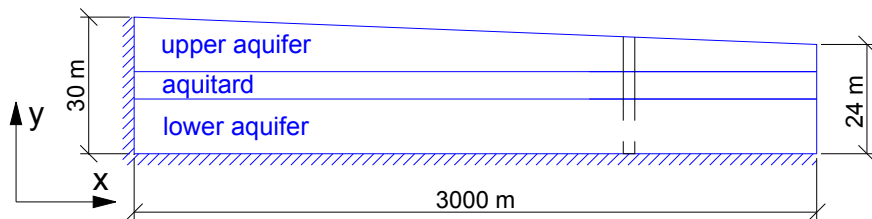
Model B



Case study – synthetic setup

Conceptual model – key parameters

1. Geological model
2. Net precipitation [mm/year]
3. Horizontal conductivity in upper aquifer
4. Horizontal conductivity in aquitard
5. Vertical conductivity in aquitard
6. Horizontal conductivity in lower aquifer
7. Vertical conductivity in lower aquifer



Case study – synthetic setup

Numerical model

Flow model:

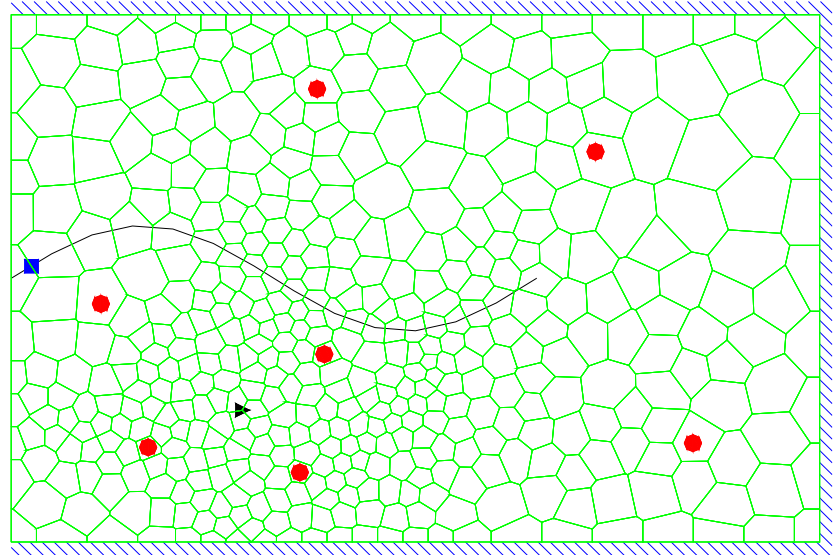
- Unstructured finite difference grid
- Steady state simulation
- River flow: 1D diffusive wave approximation.
- Overland flow: 2D diffusive wave approximation.
- Saturated zone: 3D flow

Fully integrated

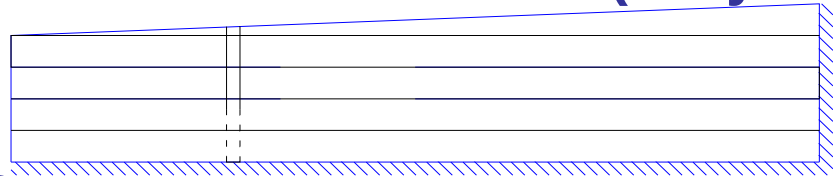
Capture zone determination

- Particle tracking (advective transport)
- Particle transport in all components

Horizontal discretisation (470 elements)



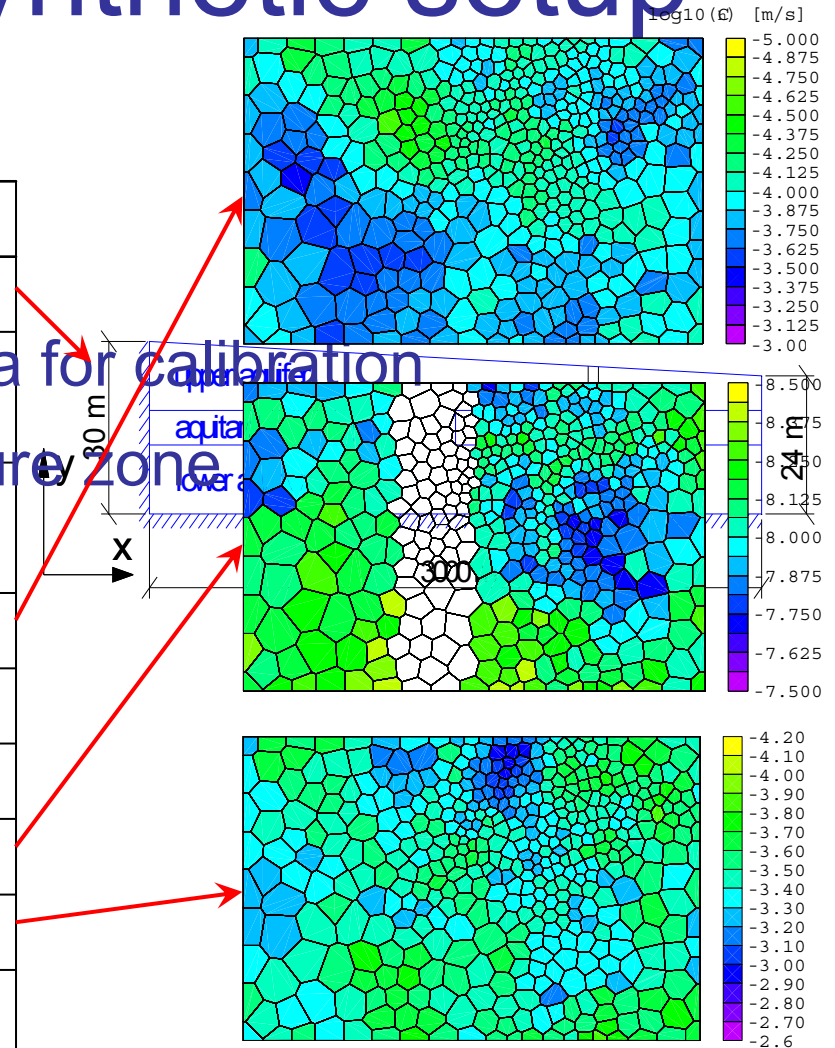
Vertical discretisation (5 layers)



