



Center for Western Weather  
and Water Extremes  
SCRIPPS INSTITUTION OF OCEANOGRAPHY  
AT UC SAN DIEGO

GEWEX Cross-Cutting Initiative: the RivEx Experiment  
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# Large-scale Runoff Estimation

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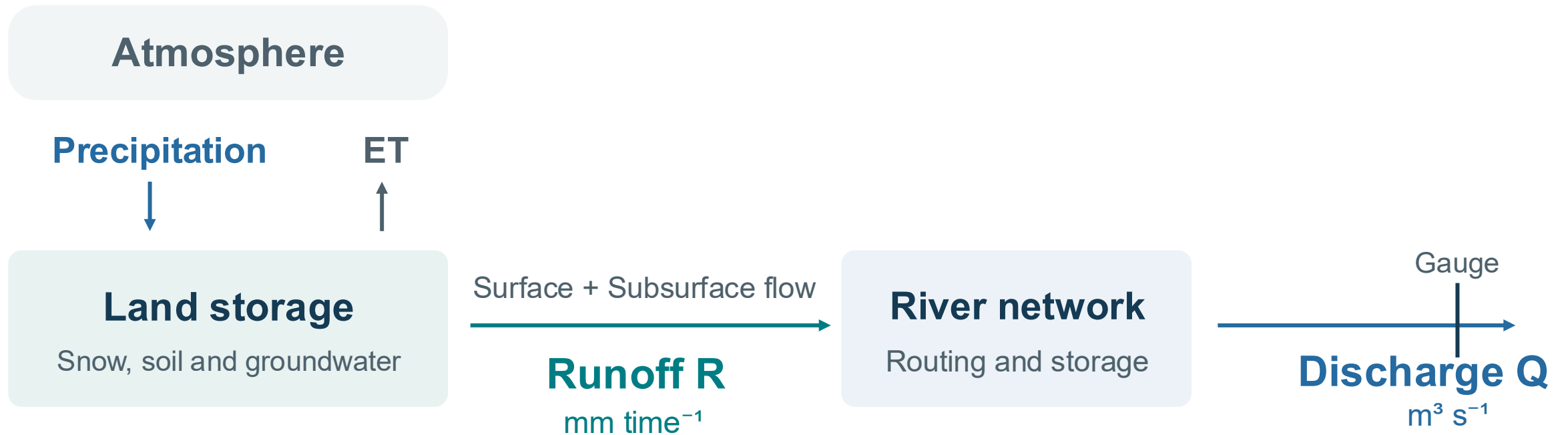
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UC San Diego



# Runoff in the terrestrial water cycle



## Not directly observed over grids

- Surface and subsurface water draining from a given land unit(i.e., grid cell)
- Generated across the land

## Observed in the river

- Water passing through a cross-section after upstream flow has been routed
- The response to the runoff field integrated in both time and space

# Three pathways for runoff estimation

Water balance

Forward modeling

Inverse inference

# Runoff estimation: water balance

$$R = P - ET - \Delta S / \Delta t$$

- Often applied at monthly or longer time scales and coarse spatial scales
- Residual runoff inherits errors in P, ET and storage. Product choice matters.

## Direct residual estimation - Michailovsky et al. (2023)

- Monthly runoff, 2003–2016
- 45 combinations: 3 P × 5 ET × 3 TWS products
- Evaluation over 931 catchments with area >10,000 km<sup>2</sup>
- Median NSE for all gauges & all product combinations: -0.02
- Only 44.9% of evaluated time series have NSE >0

# Runoff estimation: water balance

$$R = P - ET - \Delta S / \Delta t$$

- Water-budget reconciliation: jointly adjust water-budget components to achieve closure

## Constrained Kalman Filtering - Zhang et al. (2018)

- 0.5°, monthly, 1984-2010
- Merge multiple P, ET and  $\Delta S$  products. VIC runoff as a prior
- A constrained Kalman Filter to redistribute the budget errors, enforcing  $P - ET - \Delta S / \Delta t - R = 0$

## Optimal interpolation with neural networks - Heberger et al. (2025)

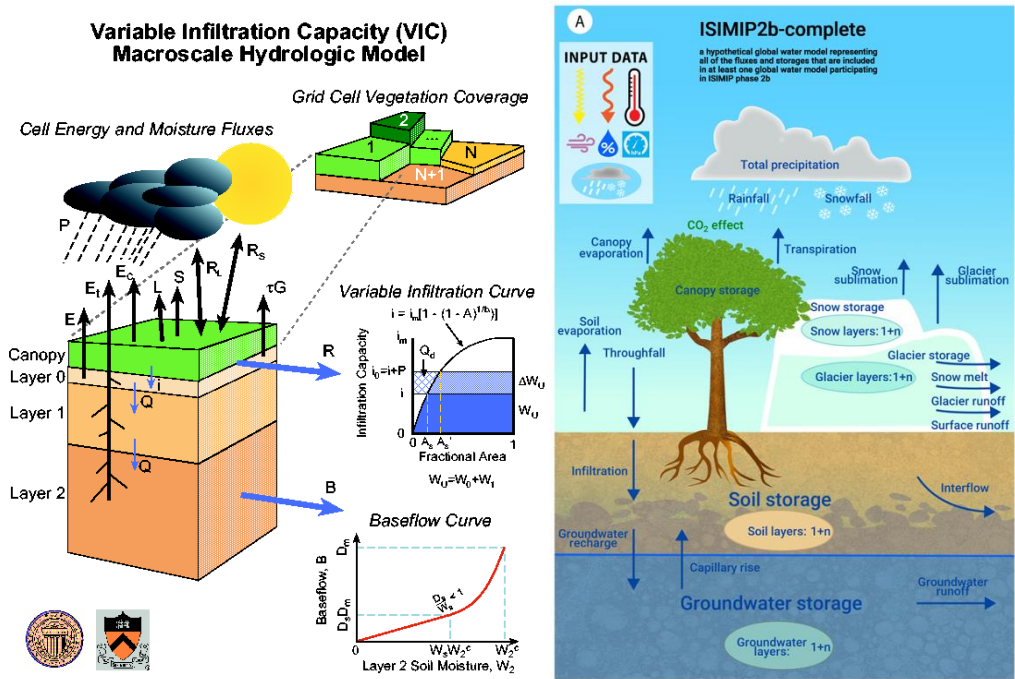
- 0.5°, monthly
- Optimal interpolation reconciles P, ET, R &  $\Delta S / \Delta t$  across basins
- Neural networks learn to reproduce these basin-scale adjustments
- Apply the learned relationships to global 0.5° grids

