Information footprint of different ecohydrological data sources using multi-objective calibration of a physically-based model as hypothesis testing

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Introduction

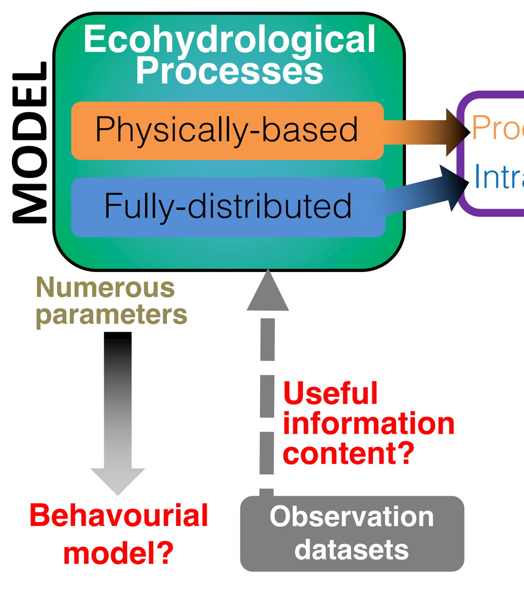


Figure 1. Opportunities and issues raised by process-based, fully-distributed modelling approaches in ecohydrology.

Critical zone science seeks an integrated understanding of hydrological processes considering ecological, geomorphological and pedological couplings [1]. Physically-based, fully-distributed modelling is a promising approach, but its inherent complexity (parameterization) requires a consistent identification of feasible model configurations.

Can we use ecohydrological datasets across processes to bring differentiated information content to such models?

We tested this approach using the EcH$_2$O model in a long-term monitored high-latitude catchment [2], where ecohydrological couplings are poorly understood and potentially climate-sensitive.

Main findings

- Ecohydrological model captures multi-process response in wet, energy-limited steep catchment.
- Using all observation types (streamflow, soil moisture, pine transpiration and net radiation) for calibration yields best performance and lowest predictive uncertainty (Fig. 2).
- Stream discharge brings poorly-focused leverage to ecohydrological simulations.
- Riparian soil moisture and transpiration observations are most informative.

