

# Crash test for groundwater recharge models: The effect of model complexity and calibration period on recharge rate predictions

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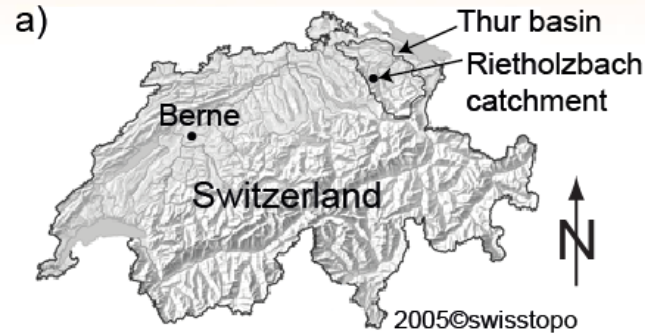
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# Motivation

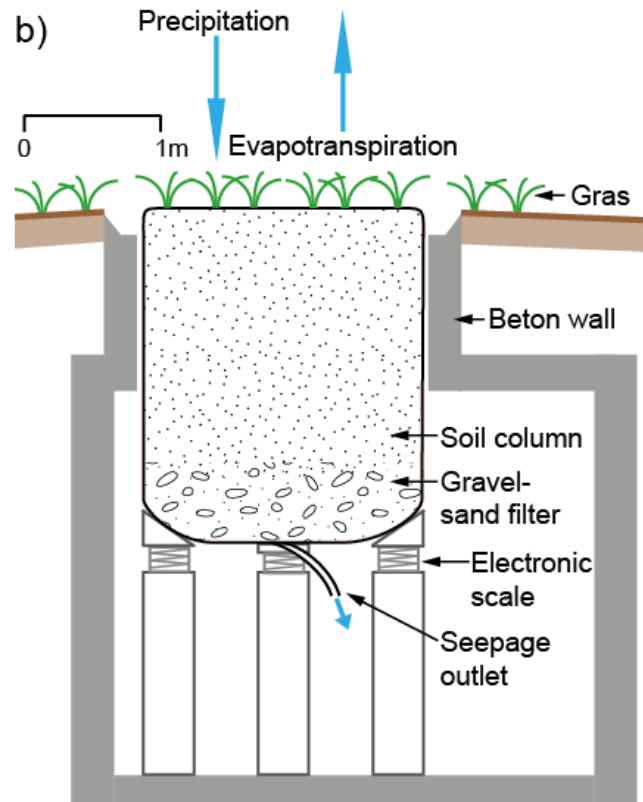
## Groundwater Recharge (GR)

- GR is a key process for water resources management
- Modelers need to know how robust their simulations are, because...
  - the **model structure**,
  - the uncertainty in the **calibrated model parameters** and
  - the **calibration period**...might influence the predictions
  - Uncertainty I: **Model structure and complexity**
- An implicit assumption is made that model parameters calibrated over historical periods are also valid for the predictions
  - Uncertainty II: **Non-Stationarity of calibrated model parameters**
- **Operational testing is rarely done** – especially for GR models, because measuring GR is challenging

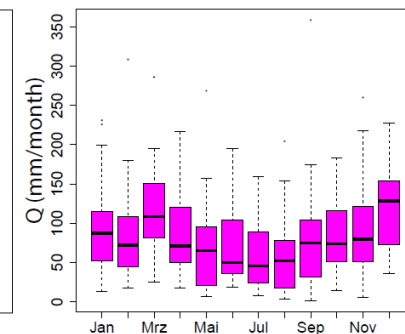
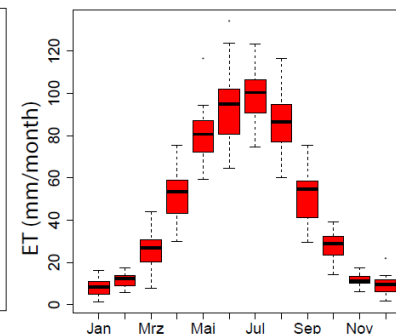
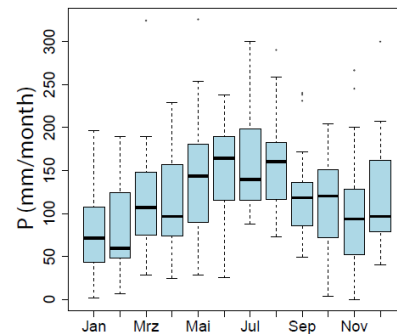
# Study Area



- Pre-alpine head watershed north-eastern Switzerland
- Large free drainage weighting lysimeter (2.5 m deep, 2 m diameter) → unique data set (~32 y TS)
- Surface is covered with grass
- Groundwater table depths shallow
- Average annual values:



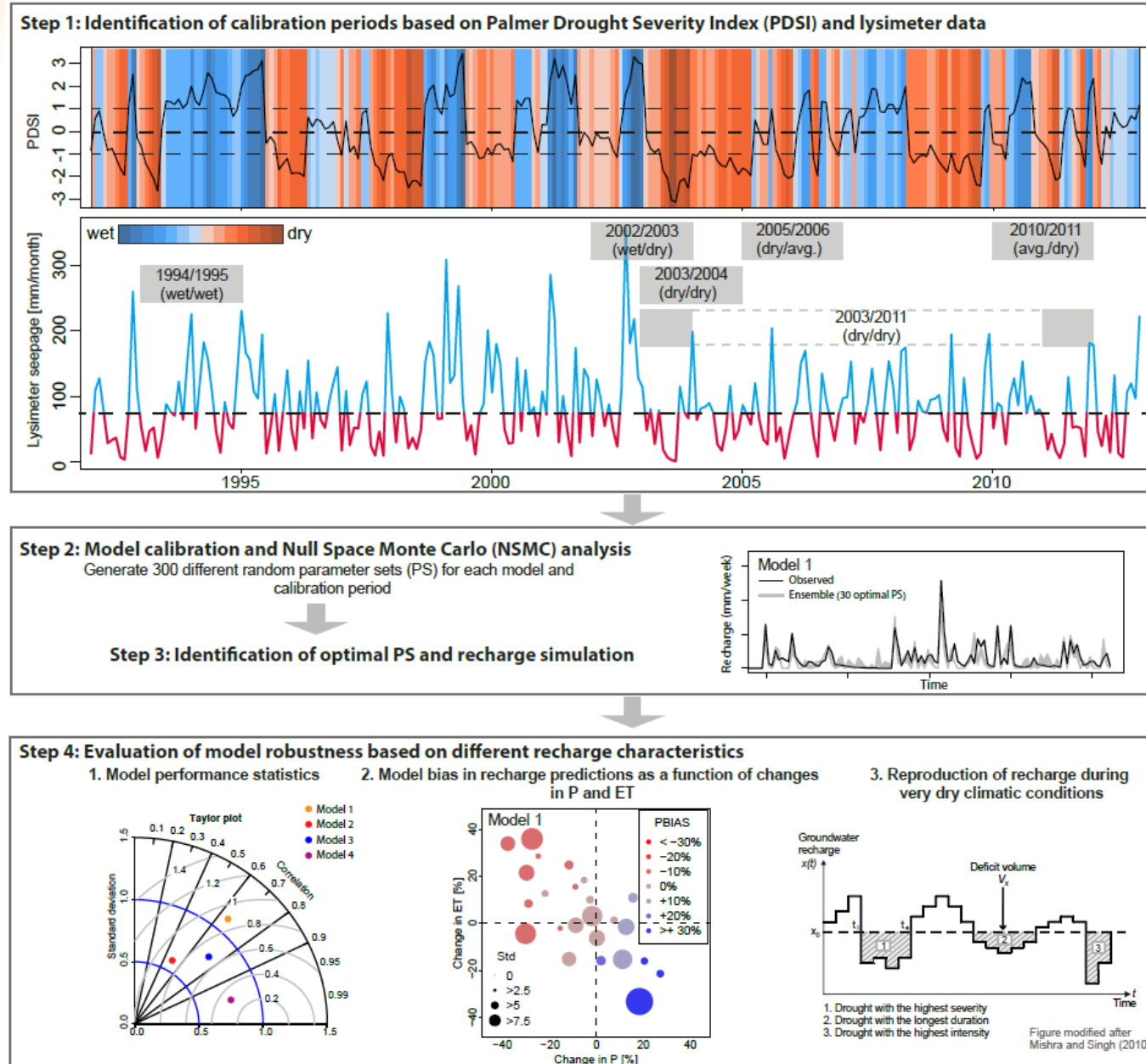
Precipitation 1473 mm/a  
Actual evapotranspiration 560 mm/a



# Methodology

## Four Step Approach

- Identification of dissimilar calibration periods
- Constrained Monte Carlo Approach
- Simulations with optimal parameter sets
- Evaluation of model robustness



# Models

## Chosen Model Structures and Complexities + Degree-day snow model

- i. Soil Water Balance Model (**FINCH, 14 parameters**):
  - Simple daily water balance equation
  - Predominately linear relationships between model parameters and outputs
  
- ii. Lumped Parameter Bucket Model (**LUMPREM, 12 parameters**):
  - Matrix and macropore flow are activated after specified delay times
  - Soil moisture content in the column controls the recharge rate
  
- iii. Physically-based Model (**HYDRUS 1D Homogenous, 16 parameters**):
  - Richards equation
  - Van Genuchten parameterisation
  - Homogenous assumption
  
- iv. Physically-based Model (**HYDRUS 1D Dual Porosity, 19 parameters**):
  - Porous medium is divided into two overlapping soil domains