Case study – synthetic setup

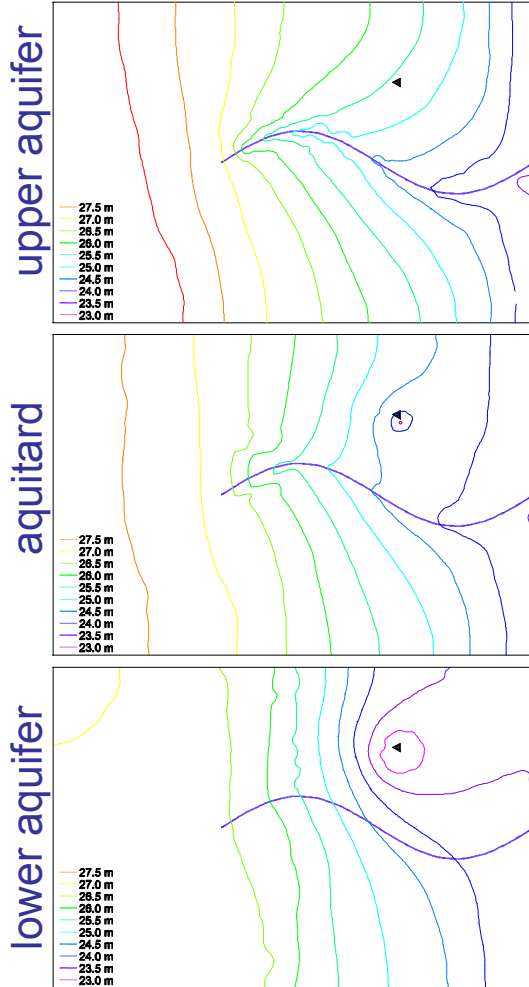
Reference model

		Dist.	Range
Geological model		D	B
Net porosity [mm/year]		D	0.5
Abstraction [mm/year]	Q	D	50
Upper aquifer [m/s]	C_h	D	random field
	C_z	D	1.e-7
Aquitard [m/s]	C_h	D	1.e-8
	C_z	D	random field
Lower aquifer [m/s]	C_h	D	random field
	C_z	D	1.e-6

