

# Impact of different soil databases on flow prediction uncertainty in SWAT+gflow for a forested catchment

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# Tree Plantation Impacts

REVIEWS REVIEWS REVIEWS

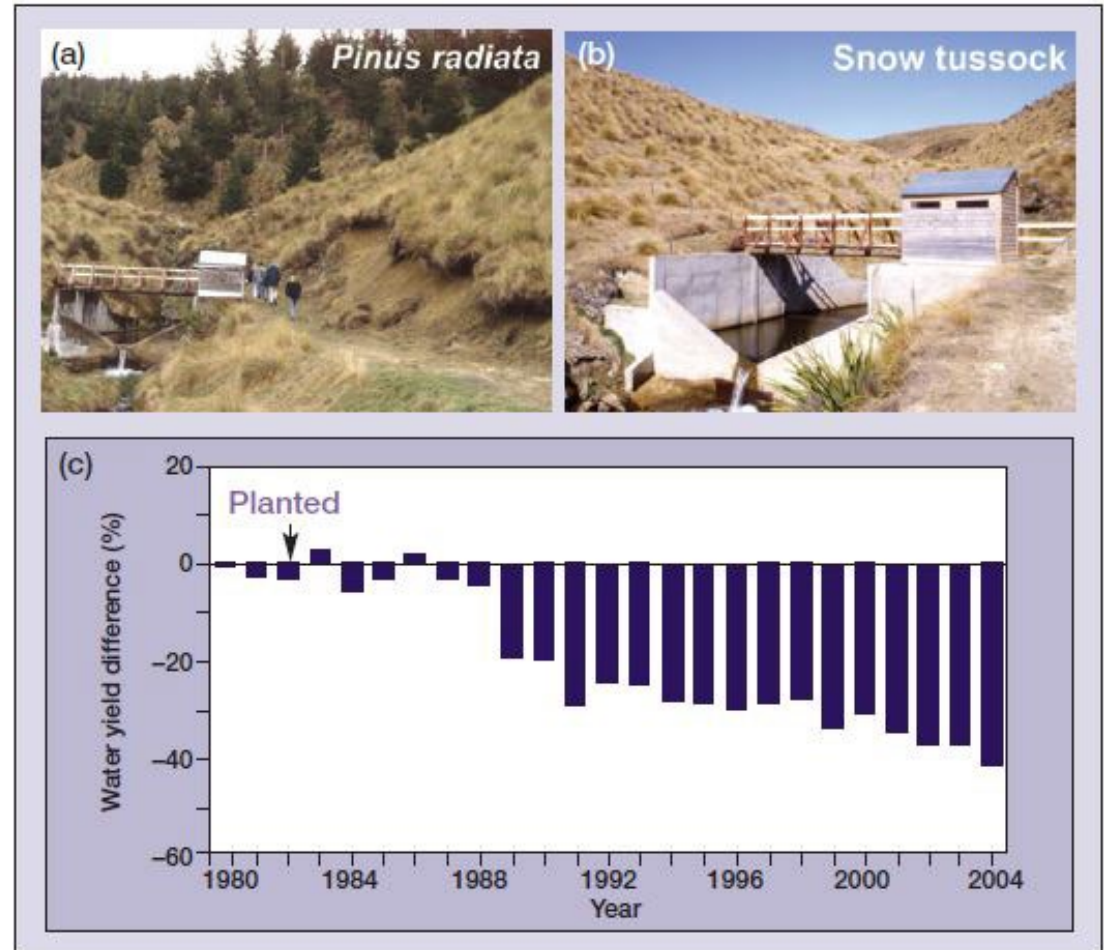
25

## Maximizing water yield with indigenous non-forest vegetation: a New Zealand perspective

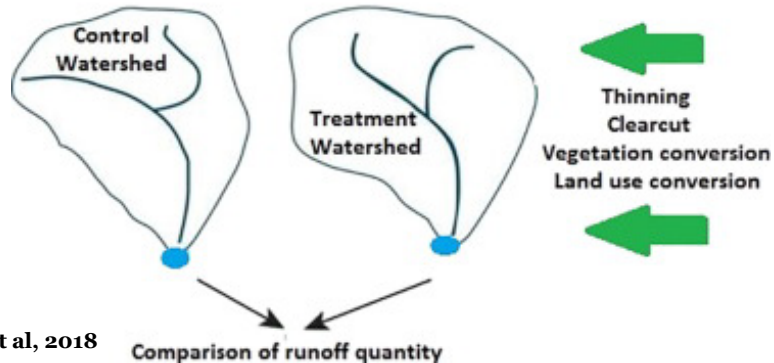
Alan F Mark\* and Katharine JM Dickinson

Provision of clean freshwater is an essential ecosystem service that is under increasing pressure worldwide from a variety of conflicting demands. Water yields differ in relation to land-cover type. Successful resource management therefore requires accurate information on yields from alternative vegetation types to adequately address concerns regarding water production. Of particular importance are upper watersheds/catchments, regardless of where water is extracted. Research in New Zealand has shown that, when in good condition, indigenous tall tussock grasslands can maximize water yield relative to other vegetation cover types. A long-term hydrological paired-catchment study revealed reductions (up to 41% after 22 years) in water yielded annually from an afforested catchment relative to adjacent indigenous grassland. Furthermore, a stable isotope assessment showed that water from fog may substantially contribute to yield in upland tussock grasslands. The tall tussock life-form and its leaf anatomy and physiology, which minimize transpiration loss, appear to be the differentiating factors. Thus, maintaining dominance of such cover is important for water production, especially in upland catchments. Ecological analogues and integrated land-use planning are discussed in the context of this essential ecosystem service. Water management programs in other countries are reviewed and that of South Africa is commended as a model.