Increasing complexity

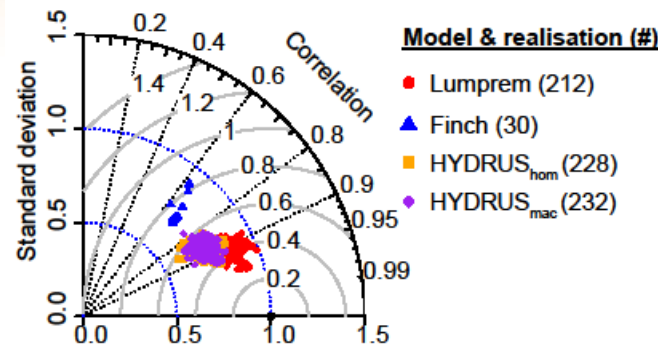


# Results: Calibration

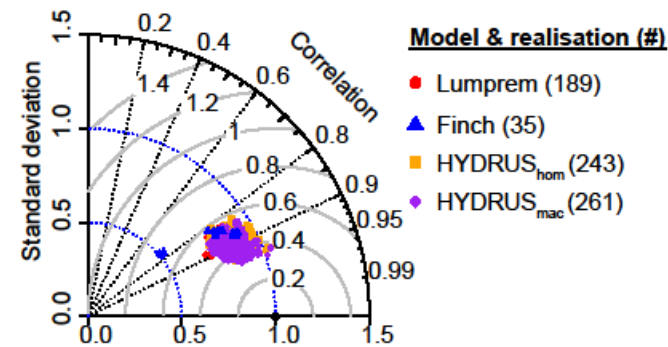
## Taylor Plot

- The similarity between patterns is quantified by using their
  - Correlation
  - Their centred root mean square differences
  - Amplitude of their variations, represented by their standard deviations
- Increasing model complexity; increasing number of acceptable parameter sets
- Model performance in calibration is quite similar under all calibration periods

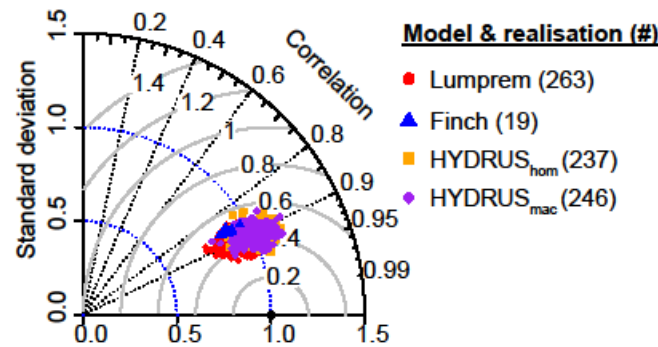
Calibration 94/95 (wet/wet)



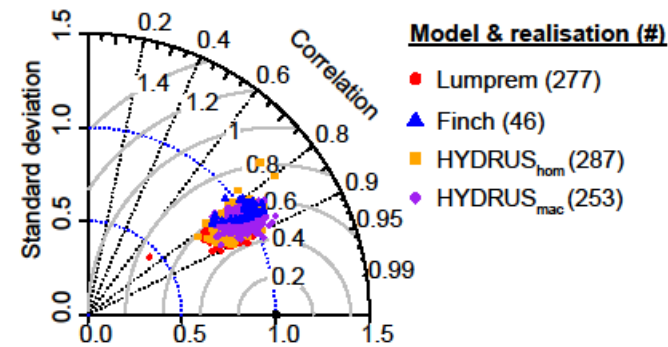
Calibration 02/03 (wet/dry)



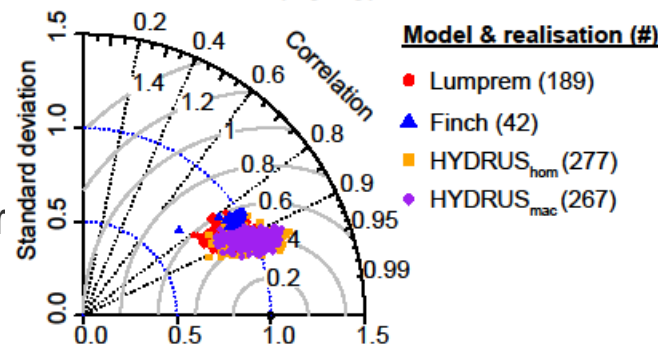
Calibration 10/11 (avg./dry)



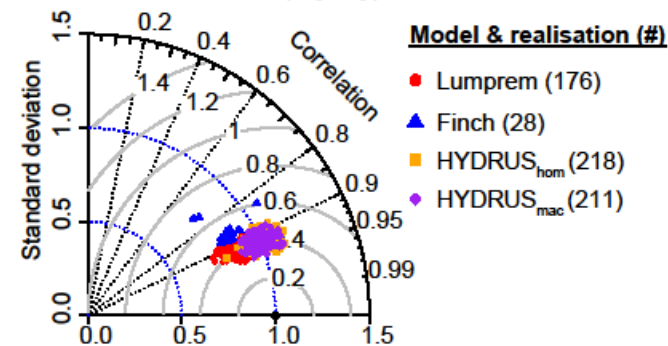
Calibration 05/06 (dry/avg.)