# Runoff estimation: forward modeling

P, T, Radiation...  $\longrightarrow$  Runoff R

- **Process-based modeling**
  - Explicit hydrologic processes to simulate how meteorological inputs become runoff
  - Generally high resolution and long time period

| Product   | Resolution      | Time period                                   |
|-----------|-----------------|-----------------------------------------------|
| ERA5-land | 0.1°, hourly    | 1950 - present                                |
| GRFR      | 0.05°, 3-hourly | 1979 - 2019                                   |
| GloFAS    | 0.05°, daily    | 1979 - present                                |
| GLDAS     | 0.25°, 3-hourly | 1948 – present                                |
| ISIMIP3b  | 0.5°, daily     | 1850– 2014 (historical)<br>2015-2100 (future) |
| ...       | ...             | ...                                           |

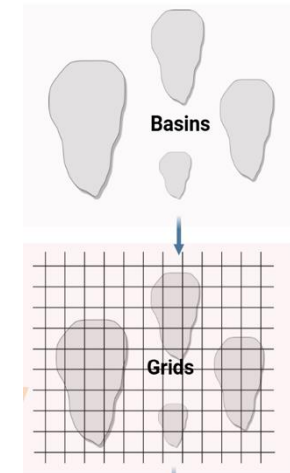


# Runoff estimation: forward modeling

P, T, Radiation...  $\longrightarrow$  Runoff R

- **Data-driven modeling**

- No explicit equations, learns the input-output relationship directly from data
- Flexible functions
- Large-scale runoff estimation:
  - Learn the relationship between the predictors (i.e., P, T) and response (R) over small catchments
  - Application of learned relationship over large-scale grids using gridded predictors



**Skill depends on the training coverage, forcing quality and basin-to-grid transfer assumptions.**

# Runoff estimation: forward modeling

P, T, Radiation...



Runoff R

- **Data-driven modeling**

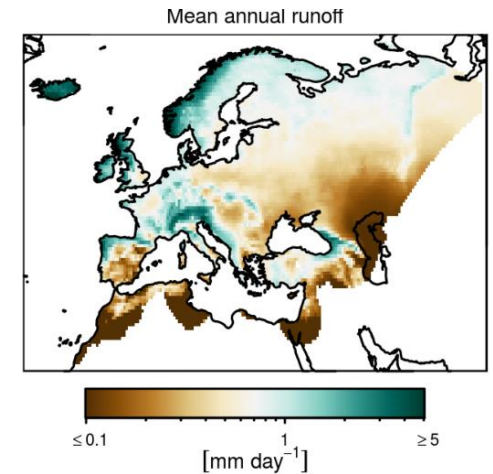
- Random Forest model

- E-RUN: Europe**

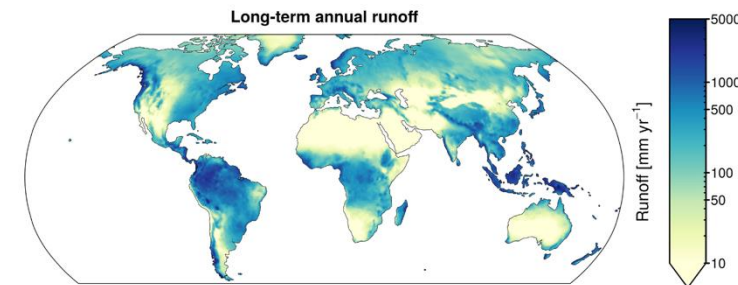
- 0.5°, Monthly runoff, Dec. 1950 – Dec. 2015
    - 2271 small catchments ( $\leq 500\text{km}^2$ ), 961 training grids
    - Relationship:  $R \sim P \ \& \ T$  in the past 12 months
    - <https://doi.pangaea.de/10.1594/PANGAEA.861371>

- G-RUN: global land**

- 0.5°, Monthly runoff, 1902 – 2014
    - 10042 small catchments (10-2,500  $\text{km}^2$ ), 5094 training grids
    - Relationship:  $R \sim P \ \& \ T$  in the past 6 months
    - <https://doi.org/10.6084/m9.figshare.9228176>



E-RUN long-term mean runoff (mm/day)



G-RUN long-term mean runoff (mm/yr)

# Runoff estimation: forward modeling

P, T, Radiation...