Front Ecol Environ 2008; 6(1): 25–34, doi:10.1890/060130

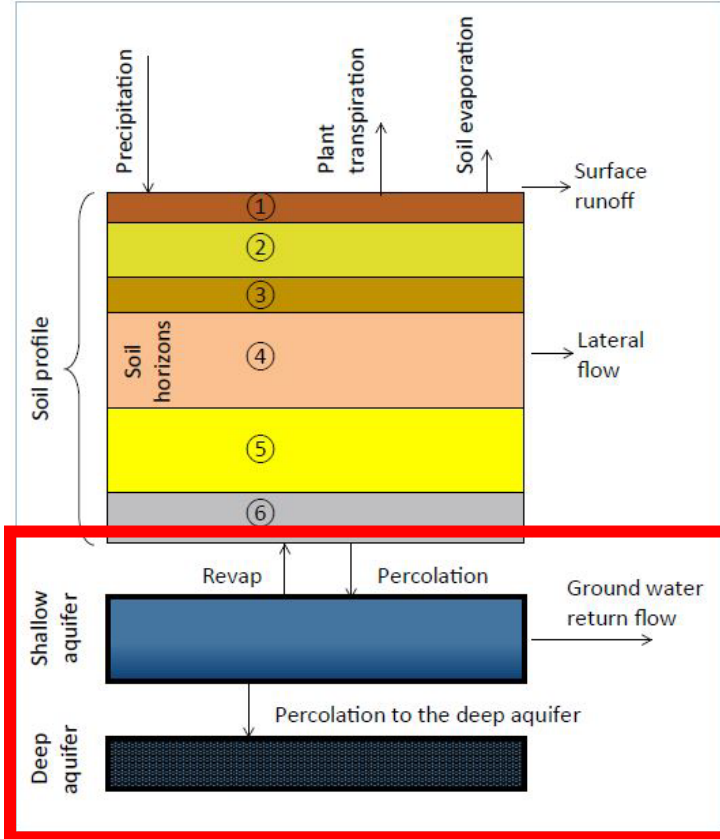


### Paired Watershed Analysis



Yurtseven et al, 2018

# Soil maps



The screenshot shows the Ministry for the Environment Data Service interface. The main content area displays the "Depth to hydrogeological basement map, 2019" data layer. The interface includes a search bar, a map view, and a list of data layers. The "Depth to hydrogeological basement map, 2019" layer is highlighted in red. The map shows the depth to the hydrogeological basement across New Zealand.

Ministry for the Environment  
Data Service

Depth to hydrogeological basement map, 2019

Info History Services and APIs

Data Type  
Grid Layer, 250m, 1 Tile

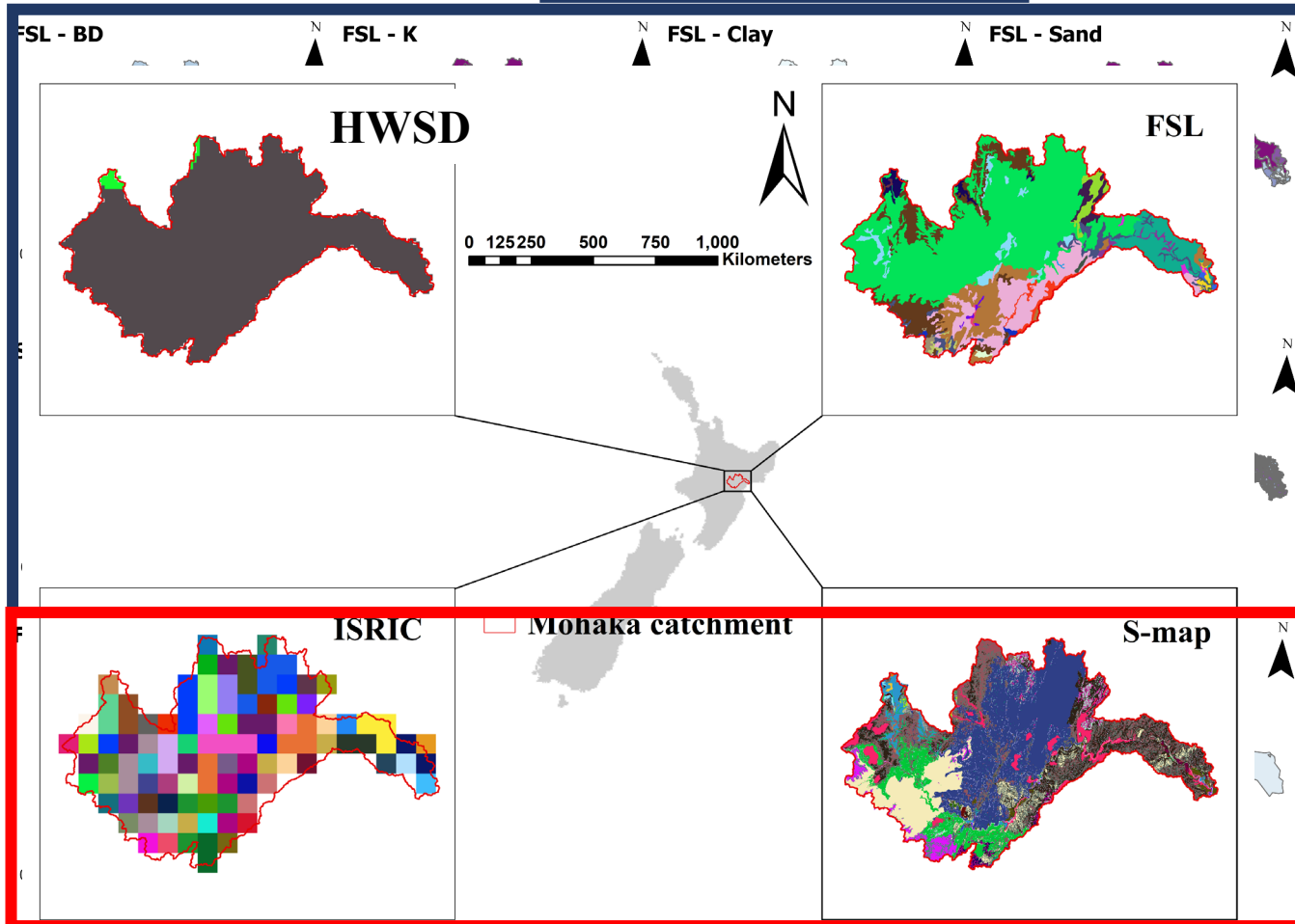
Date Added: + 27 Jan 2020  
Last Updated: 20 Sept 2022  
Views: 4.6K  
Exports: 88  
Layer ID: 104446