Calibration 03/04 (dry/dry)



Calibration 03/11 (dry/dry)



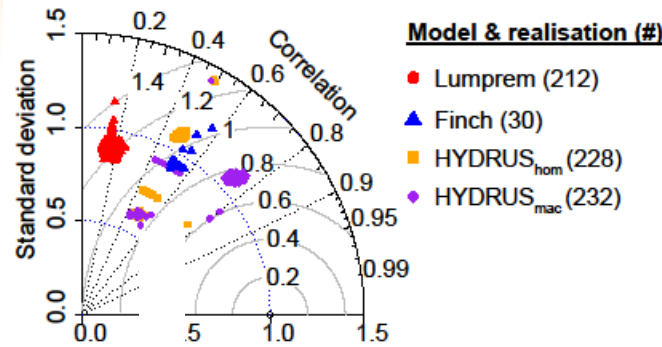


# Results: Validation

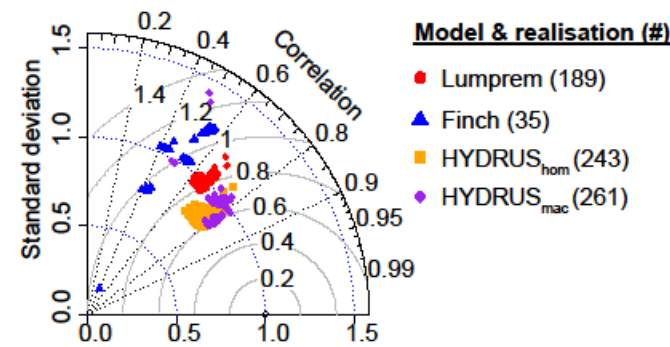
## Taylor Plot

- Decreasing model performance
- The differences are a function of the chosen model complexity
- Uncertainty in model parameters is less pronounced than model structure
- Robustness of each individual model follows the degree of model complexity

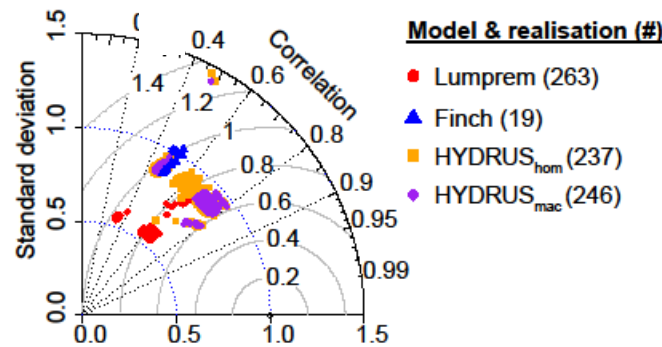
Calibration 94/95 (wet/wet)



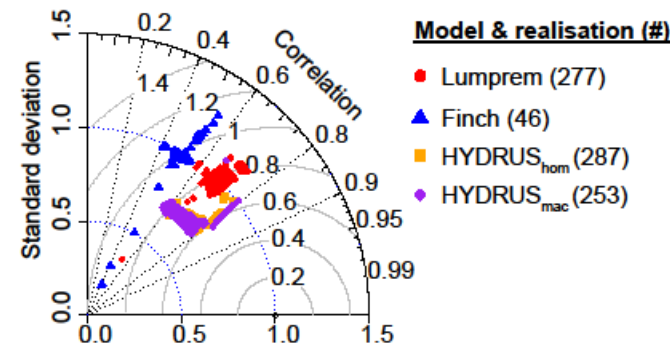
Calibration 02/03 (wet/dry)



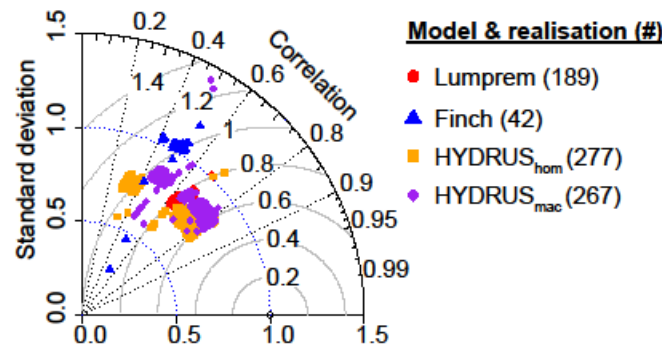
Calibration 10/11 (avg./dry)



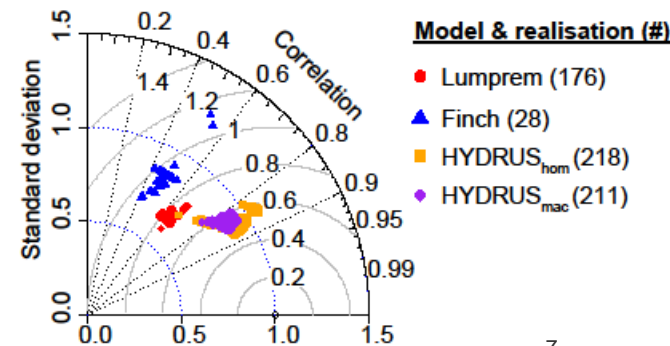
Calibration 05/06 (dry/avg.)