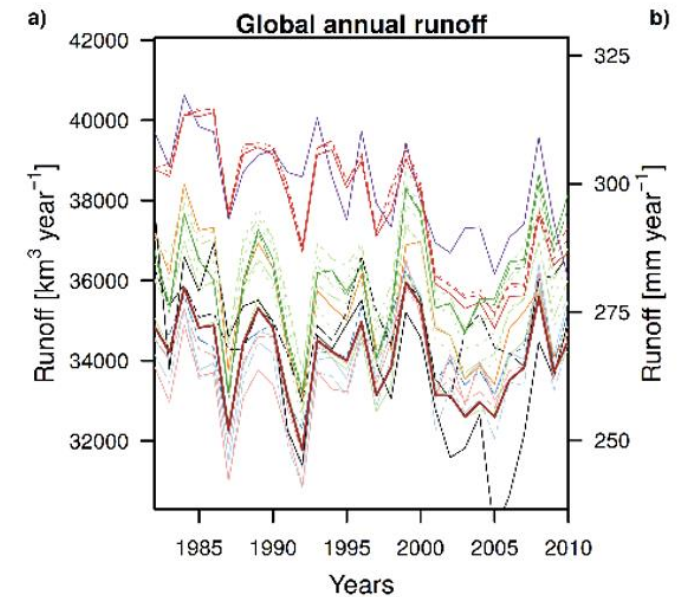
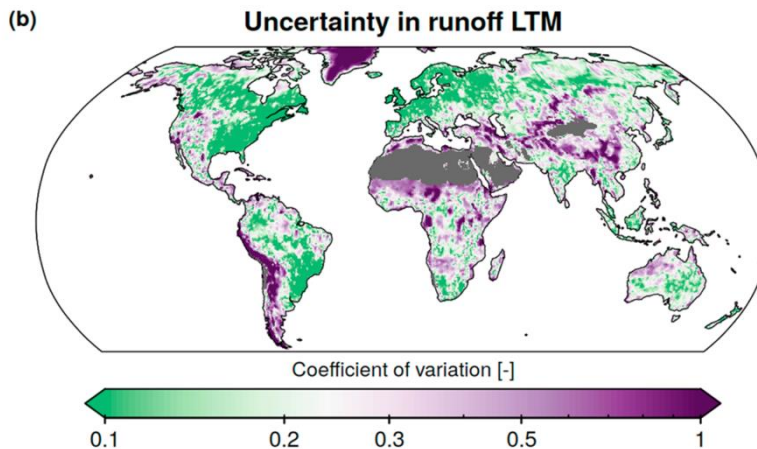
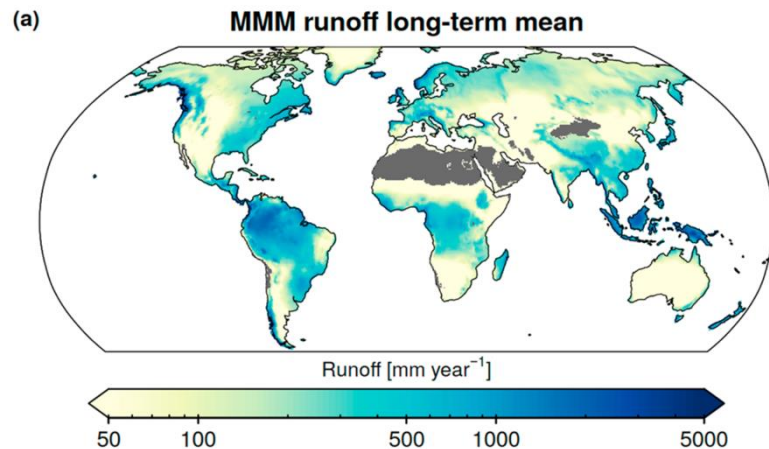
Runoff R

- **Data-driven modeling**

- Random Forest model

- **G-RUN-Ensemble: Global land**

- 0.5°, Monthly runoff, 1902 - 2019
- 525 ensemble members: 21 forcing datasets x 25 RF training subsets
- <https://doi.org/10.6084/m9.figshare.12794075>



# Runoff estimation: forward modeling

P, T, Radiation...



Runoff R

- **Data-driven modeling**

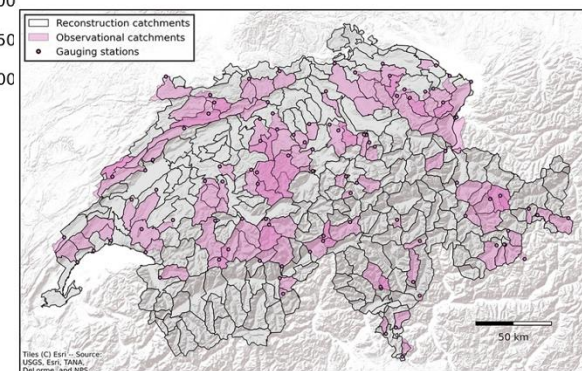
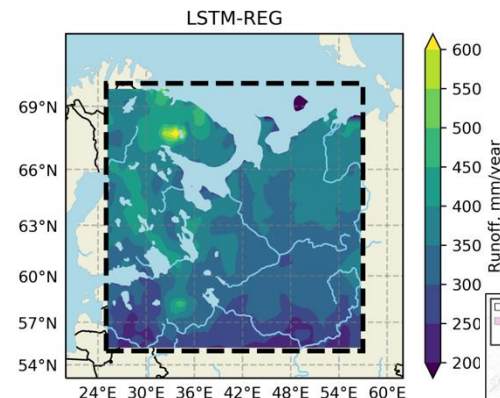
- Long Short-Term Memory (LSTM) model
- A selective memory mechanism, learns what to remember, forget and use for prediction
- Inputs: meteorological forcings + static attributes, longer input sequences (i.e., 365-day)