This data set provides an update of New Zealand's depth to hydrogeological basement map. Depth to hydrogeological basement can be loosely defined as the 'base of aquifers'; or more strictly as 'the depth to where primary porosity and permeability of geological material is low enough such that fluid volumes and flow rates can be considered negligible'. For more detail on the process and methods, see Westerhoff et al. (2019). New Zealand groundwater atlas: depth to hydrogeological basement. Lower Hutt (NZ): GNS Science. 19 p. Consultancy Report 2019/140

Depth to hydrogeological basement

# Variations in soil data sets

## Local Soil Databases



FSL - Depth [mm]

## Global Soil Databases

Name	Resolution	Soil units
HWSD	806 m	2
ISRIC	4838 m	83

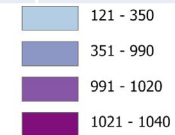
0 5 10 20 Kilometers

S-map - Depth [mm]

## Local Soil Databases

Name	Resolution	Soil units
FSL	15 m	24
S-map	15 m	36

0 5 10 20 Kilometers



## Global Soil Databases

# Input data: SWAT+gwflow

SWAT+ input data

SWAT+gwflow  
simulation

gwflow input data

Data	Source
Topography	University of Otago
Land use	<u>Landcare Research</u>
Soil	<u>Landcare Research</u> <u>Global websites (FAO, ISRIC)</u>
Climate	<u>HBRC &amp; NIWA</u>

Data	Source
Aquifer thickness	GNS Science
Geologic unit	<u>GNS Science</u>

# Soil in SWAT(+)

## Percolation

$$W_{perc,ly} = SW_{ly,excess} \cdot \left( 1 - \exp \left[ \frac{-\Delta t}{TT_{perc}} \right] \right)$$

$$TT_{perc} = \frac{SAT_{ly} - FC_{ly}}{K_{sat}}$$

**W:** percolation (mm)  
**SW:** soil water content  
**TT:** travel time for percolation (hr)

Saturated hydraulic conductivity (mm/hr)

## Transpiration

$$AWC = FC - WP$$

$$WP_{ly} = 0.4 \frac{m_c \cdot \rho_b}{100}$$

**AWC:** Available Water Capacity

**FC:** Water content at field Capacity

**WP:** Water content at wilting point

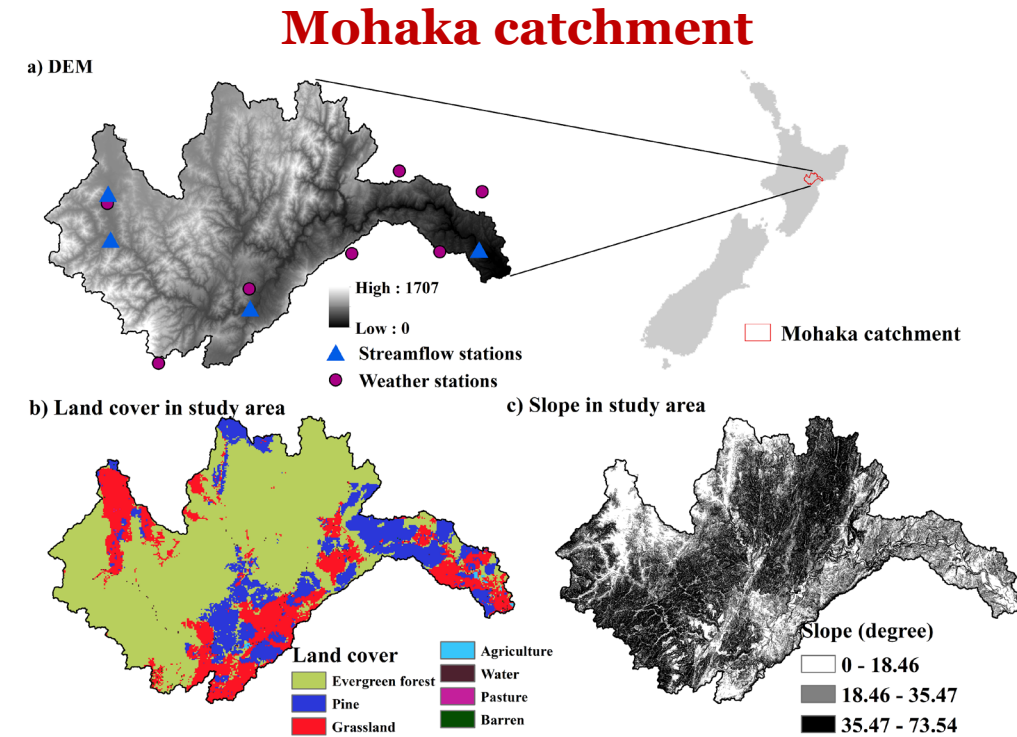
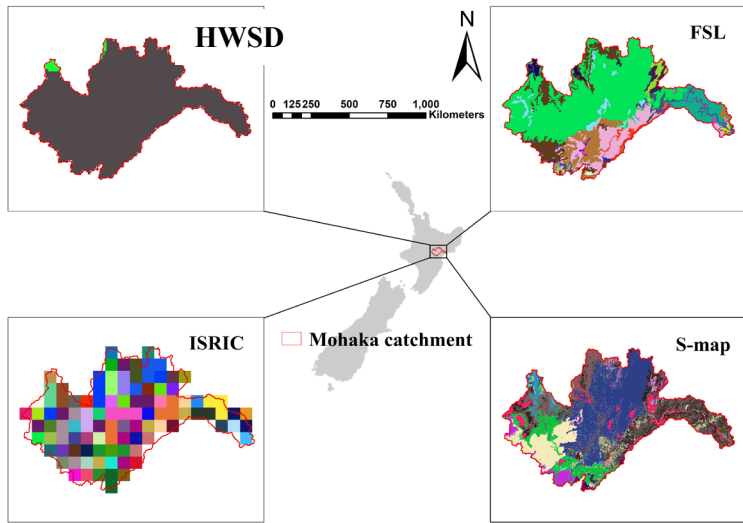
**$\rho_b$ :** soil bulk density