Calibration 03/04 (dry/dry)



Calibration 03/11 (dry/dry)



# Sensitivity of recharge to the climate characteristics of the calibration period

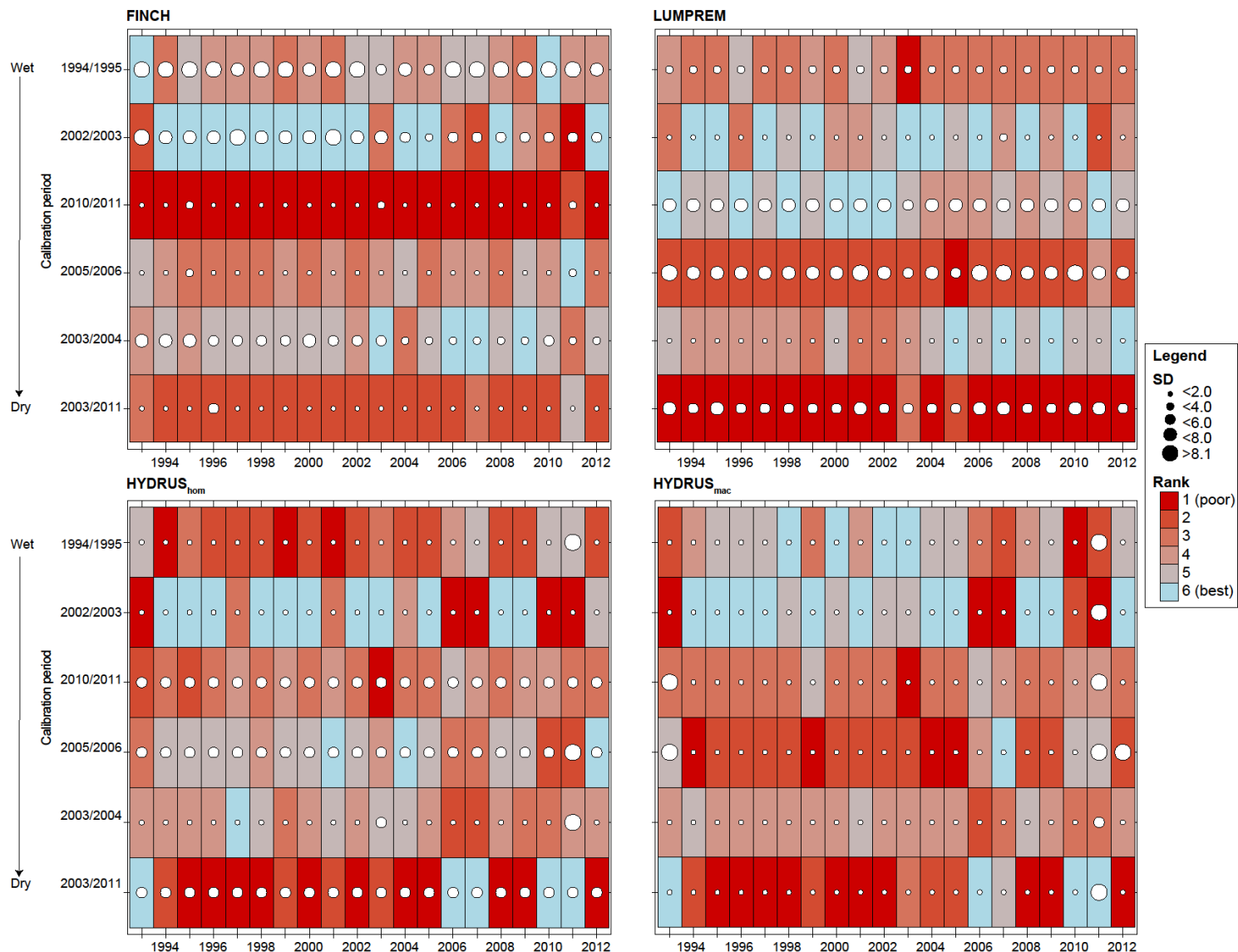
## Annual recharge patterns

○ **Period dry/dry:**  