## LSTM-REG: Norwest Russia

- 0.5°, daily runoff, 1980 - 2016
- <https://zenodo.org/records/4317327>

## CH-RUN: Switzerland

- Contiguous small & medium-sized catchments
- Daily, 1962-2023
- <https://doi.org/20.500.11850/714281>



# Runoff estimation: forward modeling

P, T, Radiation...



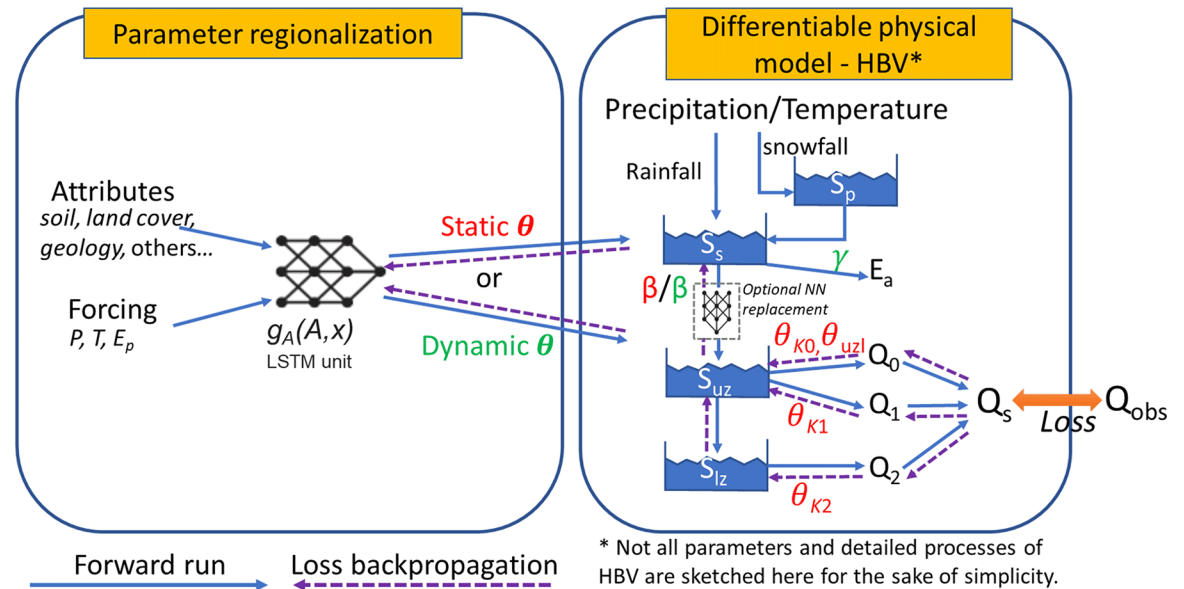
Runoff R

- **Data-driven modeling**

- Hybrid differentiable model: differentiable process-based models with embedded neural networks to provide parameterization or module replacements

- **Ongoing work:**

- Differentiable HBV: use HBV as the backbone
- Building the generic parameter transfer functions from the raw geographic attributes
- 0.1°, daily runoff, global land



Feng et al. (2022)

# Runoff estimation: inverse inference



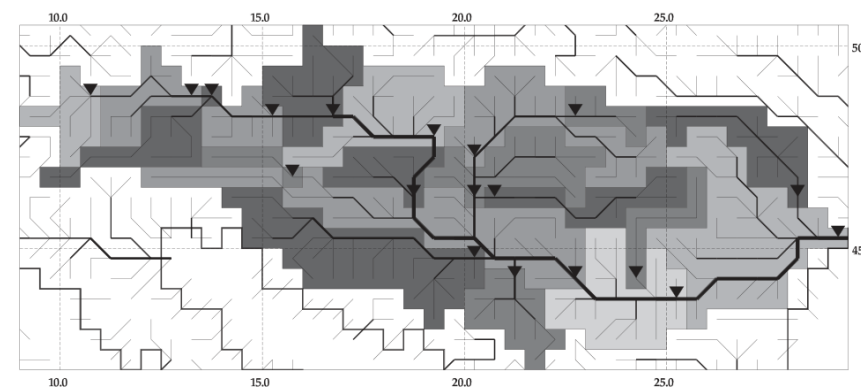
Use observed downstream Q to infer/constrain the runoff.