Clay content (%)

# Gaps/Questions: soil databases

- 1) Impact of different soil databases on streamflow estimation within a catchment, with identical input data except for the soil.
- 2) Key parameters or parameter groups contributing to prediction uncertainty reduction **[and by how much?]**.

# Methodology: Discretisation



Soil Database	# Sub-basin	# HRU	# Soil units
FAO	19	<u>385</u>	2
HWSD	19	<u>680</u>	24
ISRIC	19	<u>761</u>	83
S-map	19	<u>822</u>	27

**Area: 2,400 km<sup>2</sup>**

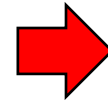
**Average rainfall: 1620 mm**

**Average slope: 28 degree**



# Methodology: Techniques/tools

**I.** Performance evaluation (in simulating streamflow)

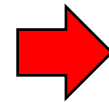


$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{oi} - Q_{si})^2}{\sum_{i=1}^n (Q_{oi} - \bar{Q})^2}$$

$$PBIAS = \frac{\sum_{i=1}^n (Q_{oi} - Q_{si})}{\sum_{i=1}^n Q_{oi}} \times 100$$

$$R^2 = 1 - \frac{\sum_{i=1}^n (Q_{oi} - \widehat{Q}_{pi})^2}{\sum_{i=1}^n (Q_{oi} - \bar{Q})^2}$$

**II.** Contribution of parameters (groups) to prediction uncertainty



**Linear Analysis:**

first-order-second moment (FOSM analysis)

# Performance evaluation: SWAT+gwflow

## Daily performance statistics

Soil Database	NSE	PBIAS	R <sup>2</sup>
FAO	-0.58	-86.4	0.34
ISRIC	-0.54	-92.9	0.31
S-map	0.35	17.6	0.61
FSL	0.45	-6.9	0.67

## Monthly performance statistics

Soil Database	NSE	PBIAS	R <sup>2</sup>
FAO	-1.26	-86.3	0.71
ISRIC	-1.62	-92.8	0.63
S-map	0.46	17.6	0.82
FSL	0.56	-6.8	0.81

# Water balance

Local soil databases

Global soil databases

	Component	S-map	FSL	ISRIC	FAO
Catchment inputs	Precipitation	1657	1667	1658	1616
	GW boundary inflow	146	169	-400	122
Catchment outputs	Surface ET	473	373	486	514
	Surface runoff	137	320	176	456
	Lateral soil flow	935	831	689	96
	GW discharge to streams	206	0	0	0
	Stream seepage to GW	-71495	-268000	-9632	-30088
	Saturation excess flow	70580	266950	6244	25592
	GW ET	0.03	0.11	0.00	0.00
	Recharge	2680	3640	31705	9783
Internal flows	Pumping irrigation	0	0	0	0
	Surface water irrigation	0	0	0	0
	GW transfer to soil	3496	4883	36990	14394

# Linear analysis (FOSM analysis)

$$\mathbf{h} = \mathbf{Z}\mathbf{k} + \boldsymbol{\epsilon}$$

$\mathbf{Z}$ : the action of a model on its parameters (Jacobian or sensitivity matrix)