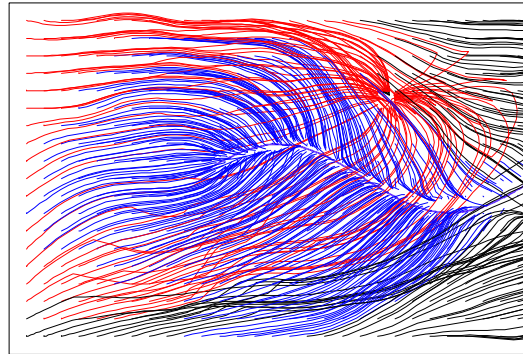


Case study – synthetic setup

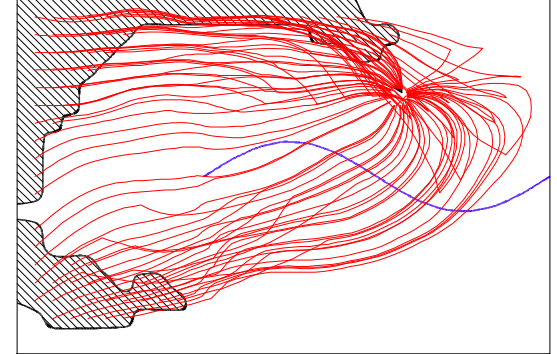
Groundwater potential



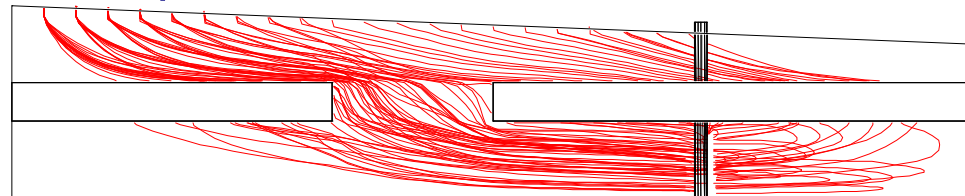
Flow paths



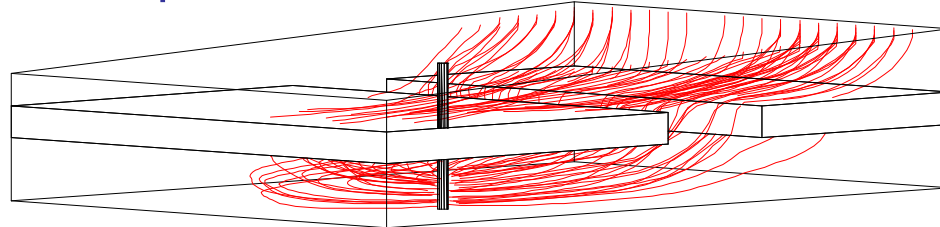
Capture zone



Flow paths – vertical view



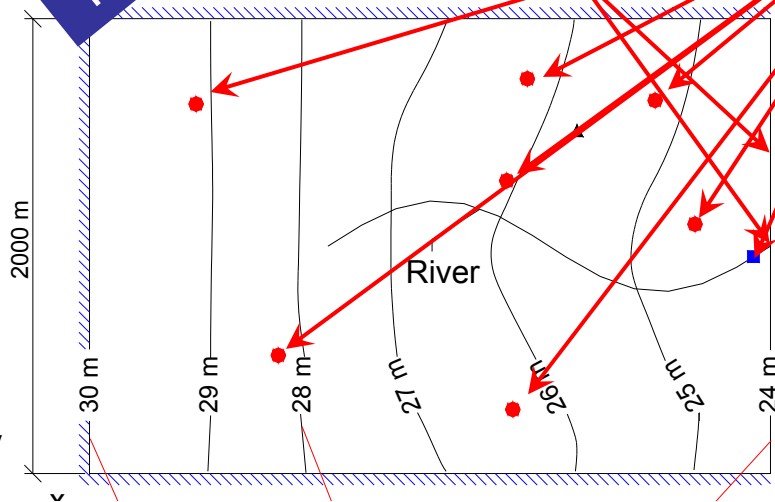
Flow paths – 3D view



Case study – synthetic setup

What have we got?

- two conceptual models
- conceptual model error
- many parameters
- few observations (lower aquifer)
- ill-posed calibration problem
- water balance



		Dist.	Range
Geological model		U	A;B
Net precipitation [mm/year]	p	U	270 – 330
Abstraction [mm/year]	Q	D	50
Upper aquifer [m/s]	C_h	$L_{10}U$	1.E-5 – 5.E-3
	C_z	D	1.0E-7
Lower aquifer [m/s]	C_h	$L_{10}U$	5.E-9 – 5.E-7
	C_z	$L_{10}U$	5.E-9 – 5.E-7
River discharge [m/s]	C_z	$L_{10}U$	1.E-5 – 5.E-3
	C_z	$L_{10}U$	1.E-6 – 1.E-4

Net precipitation unknown

Boundary base flow unknown

River discharge uncertain

Case study – synthetic setup

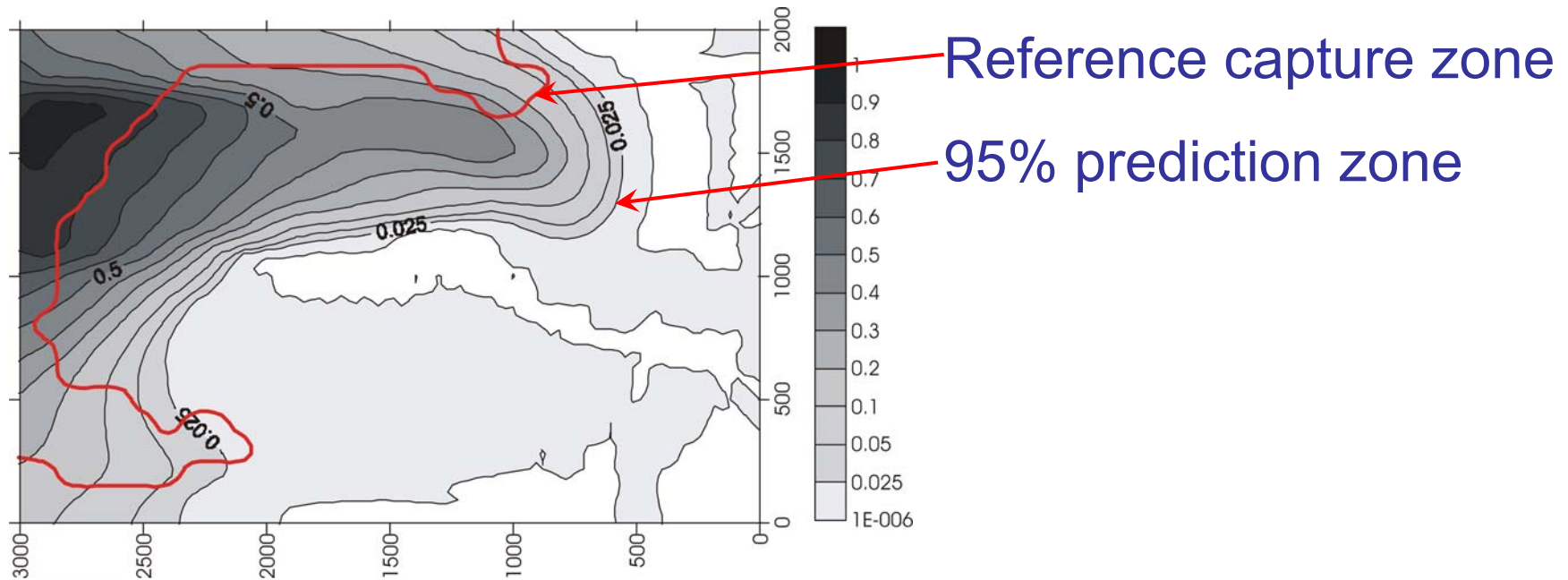
GLUE analysis

Monte Carlo simulation

- 200,000 flow and particle simulations
- ~ 4 weeks on a 4 GHz PC cluster (six PCs)