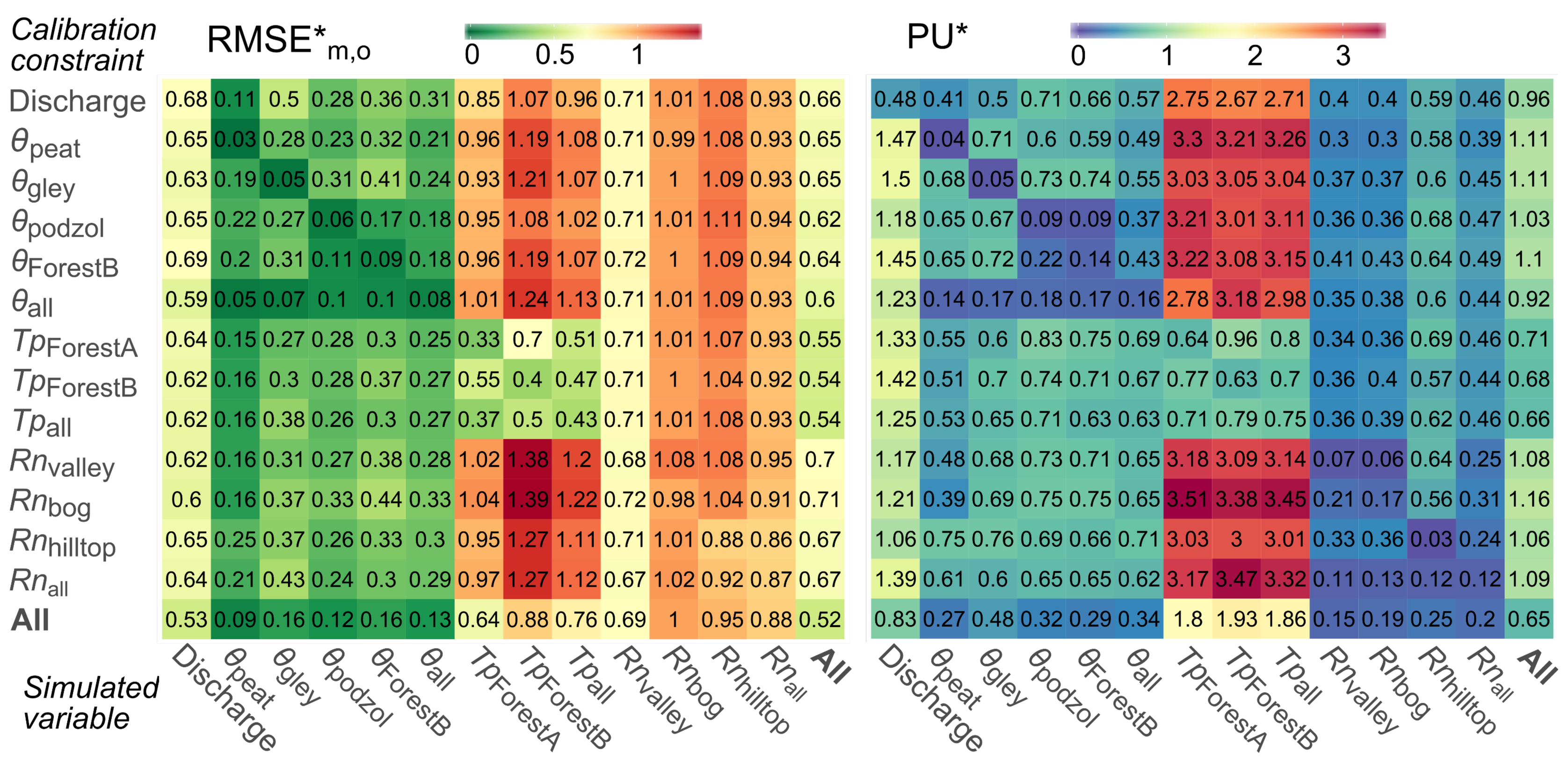


Figure 2. Heat map of best-runs-averaged **(a)** root mean square error between model and observations, normalized with the observation average (RMSE*$_{m,o}$), and **(b)** normalized predictive uncertainty (PU*): daily 90%-spread interval across the 30 best runs divided by the inter-run mean, then averaged over the evaluation period. The x-axis gives the variable or group of variables evaluated, the y-axis shows the dataset(s) used as a constraint over the calibration period.

Outlook

- Robust basis for water pathways characterization across ecohydrological compartments:
  → using process-based tracking of stable isotopes and water age (Kuppel et al., *in prep.*)
  → prediction of consequences from land use and climate alterations
- Advocates for diversifying observations in catchment instrumentation (when possible) for advancing mechanistic understanding of critical zone functioning
- Is this model-data approach efficient for other climatic and topographical settings?
  → Planned application to other well-instrumented catchments across the wider north

Study site and datasets

3.2 km² headwater catchment in Scottish Highlands (Fig. 3). **Climate:** Boreal/temperate oceanic; precipitation ~1000 mm · yr^{-1} (low seasonality, snowfall <5%), low-energy (pot. ET ~400 mm · yr^{-1}). **Topography:** glacier-shaped; wide valley bottom, underlying drift deposits.

Soils: Shallow, freely-draining (hillslopes) to saturated, deep organic-rich (riparian area). **Vegetation:** heather shrublands on hillslopes, Scots pine (steep slopes, plantations), and *Molinia* grasses and *Sphagnum* bog mosses (riparian area).

10 calibration datasets across ecohydrological processes (Fig. 4).