**Poor** model performance for all models

○ **Period wet/dry:**  
**Best** model performance

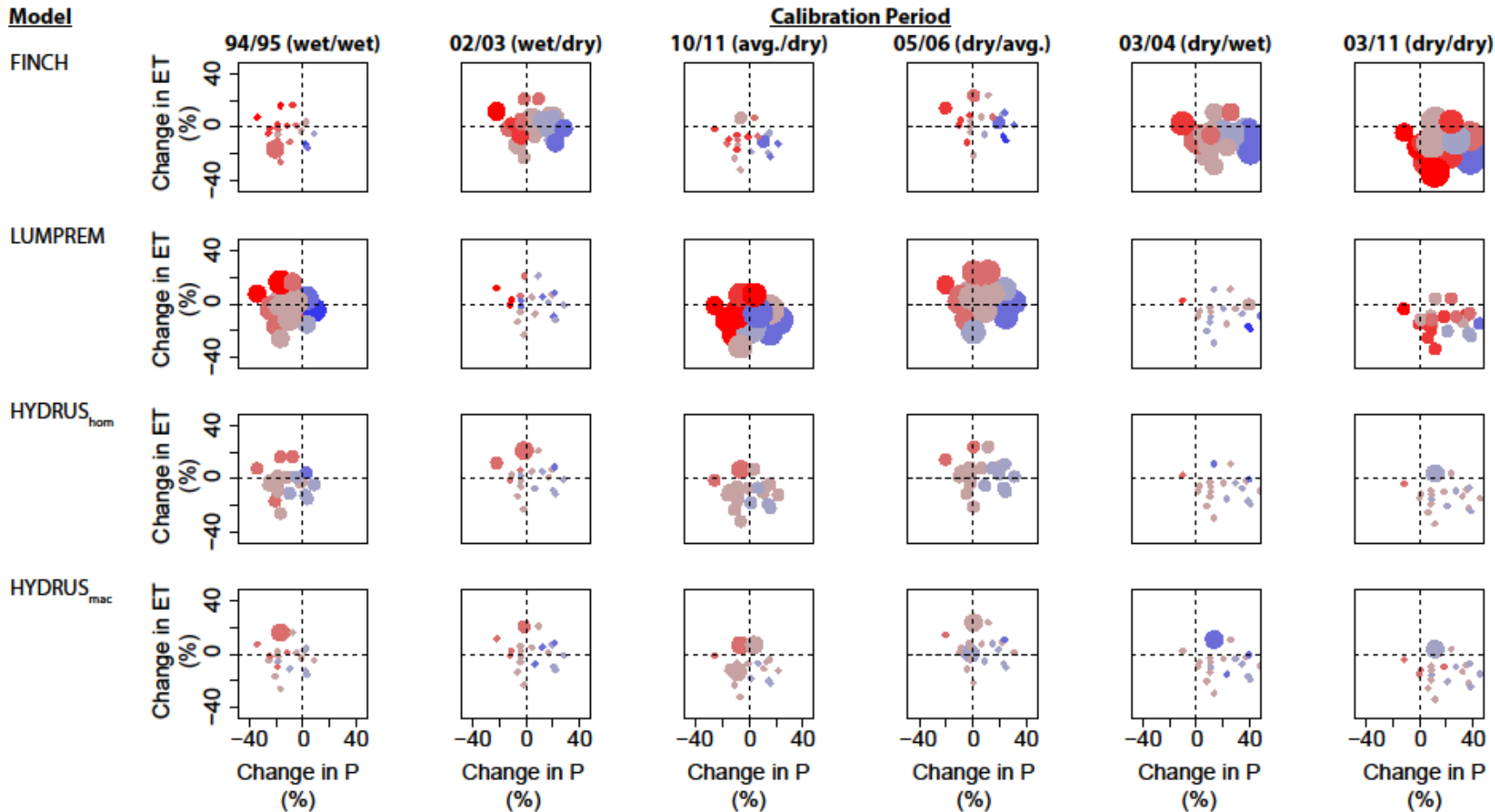
○ **No optimal calibration period**

○ Model performance depends strongly on the **model complexity** and structure rather than on the **calibration period**