Case study – synthetic setup

Capture zone results – Monte Carlo



Case study – synthetic setup

Capture zone results – GLUE results

Point likelihood function:

Head:
Gaussian, $s_h=0.2\text{m}$

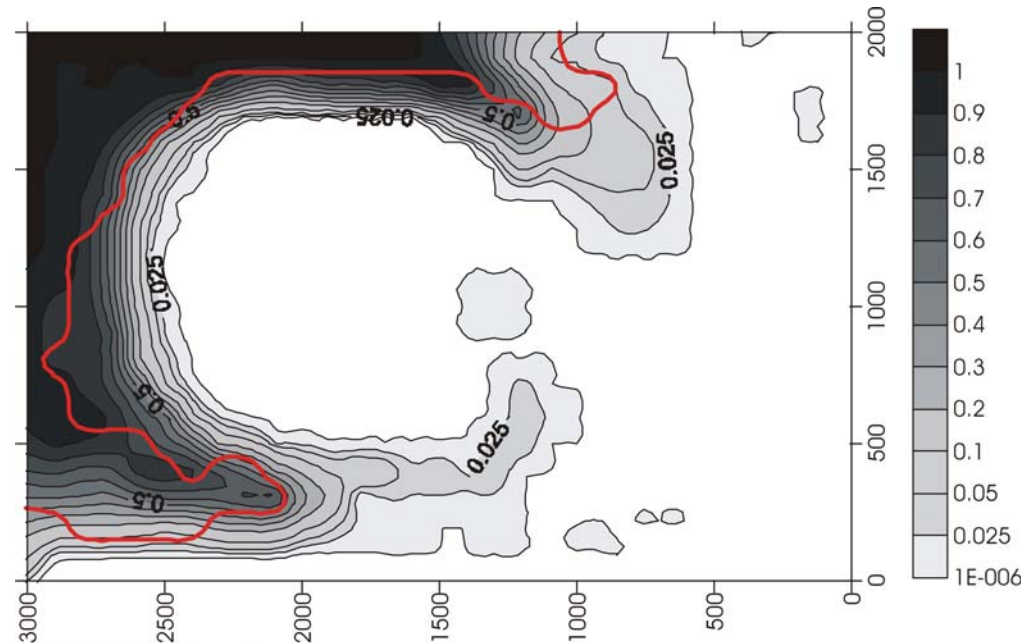
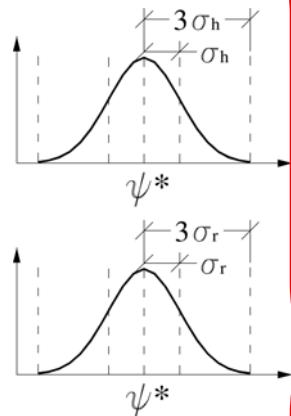
River flow:
Gaussian, $s_r=10\%$

Rejection level:

Head and river flow: 3s

Inference function:

Geometric mean

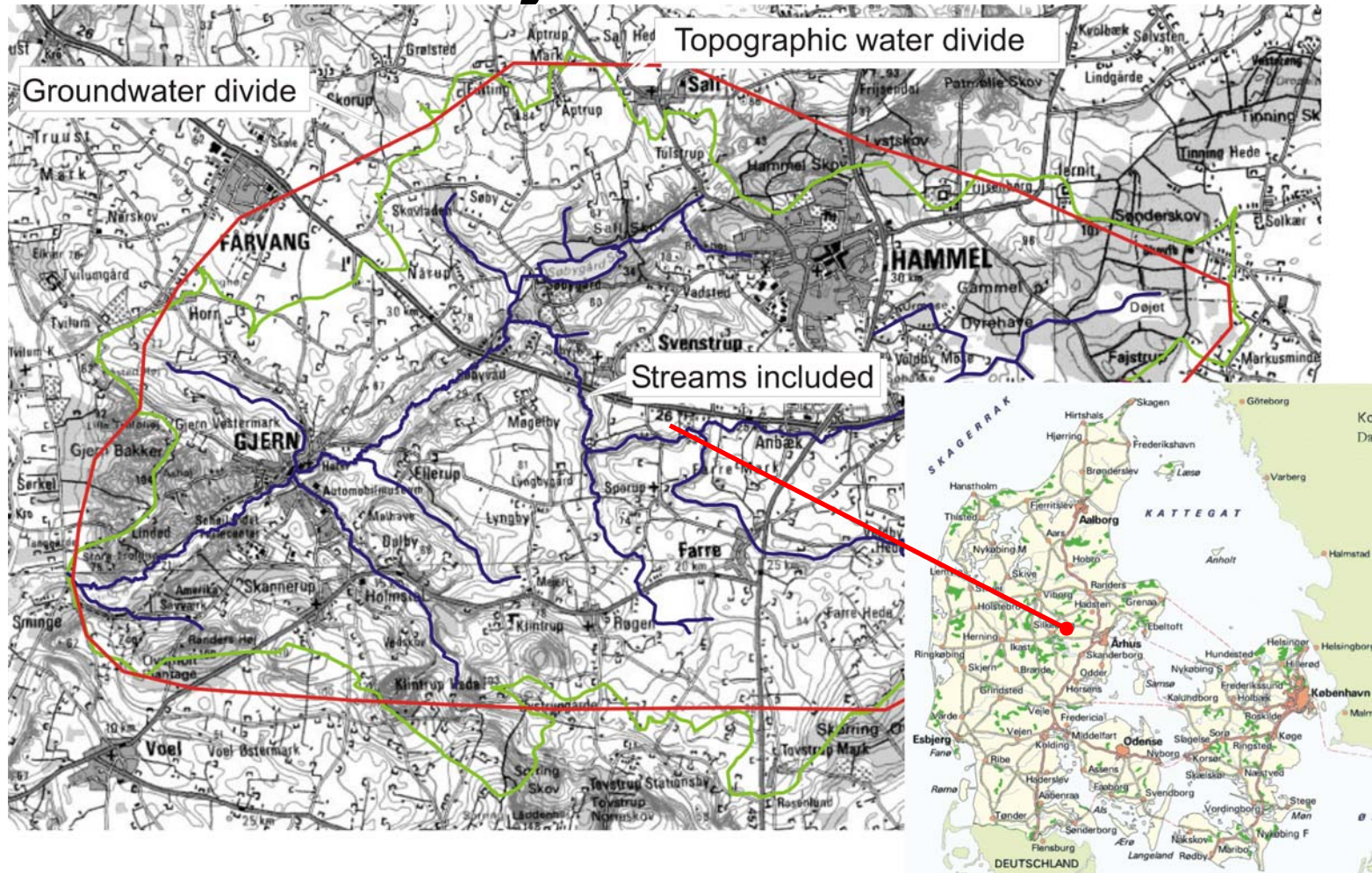


Case study – synthetic setup

The “optimal” solution (highest likelihood)

Parameter		Reference model	Best fit
		Value/range	Value
Geological model		B	A
Net precipitation [mm/year]	p	315	309
Abstraction [mm/year]	Q	50	-
Upper aquifer [m/s]	C _h	log ₁₀ (1.5E-04,0.75E-04,500)	1.88e-4
	C _z	1.e-7	-
Aquitard [m/s]	C _h	1.e-8	3.72e-7
	C _z	log ₁₀ (1.E-08,0.5E-08,500)	5.08e-9
Lower aquifer [m/s]	C _h	log ₁₀ (5.E-04,2.5E-04,500)	2.62e-4
	C _z	1.e-6	1.36e-6

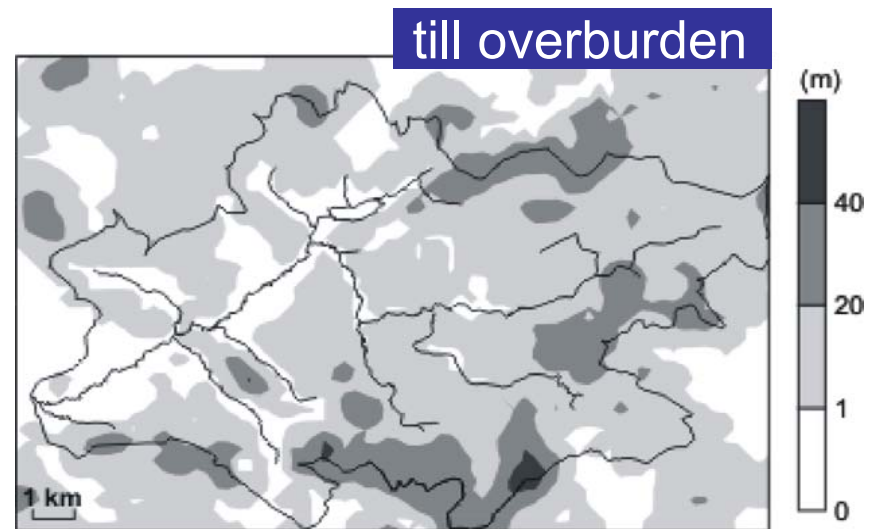
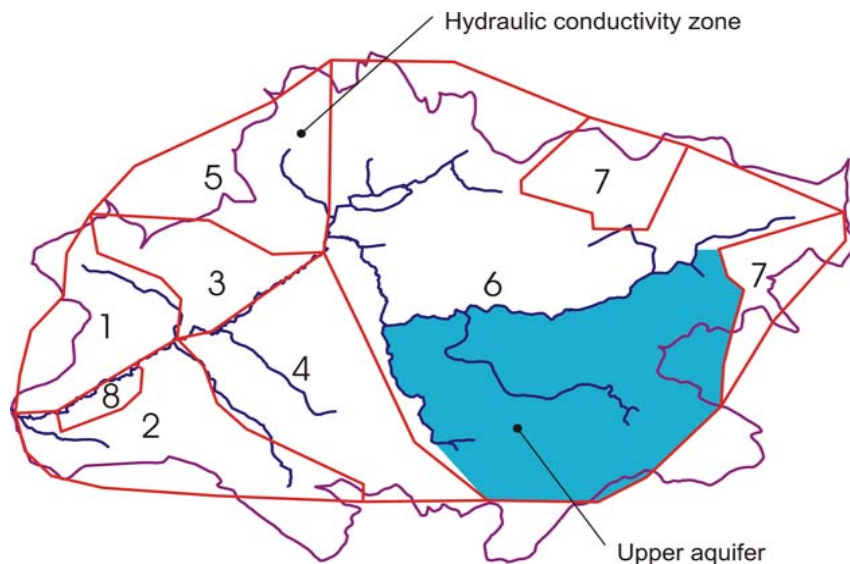
Gjern model