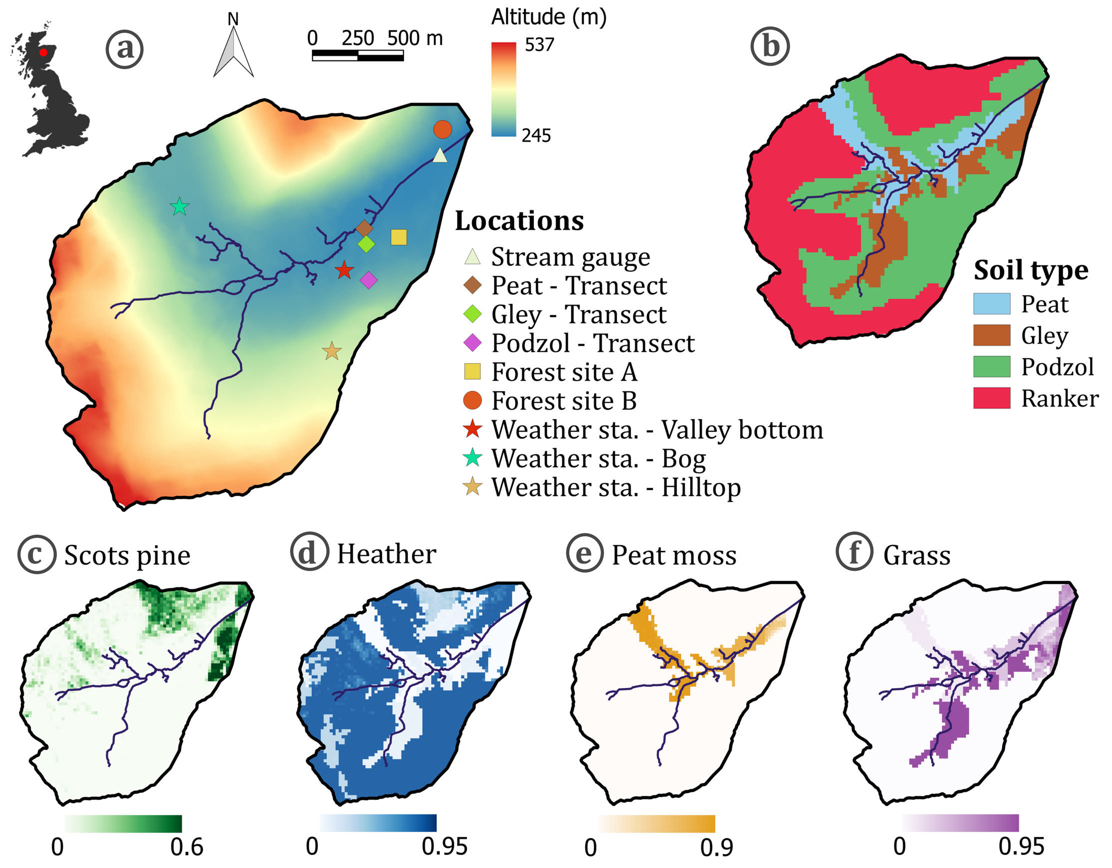


Figure 3. Bruntland Burn catchment, showing **(a)** topography, stream network, and the monitoring locations and associated instrumentation: stream gauge (triangle), soil moisture sensors (diamonds and circle), sapflow transpiration (square and circle), and micrometeorology (including net radiation, star). The conceptualisation used for simulations (b-f, 30×30m² resolution) comprises **(b)** pedology, aggregated from the Hydrology of Soil Types (HOST) classes, and **(c-f)** the pixel fraction covered by the four considered vegetation types (in addition to scree/bare soil, not shown).