# Sensitivity of recharge to the climate characteristics of the calibration period



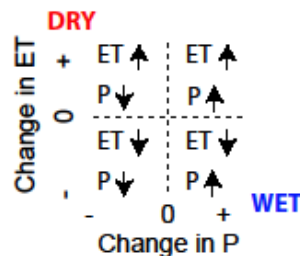
**Legend**

**PBIAS**

- < -30%
- -20%
- -10%
- 0%
- +10%
- +20%
- > +30%

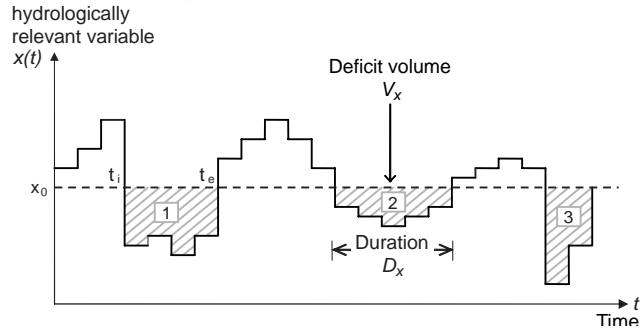
**SD**

- 0.0-2.0
- 2.1-4.0
- 4.1-6.0
- 6.1-8.0
- >8.1



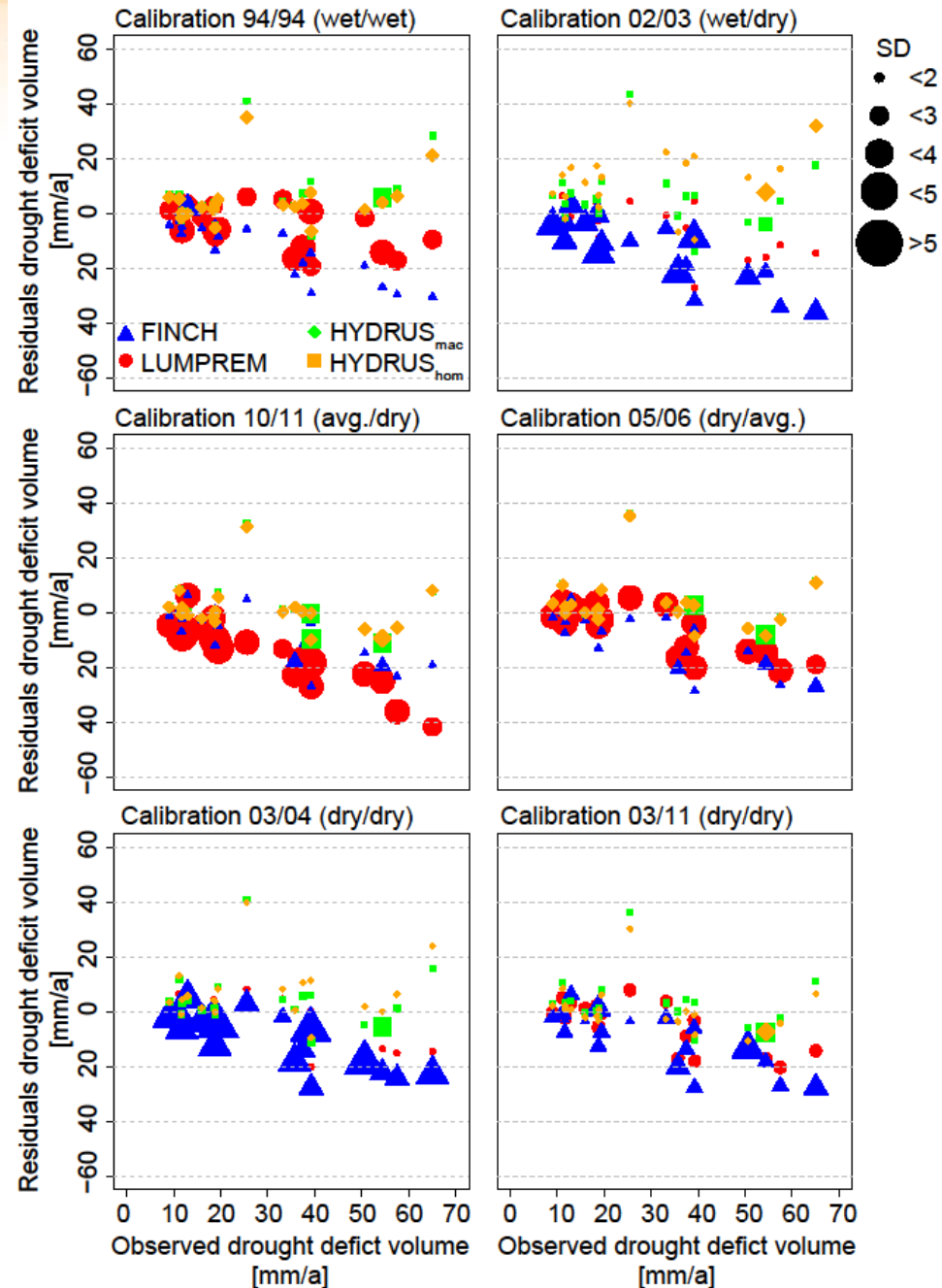
# Impact on simulated recharge rates

## Drought deficit volumes



Mishra and Singh (2010)

- Largest deviations for the drought years 2003, 2009 and 2011
- Differences are minor for observed volumes < 20 mm.
- Drought deficit volumes increase with decreasing model complexity
- Dry-Dry calibration most efficient to simulate droughts