Gjern model

Geology

- Main aquifer: sand and gravel – eight conductivity zones
- Aquitard - Till overburden > 1 m
- Secondary upper aquifer



Gjern model

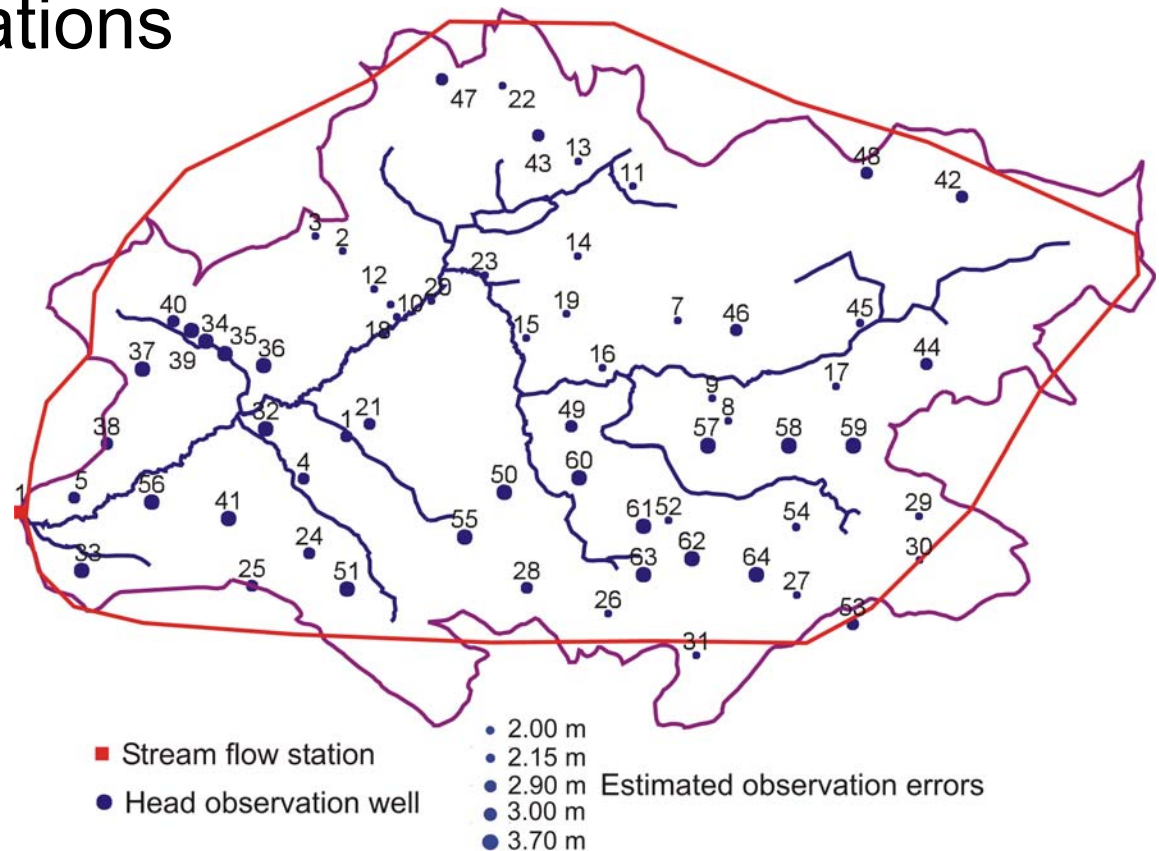
Recharge

1. Recharge directly to the lower main aquifer
2. Recharge to the upper secondary aquifer
3. Leakage from the aquitard to the lower main aquifer

Gjern model

Observation data – calibration

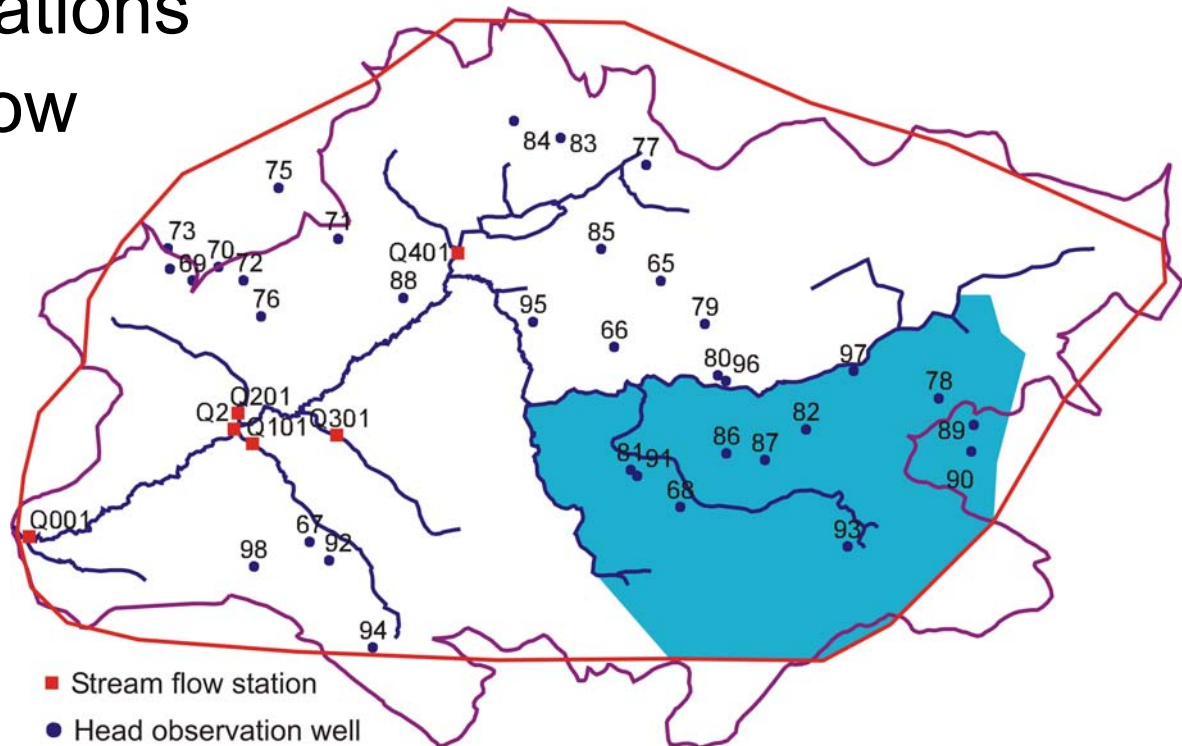
- 64 head observations
- one stream flow observation