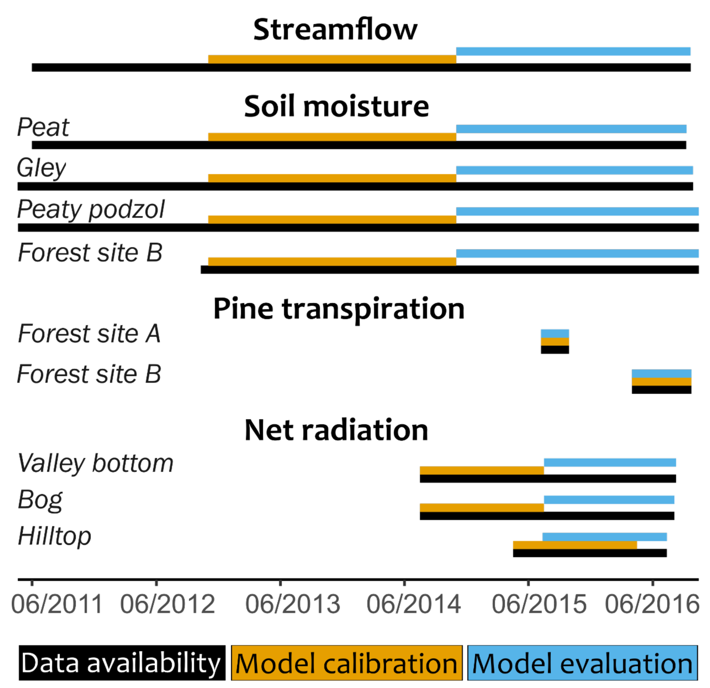


Figure 4. Temporal window covered by each of the data sets (black), used to constrain the model during the calibration period (orange), and then to evaluate the calibrated model (blue).

Model and calibration

EcH$_2$O model [3]: Process-based, fully-distributed. Tightly couples two-layer (canopy and surface) energy balance, hydrologic module for lateral (kinematic wave) and vertical transfers (Fig. 5), and transpiration-based plant phenology (trees and grasses [4]). Resolution: 30×30 m², daily.

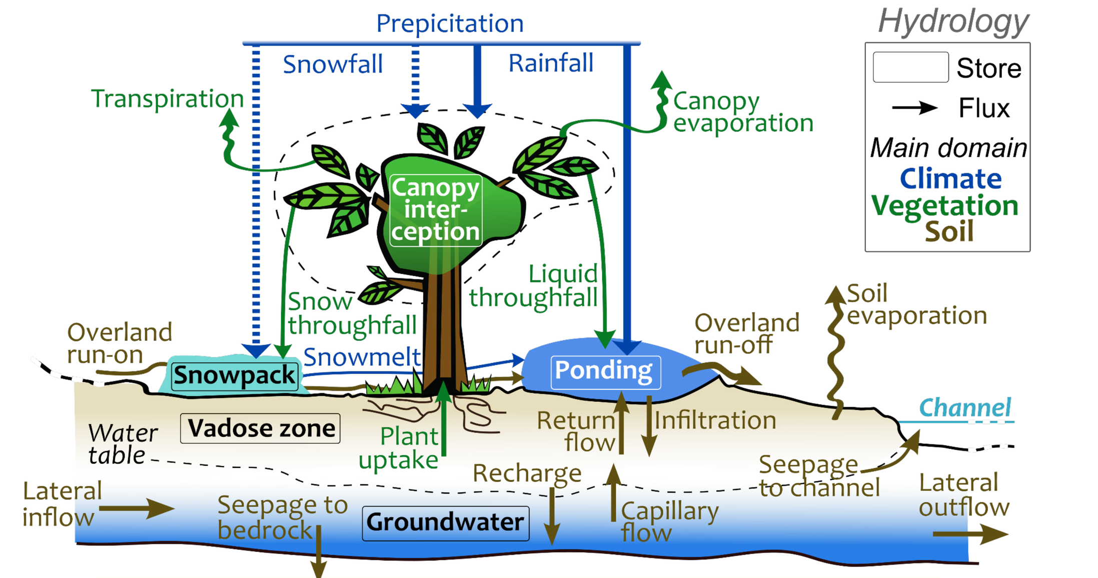
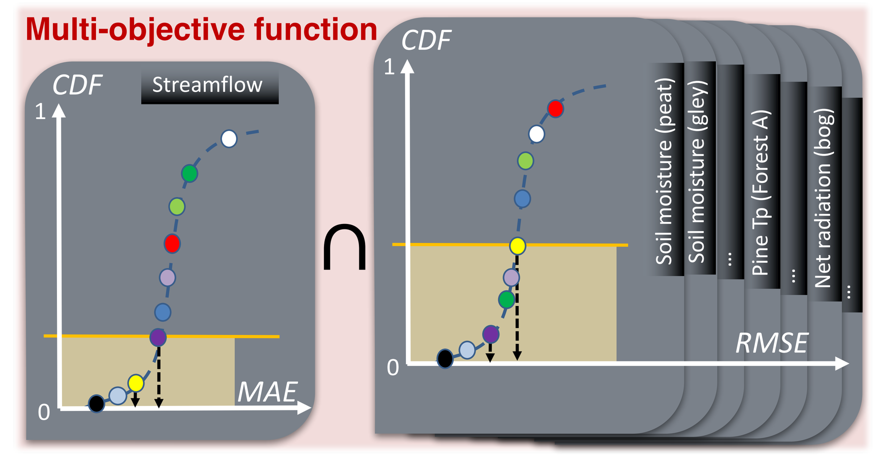