$\mathbf{h}$ : observation of the system states and fluxes

$\boldsymbol{\epsilon}$ : observation noise/errors

Jacobian or sensitivity matrix

$\frac{\partial o_1}{\partial p_1}$	$\frac{\partial o_1}{\partial p_2}$	$\frac{\partial o_1}{\partial p_3}$	$\frac{\partial o_1}{\partial p_4}$	etc
$\frac{\partial o_2}{\partial p_1}$	$\frac{\partial o_2}{\partial p_2}$	$\frac{\partial o_2}{\partial p_3}$	$\frac{\partial o_2}{\partial p_4}$	
$\frac{\partial o_3}{\partial p_1}$	$\frac{\partial o_3}{\partial p_2}$	$\frac{\partial o_3}{\partial p_3}$	$\frac{\partial o_3}{\partial p_4}$	
$\frac{\partial o_4}{\partial p_1}$	$\frac{\partial o_4}{\partial p_2}$	$\frac{\partial o_4}{\partial p_3}$	$\frac{\partial o_4}{\partial p_4}$	
$\frac{\partial o_5}{\partial p_1}$	$\frac{\partial o_5}{\partial p_2}$	$\frac{\partial o_5}{\partial p_3}$	$\frac{\partial o_5}{\partial p_4}$	
etc				

$$s = \mathbf{y}^t \mathbf{k}$$

$$\sigma_s^2 = \mathbf{y}^t \mathbf{C}(\mathbf{k}) \mathbf{y}$$

$$\sigma_{s'}^2 = \mathbf{y}^t \mathbf{C}'(\mathbf{k}) \mathbf{y}$$

$\sigma_s^2$ : prior variance of prediction  $s$

$\sigma_{s'}^2$ : posterior variance of prediction  $s$

$$\frac{\partial s}{\partial k_1} \quad \frac{\partial s}{\partial k_2} \quad \frac{\partial s}{\partial k_3} \quad \frac{\partial s}{\partial k_4} \quad \text{etc}$$

$\mathbf{S}$ : prediction of interest



Measurements of system state



Site characterisation



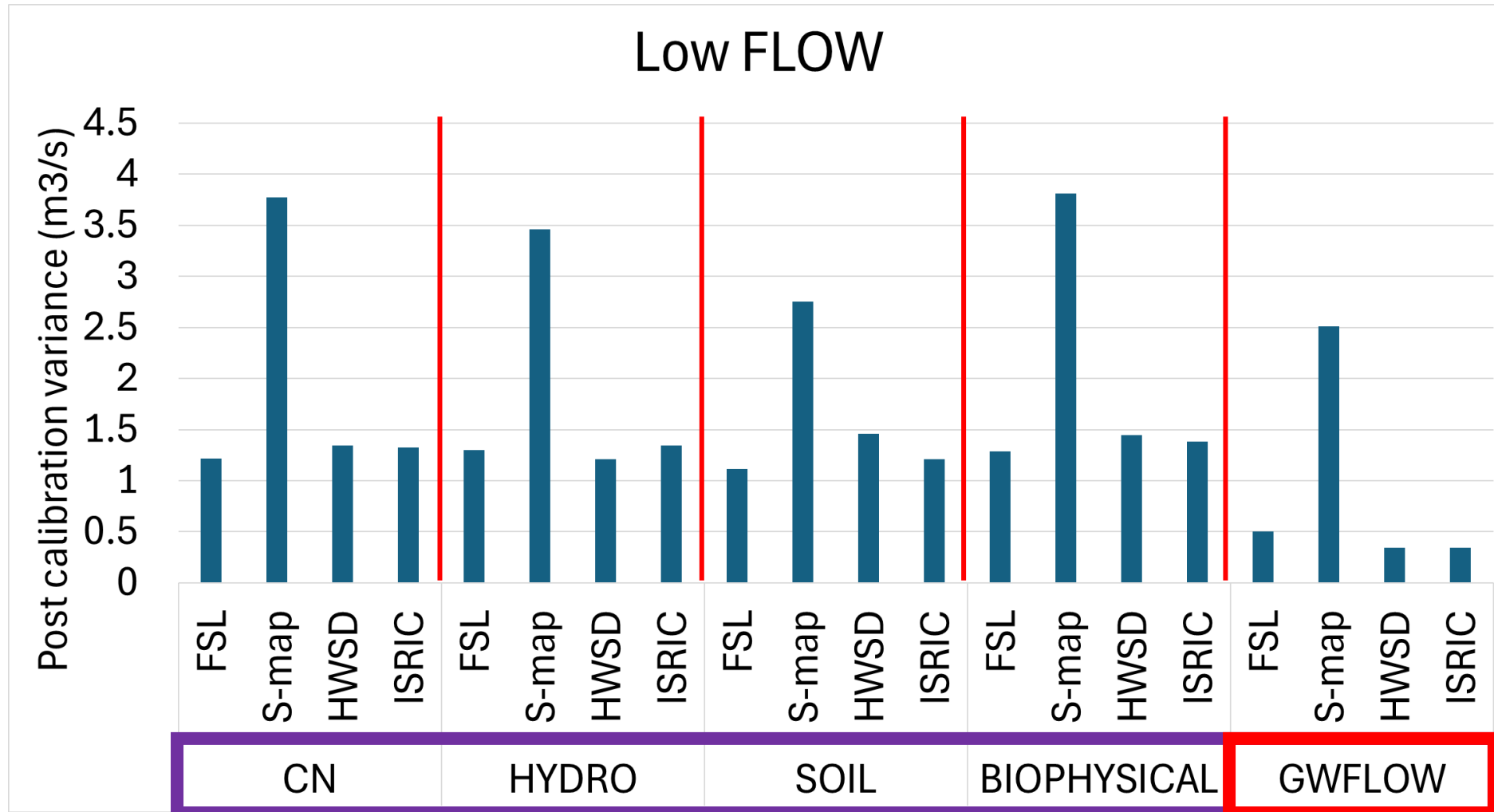
$$P(\mathbf{k}|\mathbf{h}) \propto P(\mathbf{h}|\mathbf{k}) P(\mathbf{k})$$