# Summary and Conclusions

- Acceptable model performance during the calibration will not ensure reliable predictions under dissimilar conditions
  - **BUT** differences are a function of the chosen model complexity
- Model structure becomes more important under **extremes or very contrasting climatic conditions**
- **Uncertainty in model parameters** is generally **less pronounced** than **model structure**
  - Elaborate calibration procedure does not automatically provide robust model parameters and accurate predictions
- **No optimal calibration period**
  - Model performance depends strongly on the **model complexity** and structure **rather** than on the **calibration period**
  - Wet calibration period → appears detrimental to simulate dry validation periods
  - Dry-Dry calibration most efficient to simulate droughts but for “average” or wet conditions the calibration period failed
  - Calibration period is less important for the physically based models

**Results should raise the concern of model reliability when using simple models for extreme events or under dissimilar climatic conditions**



Thank you for your attention

The authors gratefully acknowledge the financial assistance provided by the Swiss National Science Foundation, Projects 200021-129735/1 and 200020-143688.

The group of S. Seneviratne (Land-Climate-Dynamics), Institute for Atmospheric and Climate Science (IAC), Swiss Federal Institute of Technology Zurich (ETHZ) provided data from the meteorological station and the lysimeter from the study area.

# Constrained Null Space Monte Carlo Simulation

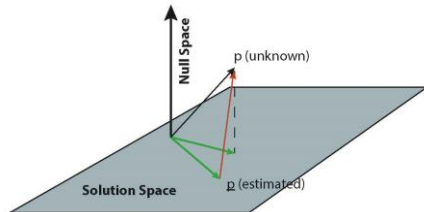
**Approach:** 2 steps are required:

- Calibrate base model
- Null Space Monte Carlo Procedure

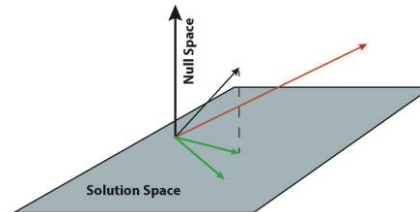
**Advantages:**

- Many different realizations are possible
- Parameter flexibility (reduce structural noise)
- Using pre-calculated sensitivities reduce computational effort
- SVD-Assist calibrate just the parameters in the solution space

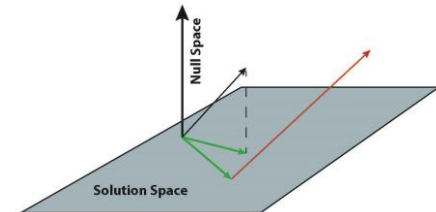
1. Calibrate the model



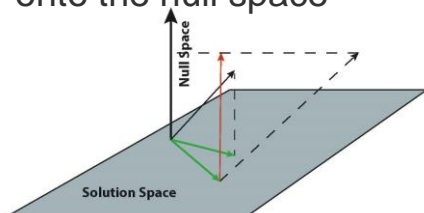
2. Generate parameter set:  $C(p)$



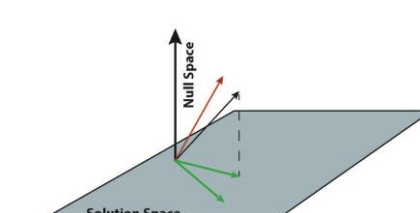
3. Take difference with calibrated model



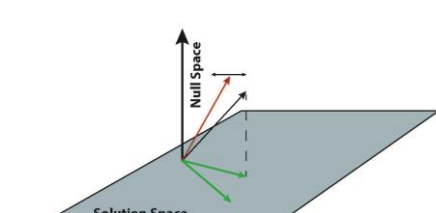
4. Project differences onto the null space



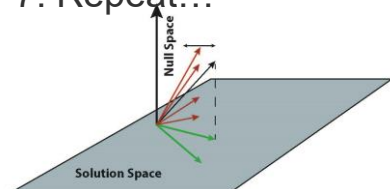
5. Add to calibrated field



6. Adjust solution space components



7. Repeat...



# Constrained Null Space Monte Carlo Simulation

## Approach:

Two steps are required

## Advantages:

- Many different realizations are possible
- Parameter flexibility (reduce structural noise)
- Using pre-calculated sensitivities reduce computational effort
- SVD-Assist calibrates just the parameters in the solution space

### Calibrate base model

PEST  
 1. Base model parameterization (Pilot Point approach)  
 2. Base parameter sensitivities (Jacobian matrix)  
 3. Tikhonov constrains

PEST calibration output files

### Null Space Monte Carlo Procedure

Random parameter sets based on  $C(p)$

PNULPAR (Pest suite)  
 1. Calculate  $V2V2t$  and project differences between random parameters and the calibrated parameters onto the calibration null-space  
 2. Add projected differences to calibrated parameter values  
 3. "Almost calibrated" random parameter sets

PEST  
 1. Re-calibration  
 2. SVD-Assist  
 3. Beopest (parallel computing)

Evaluate predictive uncertainty