Figure 5. Hydrological processes simulated by the EcH$_2$O model.

Table 1. List of optimized parameters.

Group	Parameter
Soil hydrology (× 4 soil types)	Soil depths (total, 1st & 2nd layers)
	Soil porosity
	Saturated hydraulic conductivity
	Anisotropy
	Brooks-Corey pedotransfer coefficient
	Air-entry pressure head
	Residual soil moisture
	Exponential root profile
Ecology (× 4 veg. types)	Maximal stomatal conductance
	Max. interception storage / unit LAI
	Optimal photosynthesis temp.
	Matrix potential halving stomatal conductance
	Sensitivity of stomatal cond. to soil water potential
	Light attenuation coefficient



Calibration: uniform Monte-Carlo sampling, 100000 sets of the 64 parameters (Table 1). Several combination of data constraints using a multi-objective function (Fig. 6).

Figure 6. Methodology used to select the 30 best model configurations, using the cumulative distribution functions (CDF) of dataset-specific goodness-of-fit (GOF) [2,5]: mean absolute error (MAE) for streamflow and root mean square error (RMSE) for all other datasets. It identifies the quantile threshold common to all GOF's CDFs below which 30 model runs simultaneously meet the calibration target.

Results

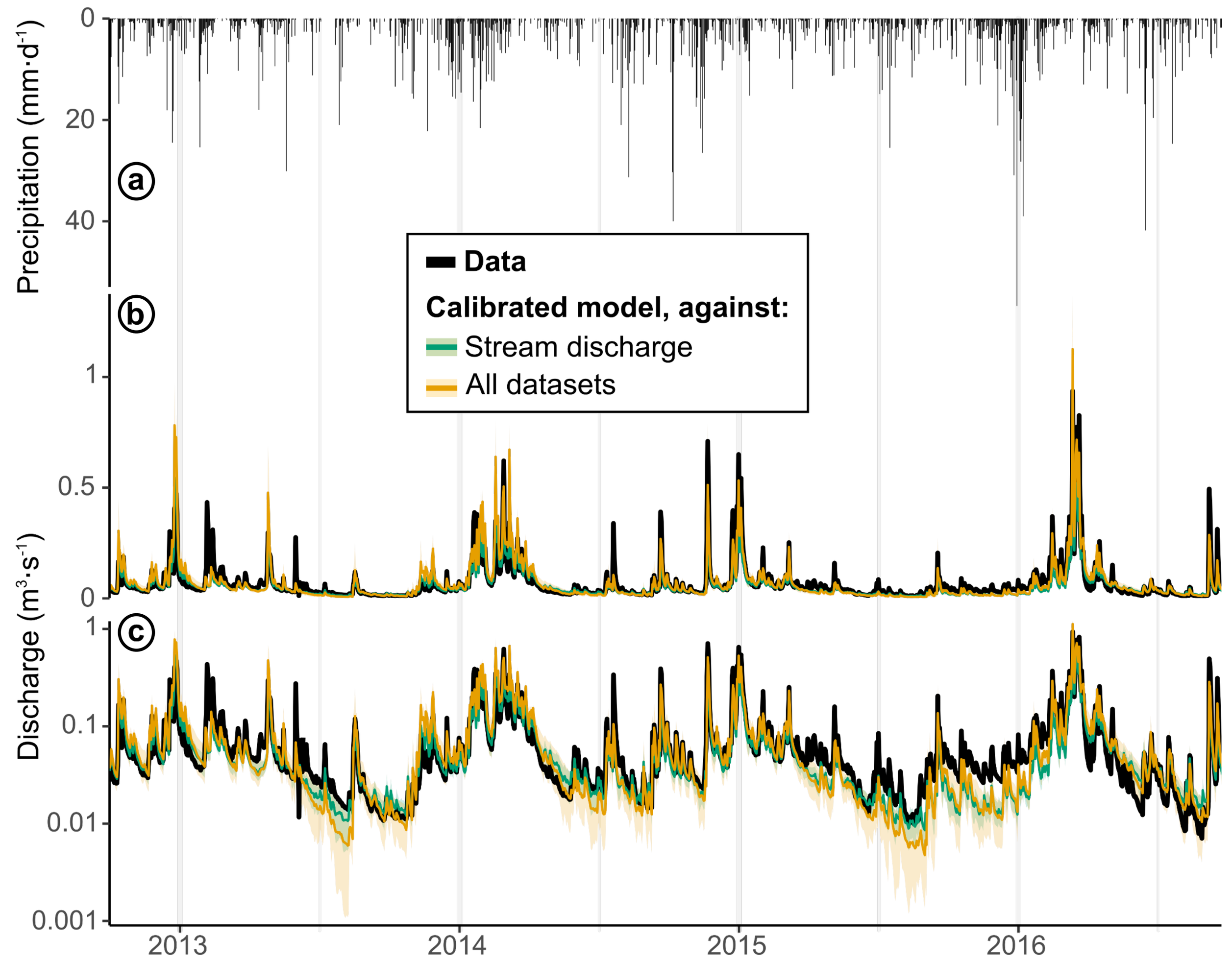


Figure 7. Time series of **(a)** measured precipitation, and stream discharge, with **(b)** normal and **(c)** logarithmic scale the data in black and in colour the average of the 30 best and 90%-spread interval for two types of calibration: (green) using only stream discharge and (yellow) when simultaneously constraining the model against all datasets.

Stream discharge (ensemble mean and 90%-spread) well simulated, with low spread (Fig. 7): 0.6 < KGE$_{2012}$< 0.95. Slight underestimation of low flows.

Good seasonal and high-frequency timing of **volumetric soil water content** (θ) (Fig. 8).
Riparian area: Amplitude overestimated (Fig. 8a)
Hillslope: Amplitude underestimated (Fig. 8b)
Adding more constraints increases *observation-specific* 90%-spread. Less marked on hillslopes.