- When routing effects are small

A uniform runoff spatial distribution and use  $Q/A$  to approximate basin-mean runoff

## UNH/GRDC composite runoff fields

- $0.5^\circ$ , long-term monthly
- Runoff between gauges:  $R_i \approx \Delta Q_i / A_i$
- Runoff correction coefficient:  $C_i = \text{observed } R_i / \text{modeled } R_i$
- Corrected runoff for each grid cell:  $R_c = C_i \times \text{modeled gridded } R$
- Gauge observations constrain regional totals, and the model supplies the within-region pattern



Inter-station areas in the Danube basin

# Runoff estimation: inverse inference



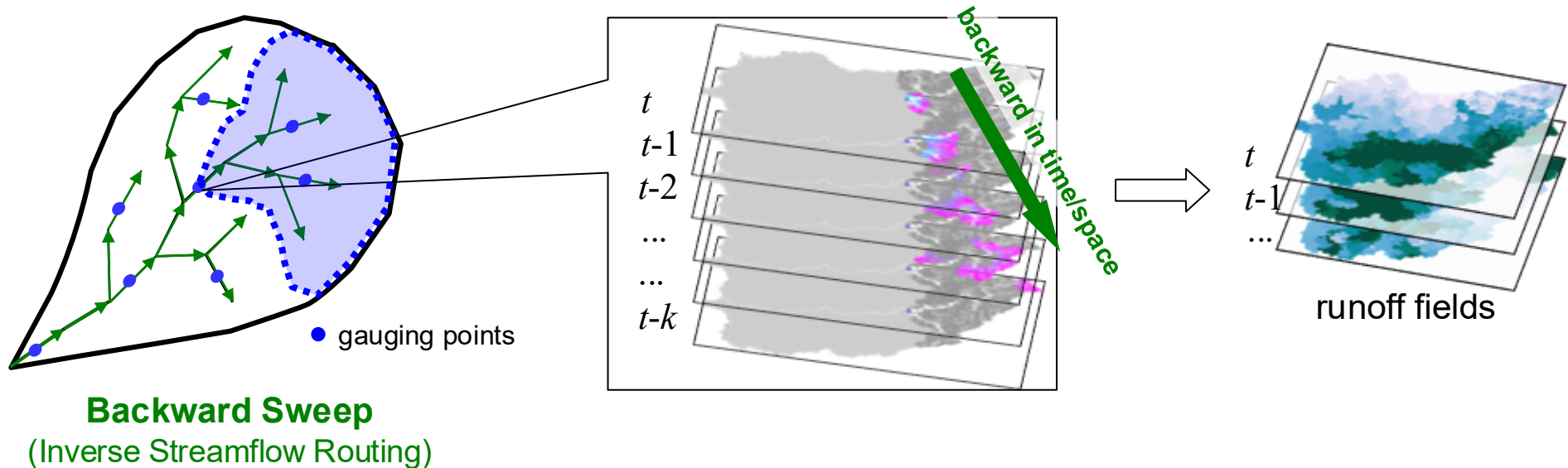
Use observed downstream Q to infer/constrain the runoff.

- When travel time matters

Invert a river-routing model to update a prior runoff field across upstream locations and earlier time steps.

Forward model (linear):  $y = Hx$

Inverse model:  $x = H^{-1}y$



# Runoff estimation: inverse inference

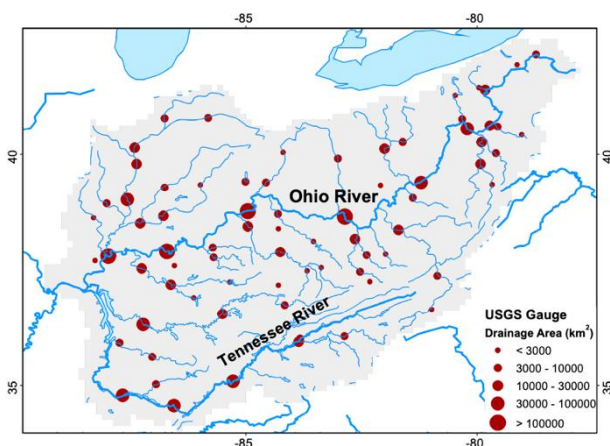


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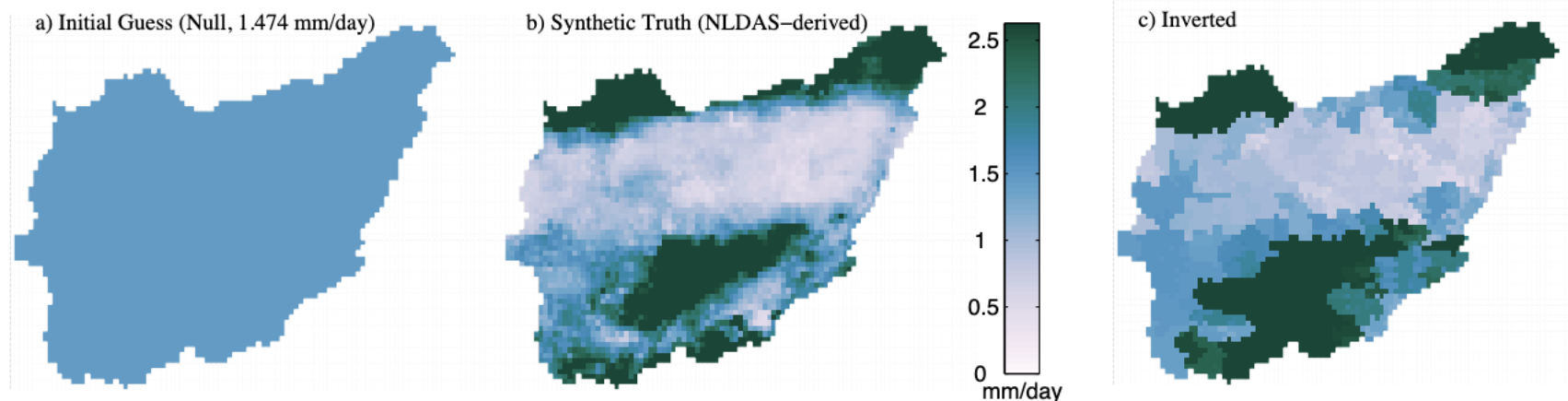
- When travel time matters