posterior probability

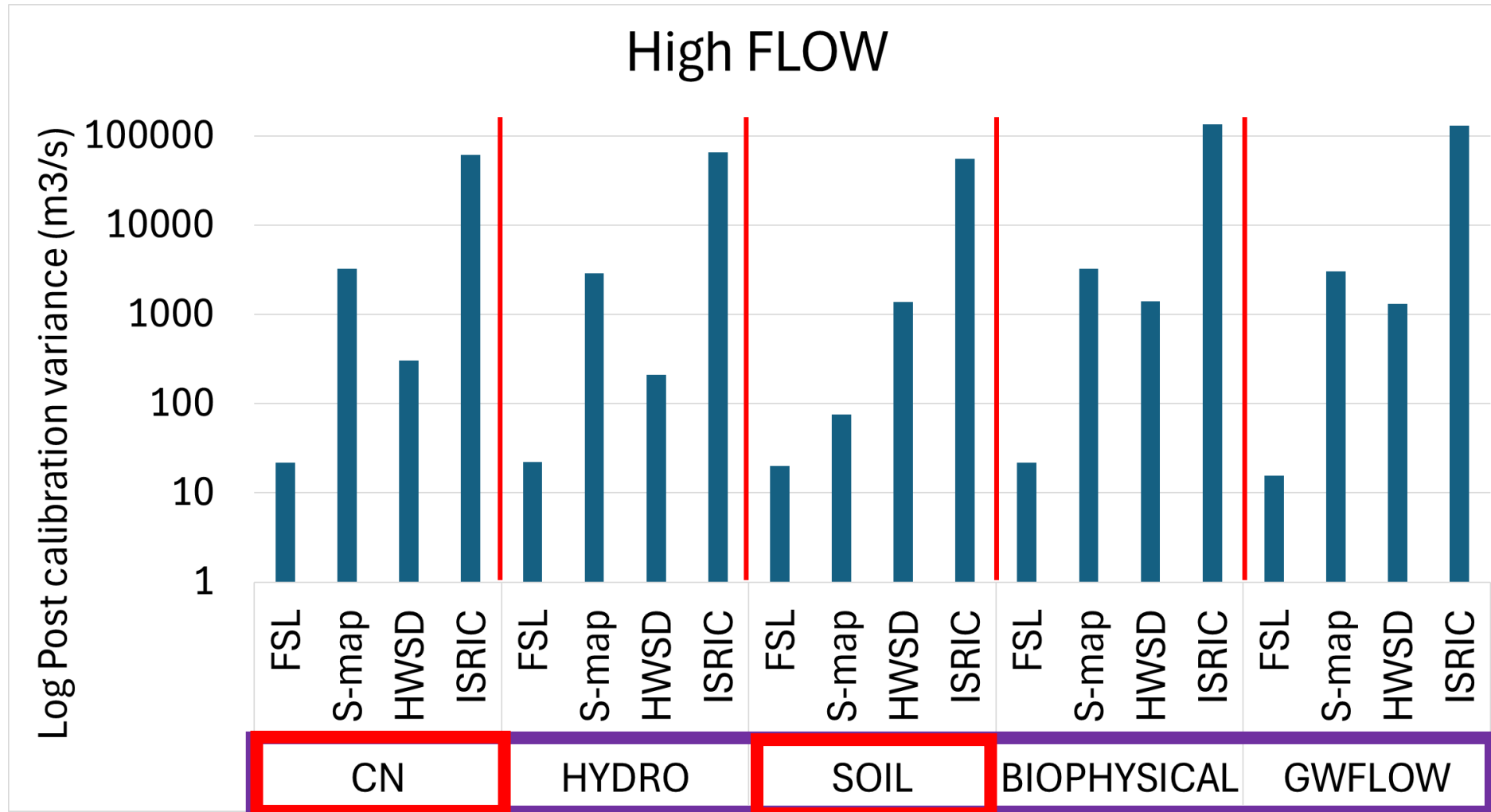
likelihood function

prior probability

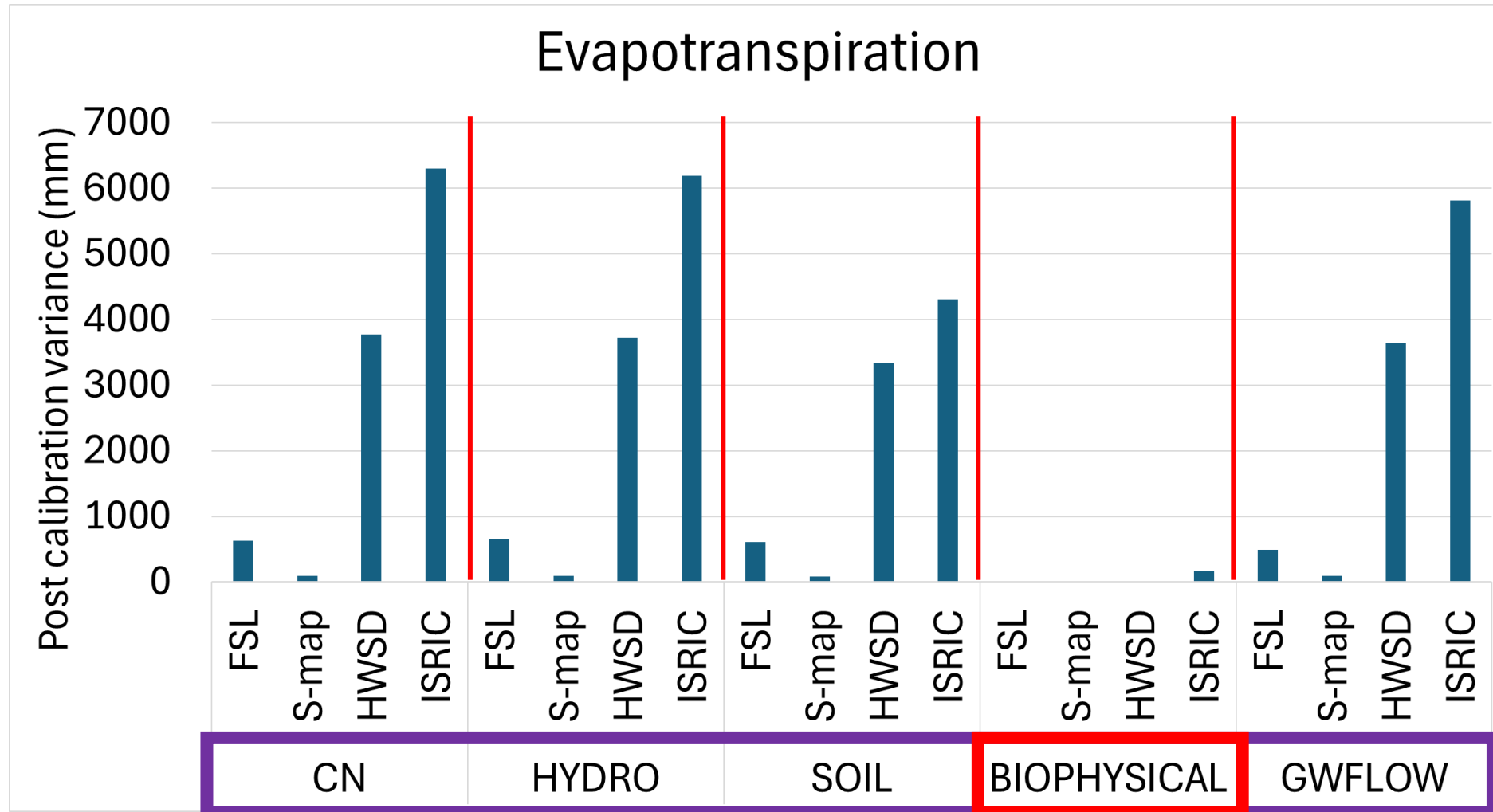
# Linear uncertainty analysis (Low flows)



# Linear uncertainty analysis (High flows)



# Linear uncertainty analysis (ET)



# Conclusion

**Thank you!**

- 1) Local soil databases outperformed global soil databases in estimating the streamflow at the outlet of the catchment.
- 2) Contribution to prediction uncertainty reduction:

Low flow simulation → groundwater-related parameters (maintaining the baseflow during low flow conditions)

High flow simulation → Soil parameters and CN (critical parameters in runoff and infiltration rates)

Evapotranspiration → Biophysical parameters (vegetation dynamics)



# Global sensitivity analysis

## Morris Screening (Elementary Effects)

$$EE_i = \frac{f(x_1, \dots, x_i + \Delta_i, \dots, x_p) - f(x)}{\Delta_i} \quad \text{Elementary Effect}$$