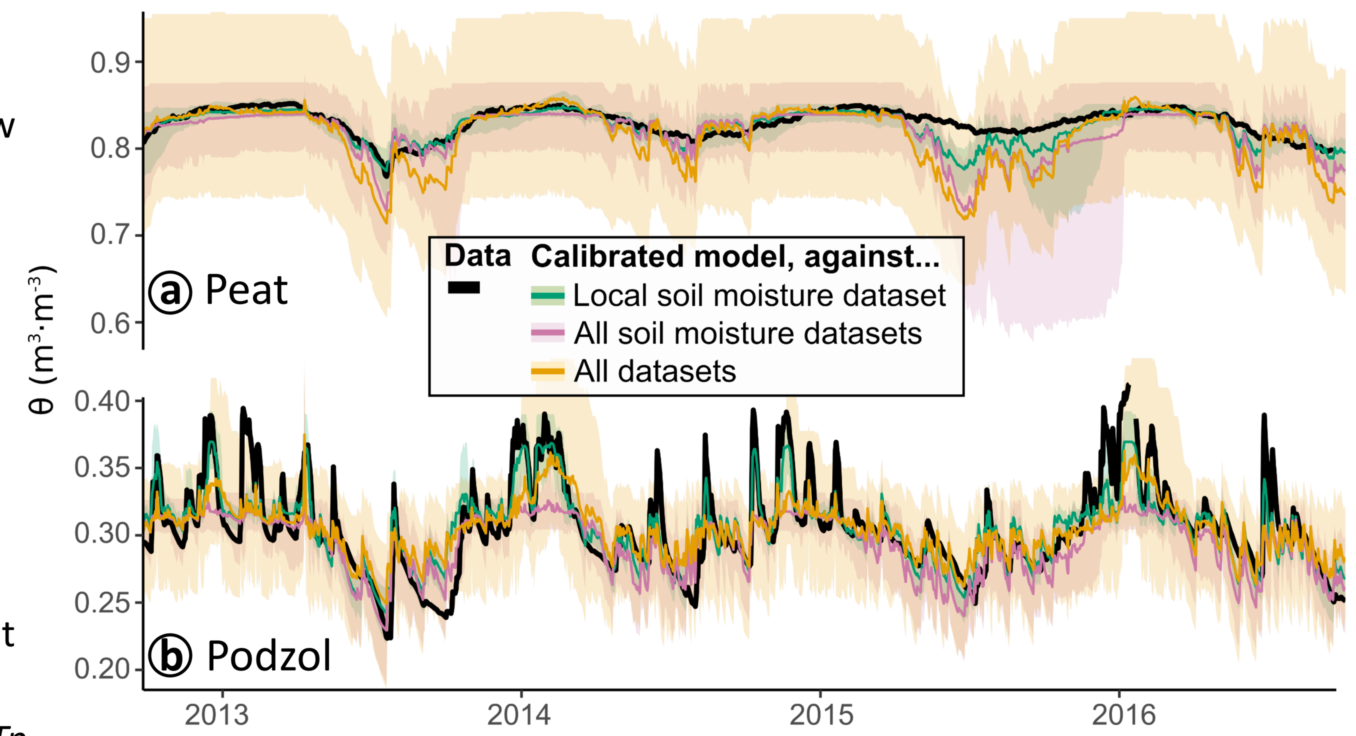


Figure 8. Time series of profile-averaged soil volumetric water at the two transect sites: peat **(a)** and podzol **(b)**. Observations are shown in black, while colours display the average of the 30 best runs and 90%-spread interval for three types of calibration: (green) using only the plotted quantities, (pink) using all soil moisture datasets and (yellow) using all collected datasets.

Summer **pine transpiration** (*Tp*) well simulated at both forest sites (Forest site A shown in Fig. 9).
Adding more constraints yields underestimated *Tp*.