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Forward model (linear):  $y = Hx$       Inverse model:  $x = H^{-1}y$



Synthetic Q at 75 USGS gauges



# Runoff estimation: inverse inference

Runoff  $R$



Discharge  $Q$

observable at gauges

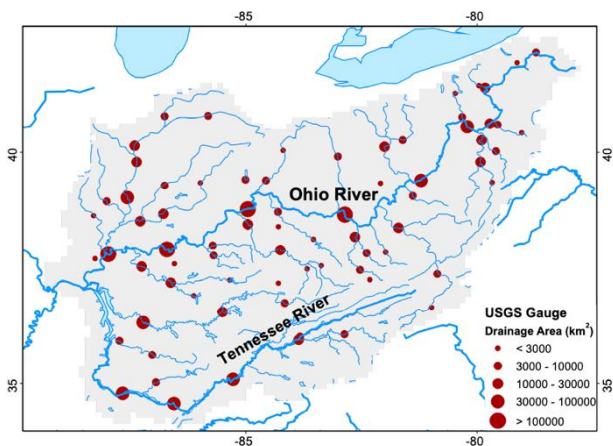
Use observed downstream  $Q$  to infer/constrain the runoff.

- When travel time matters

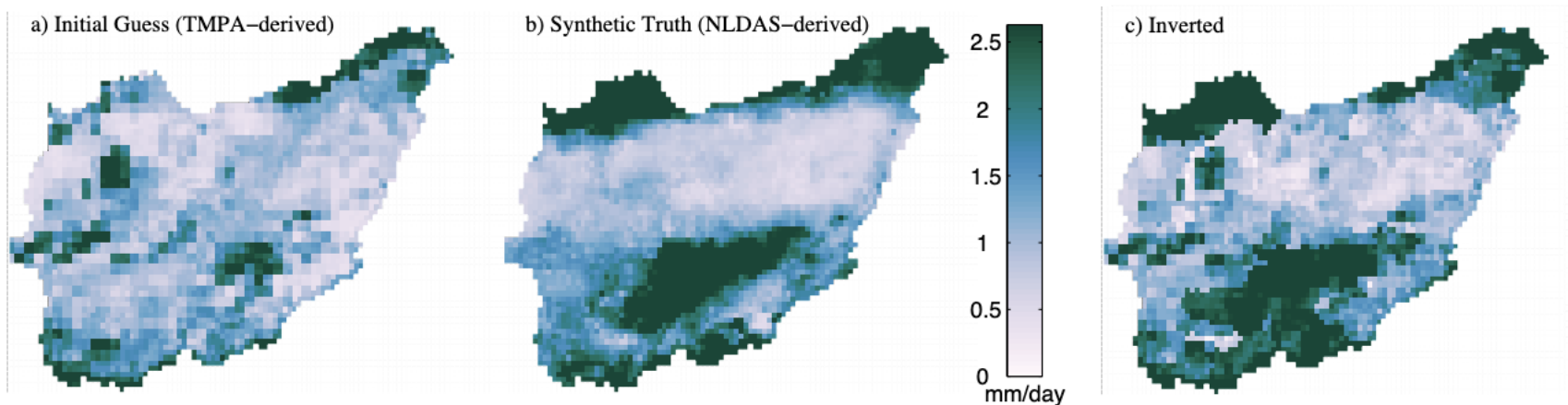
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Synthetic  $Q$  at 75 USGS gauges