Gjern model

Observation data – validation

- 34 head observations
- seven stream flow observations



Gjern model

Unknown parameters

- Recharge: RCH1, RCH2
 - Horizontal hydraulic conductivity, C1–C7 (main aquifer)
 - Vertical hydraulic conductivity, Cv (aquitard)
 - Transmissivity, Tu (secondary aquifer)
- ➔ In a total of eleven parameters

Gjern model

GLUE analysis

Point likelihood function:

Head:

Gaussian, $s_h = 2.0 - 3.7\text{m}$

River flow:

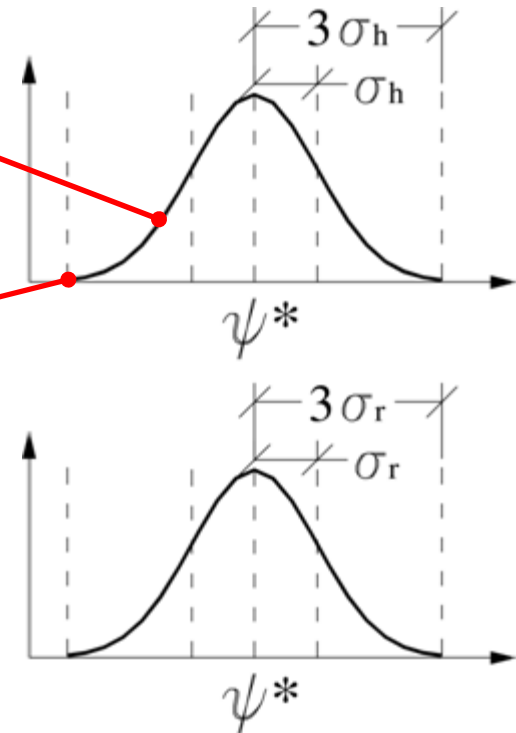
Gaussian, $s_r = 10\%$

Rejection level:

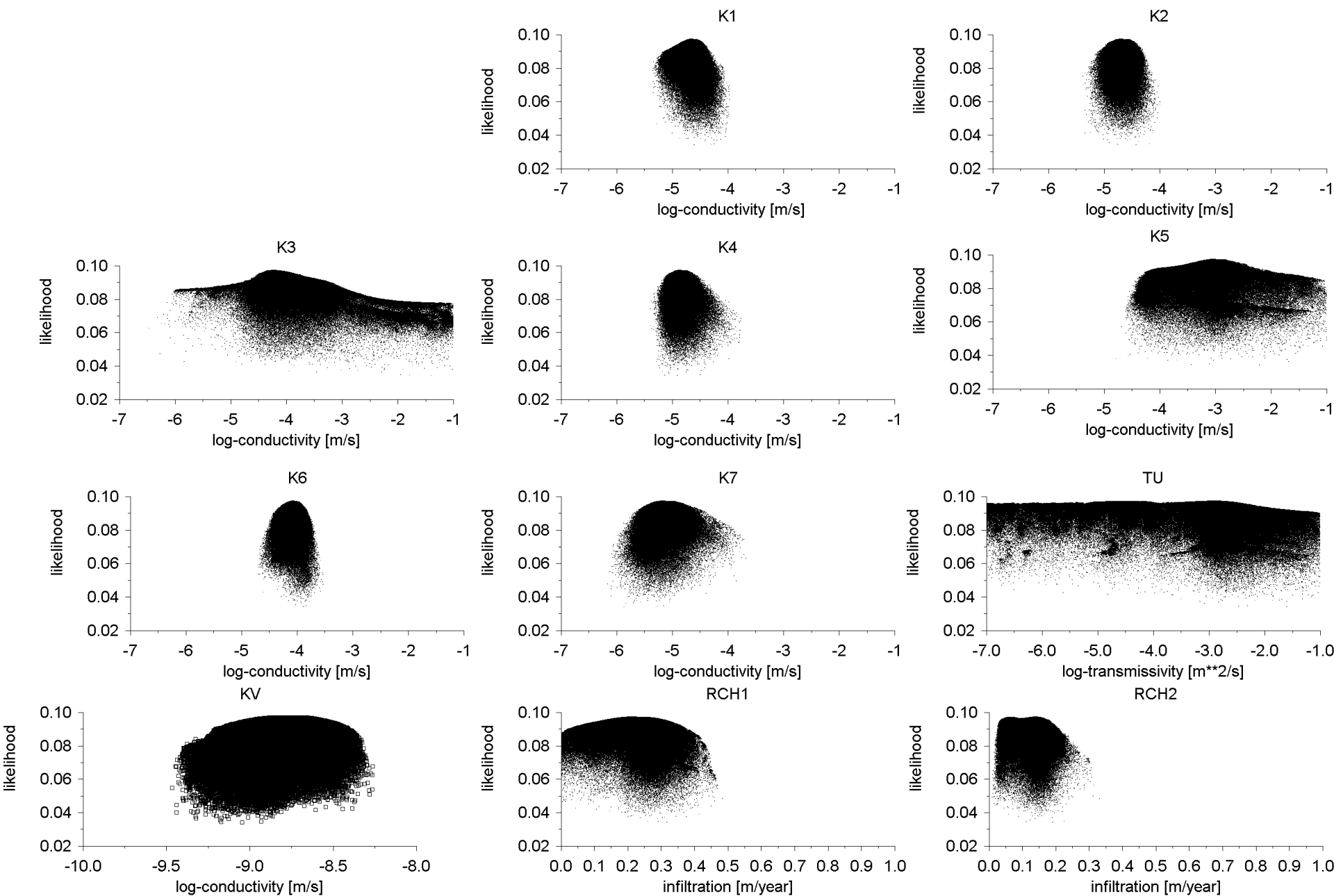
Head and river flow: 3s

Inference function:

Geometric mean

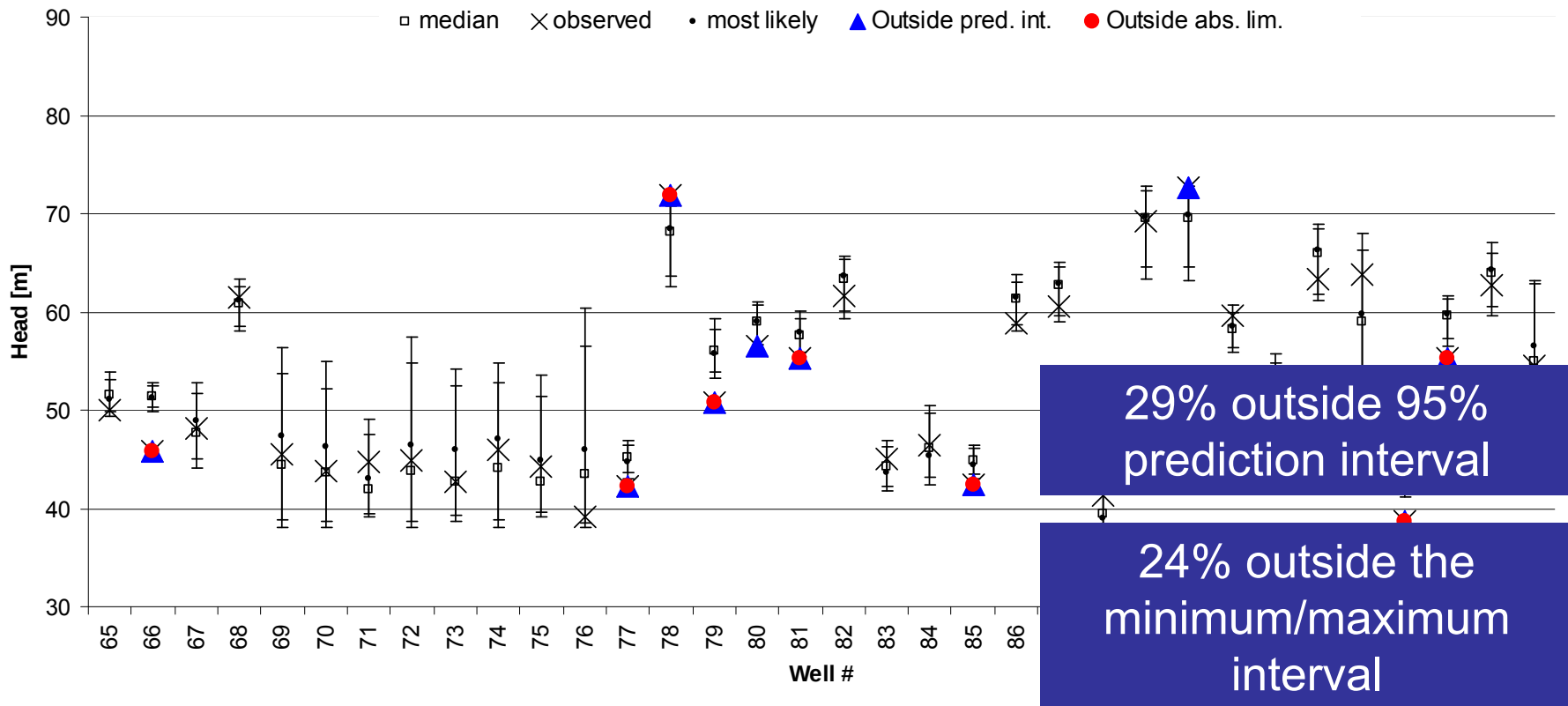


Parameter scatter plots



Gjern model

Validation – 34 head obs. (validation data)



Gjern model

Validation – 98 head observations