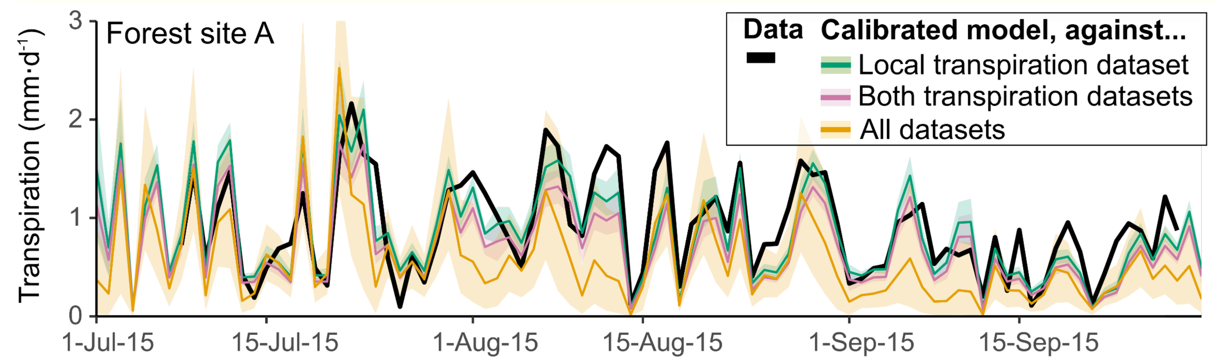


Figure 9. Time series of measured and simulated pine stand transpiration at Forest site A, showing data in black and in colour the average of the 30 best runs and 90%-spread interval for three types of calibration: (green) using only the plotted quantities, (pink) using all soil moisture datasets and (yellow) using all collected datasets.

Top-of-canopy **net radiation** well captured, seasonally and daily, with low 90%-spread.
Underestimation of summer values on hilltop (not shown).

Overall performance and uncertainty (Fig. 2)
Streamflow well reproduced regardless of calibration data.
Simulation of θ and *Tp* most sensitive to including local/same-type datasets → *specific information footprint.*
Best (lowest) overall score (uncertainty) when using all datasets as constraints.

Independent evaluation

Reasonable consistency of EcH$_2$O with catchment-wide estimate of **saturated area fraction** (Fig. 10).
Good timing, general overestimation outside saturation peaks.

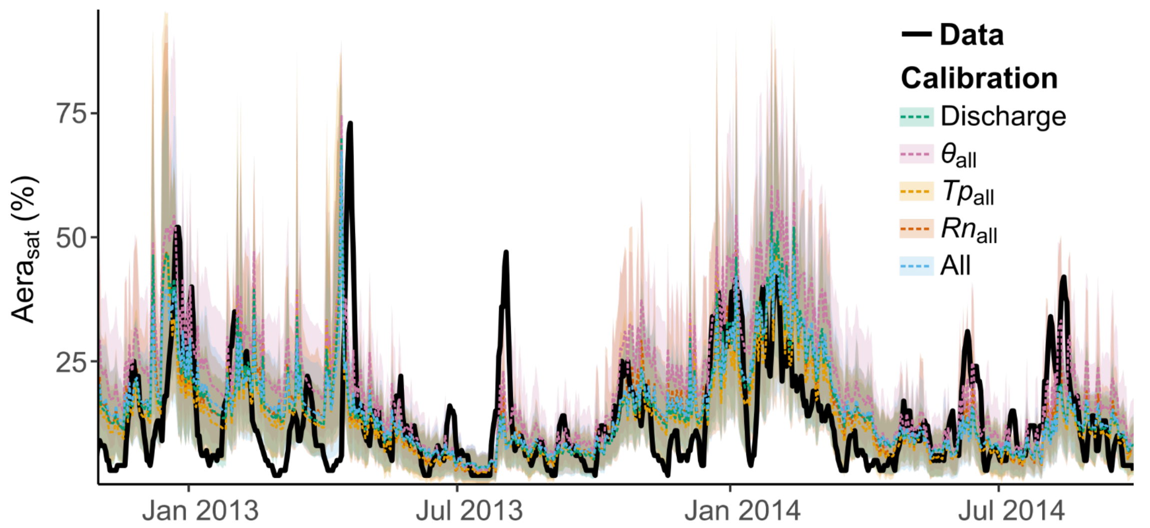


Figure 10. Time series of saturated area at the catchment scale, comparing an independent data-driven estimate [6] (black) to simulation outputs using parameters sets from different calibration cases (average and 90%-spread interval).

Acknowledgements

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