# Runoff estimation: inverse inference

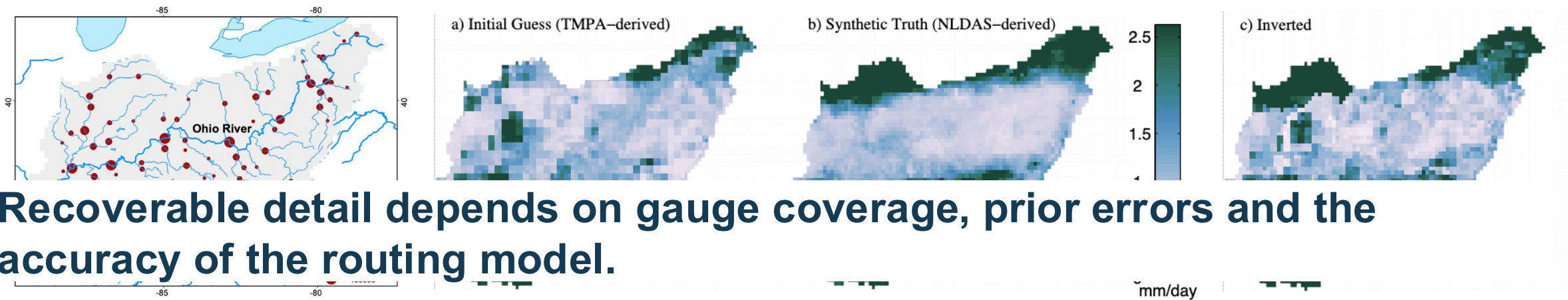


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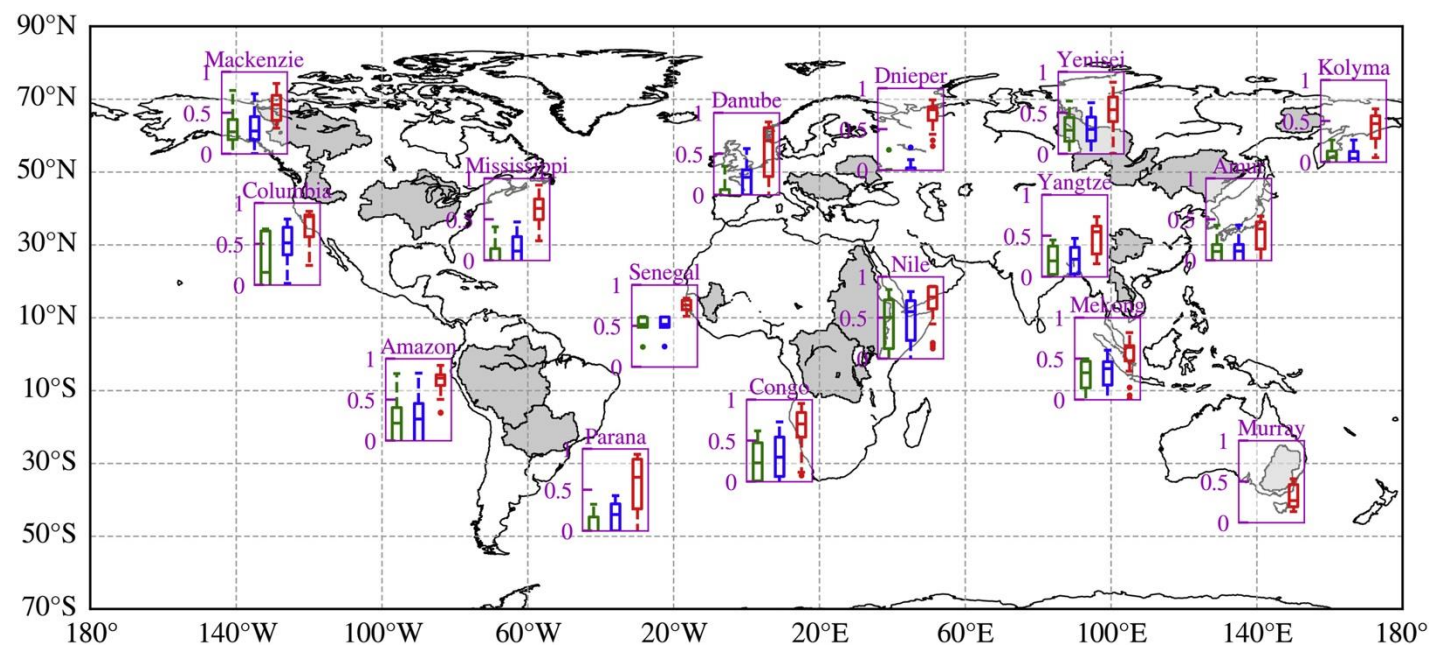
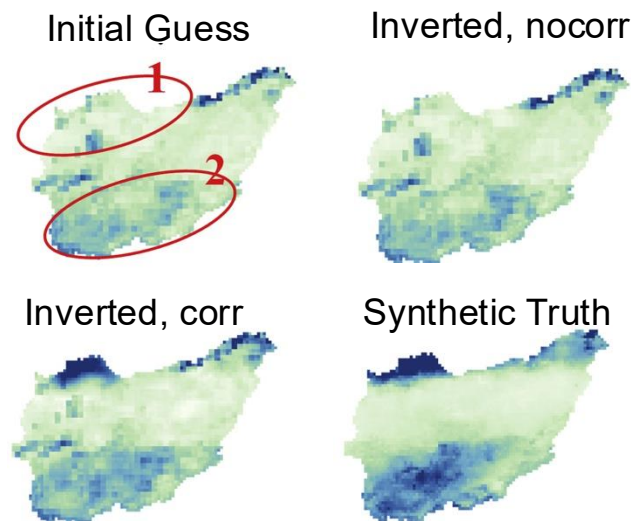
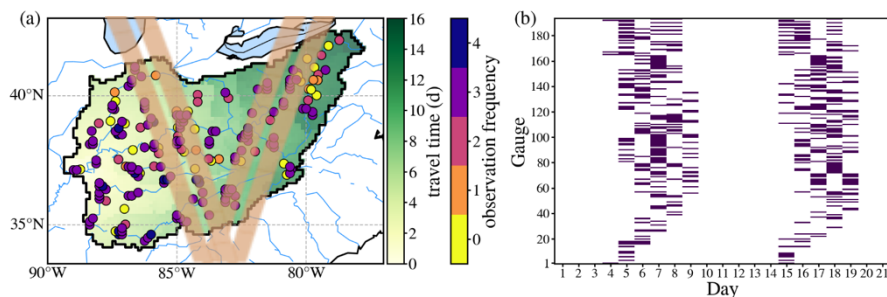
Recoverable detail depends on gauge coverage, prior errors and the accuracy of the routing model.