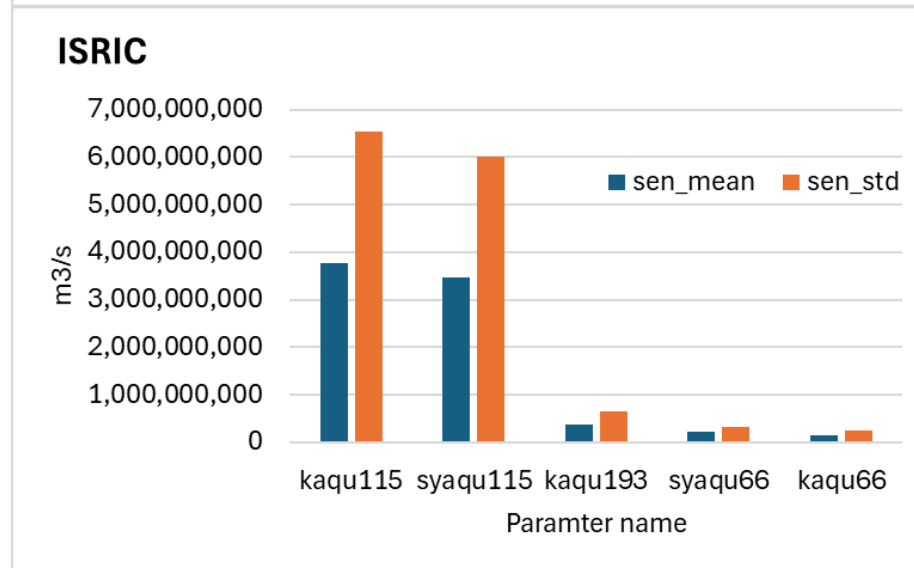
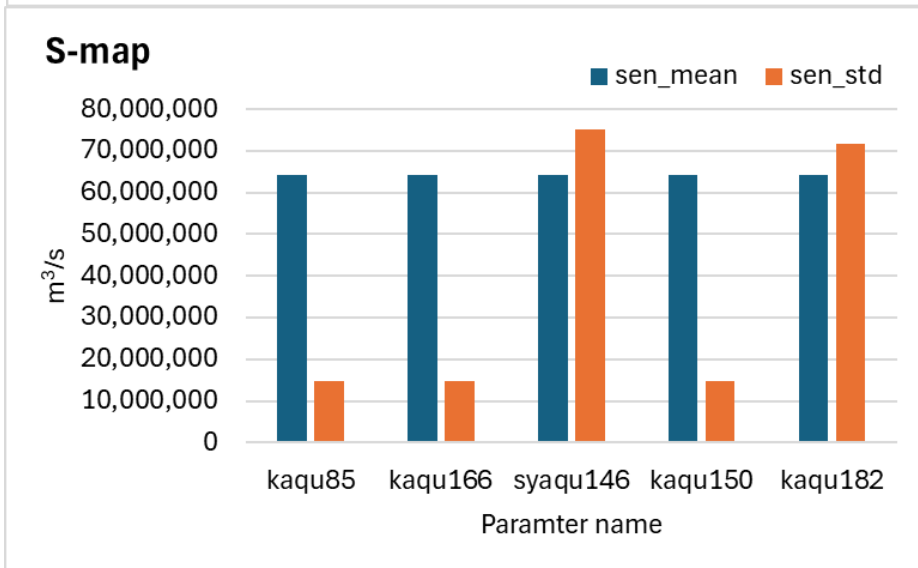
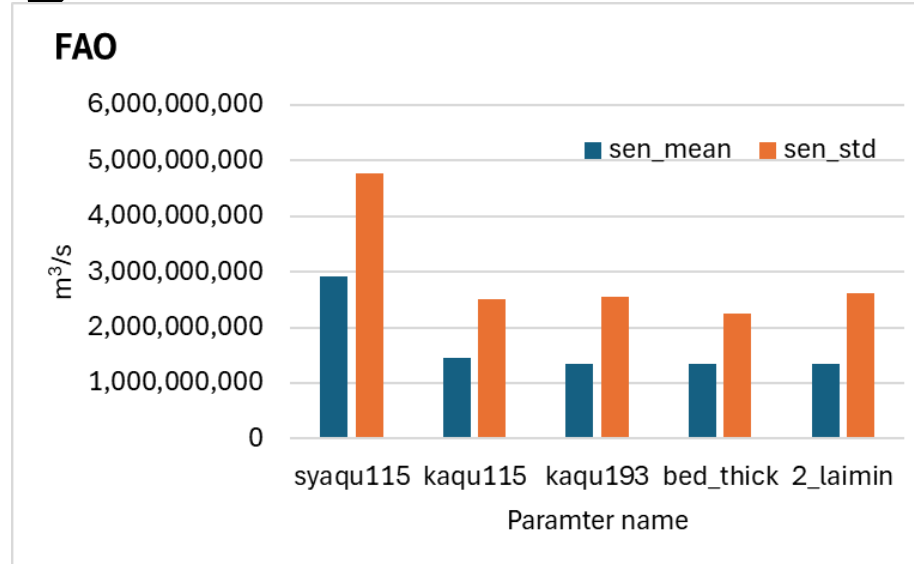
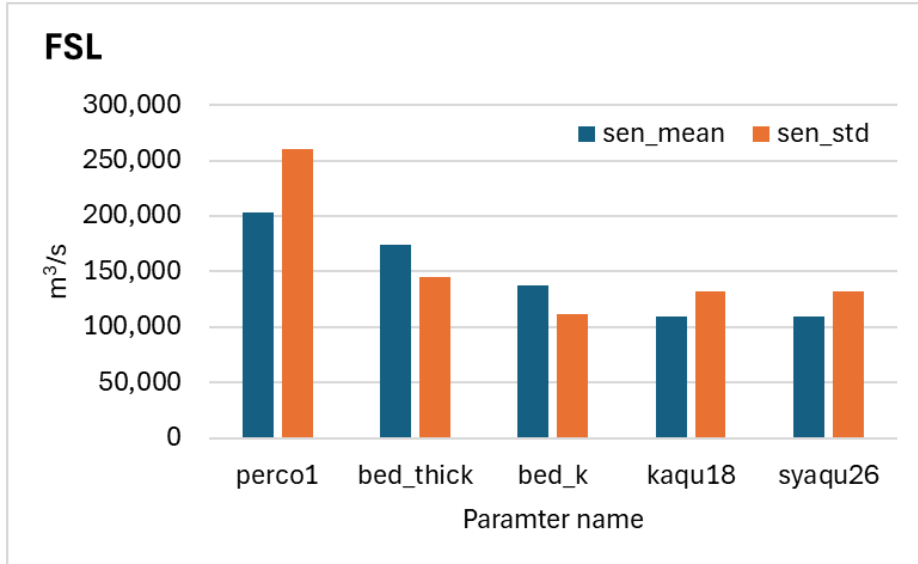
$$\mu_i^* = \frac{1}{n} \sum_{j=1}^n |EE_i(j)|$$

**Sensitivity index**

$$\sigma_i = \sqrt{\frac{1}{n-1} \sum_{j=1}^n \left[ EE_i(j) - \frac{1}{n} \sum_{j=1}^n EE_i(j) \right]^2}$$

**Non-linearity/interaction index**

# Global sensitivity results



# Global sensitivity results

- 1) Groundwater flow/properties/processes (GWFLOW) control the streamflow → improving the GW algorithm will be beneficial
- 2) Model outputs in GLOBAL soil databases showed MUCH higher sensitivities to parameter changes (**sen\_mean**)
- 3) Parameters in global soil databases showed MUCH higher non-linearity and/or interactions with each other (**sen\_std**)

**Large differences in sensitivity indices → higher uncertainty in model predictions →→**  
**importance of choosing the right soil database**

**Ultimate goal of a model:**

**Make a prediction!**

**Parameter contribution to prediction uncertainty???**