Synthetic  $Q$  at 75 USGS gauges

# Runoff estimation: inverse inference

## Yang et al. (2019) – assimilate SWOT-like intermittent observations

- Inverse streamflow routing + spatiotemporal correlations in runoff errors: propagate observed discharge information across the river network **within the basin & beyond basin boundaries**

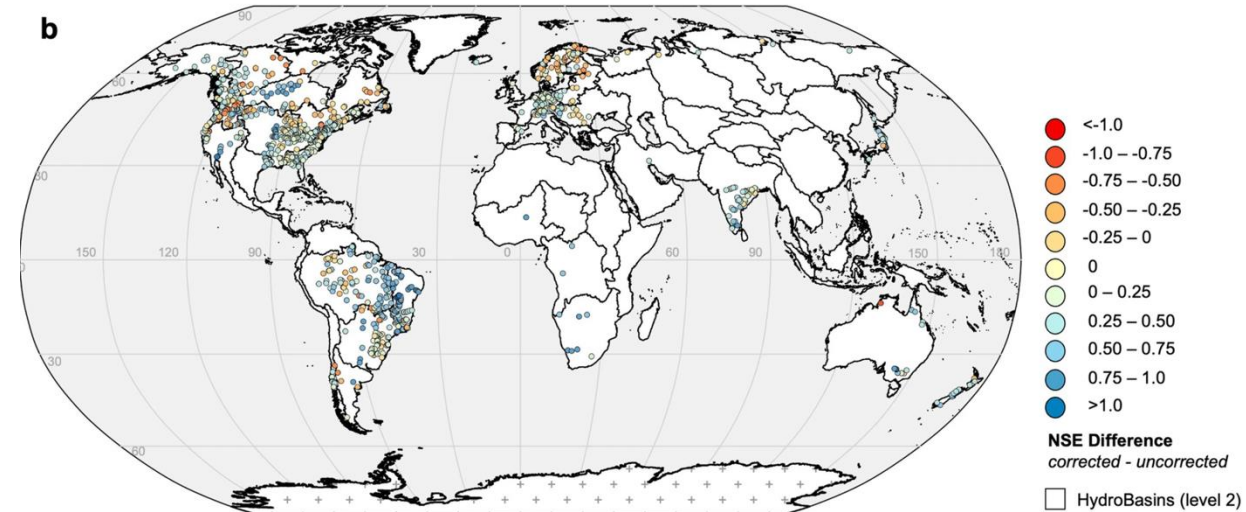
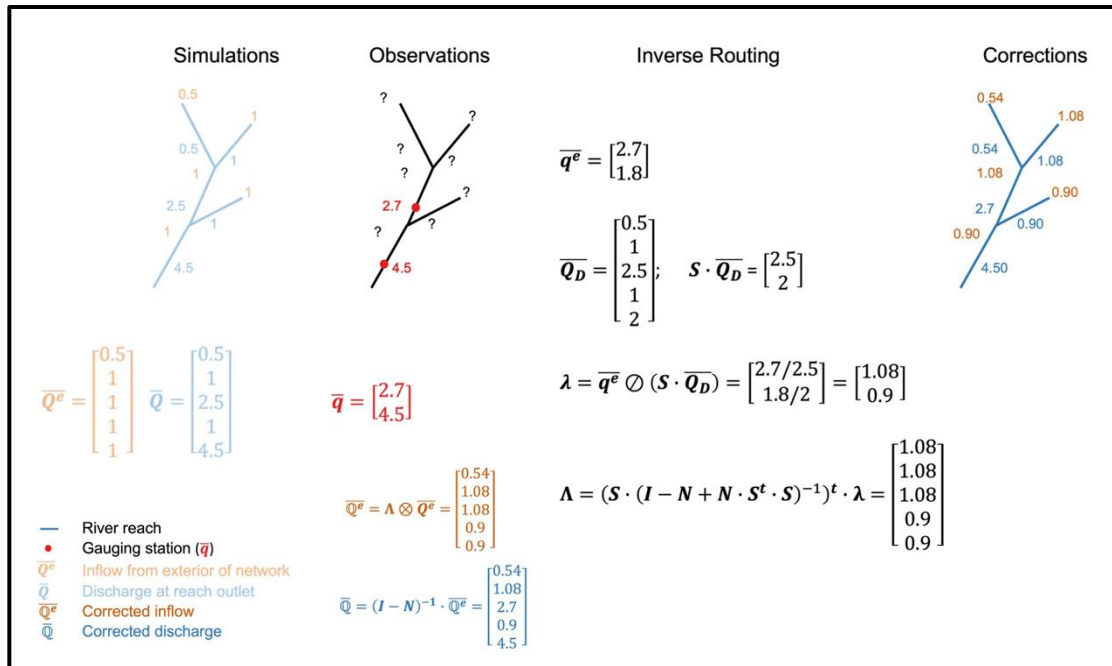


GREEN: initial guess    BLUE: experiments without correlations  
RED: experiments with correlations

# Runoff estimation: inverse inference

## Collins et al. (2024) – global long-term inverse routing

- Used monthly Q from ~1,000 gauges & propagated corrections across a 3-million-reach network
- Corrected mean runoff for ~ 30% of river reaches globally



# Main sources of runoff uncertainty

| Source                     | Examples and consequences                                     |
|----------------------------|---------------------------------------------------------------|
| Meteorological forcing     | Precipitation bias, snowfall undercatch and timing errors     |
| Model structure            | Snow, ET, infiltration and groundwater process assumptions    |
| Parameterization           | Calibration, regional transfer and parameter non-uniqueness   |
| Observations and land data | Rating curves, gauge coverage, basin area and soil properties |
| Human influences           | Land-use change, irrigation, withdrawals and return flows     |