Confronting Runoff Sensitivity in Earth System Models: An Opportunity to Correct Runoff Projections

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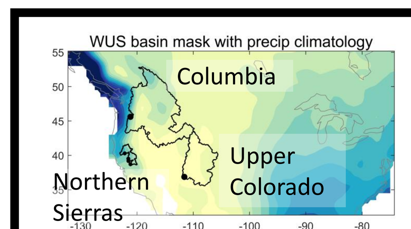
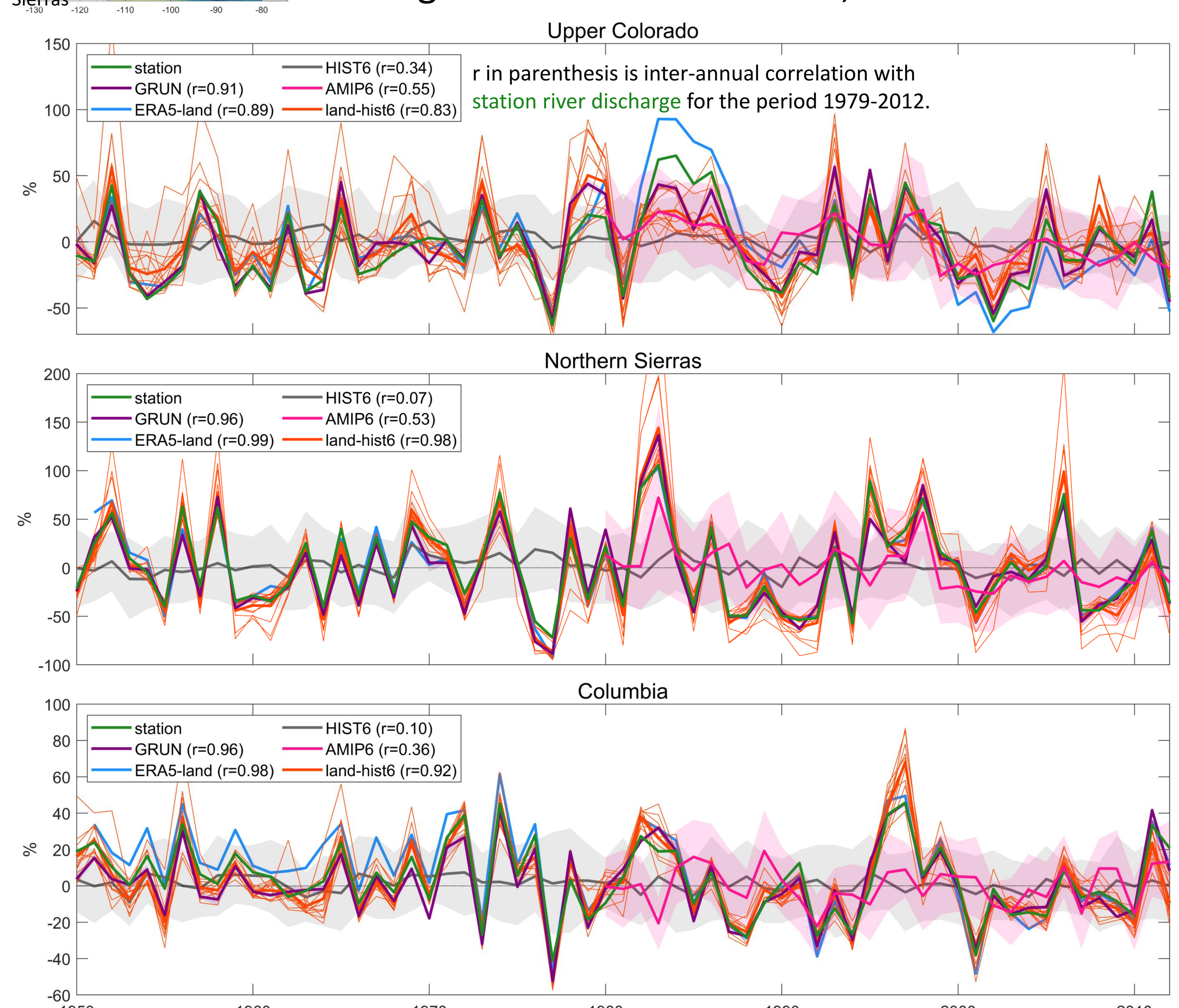
Synopsis

- ✓ Projections of runoff (Q) from Earth System Models (ESMs) are now being utilized for assessing water resource-related risks under climate change.
- ✓ However, runoff projections in ESMs are highly uncertain. While variances in precipitation (P) and surface air temperature (T) responses among ESMs are the primary cause, biases in the representation of land processes are also shown to be important.
- ✓ Using both ESMs and observational data, we quantify biases in land processes through the lens of runoff sensitivity (dQ/dP and dQ/dT). The biases in present-day sensitivity offer an opportunity to correct future runoff projections.

How accurate do the ESMs simulate runoff variations?



Target region: Three river basins over Western United States (WUS).
Target variable: % anomalies of runoff (Q) relative to 1979-2012 baseline.
Average shown with solid lines; individual land-hist6 members in thin orange lines.



The Good: GRUN ≈ station

Machine learning-based product (GRUN) effectively reconstructs observed Q variations. → GRUN can be used for basins lacking data.

The Good: AMIP6 ∝ station

SST variations indeed matter for runoff as they modulate regional precipitation.

The Bad: HIST6 ≠≠ station

Historical simulations fail to explain the runoff variations.

The Ugly: Spread in land-hist6

Even when forced by identical atmospheric observation, each ESM produces different runoff. → There are biases in ESM's land process representation.

Station: Naturalized river discharge measurement divided by basin area (1 per station)
GRUN: A machine learning-based global runoff reanalysis (4 atmospheric forcings)
HIST6: CMIP6 simulation with historical radiative forcings (24 water-budget closed models)
AMIP6: CMIP6 simulation with observed SST (24 water-budget closed models)
land-hist6: offline land-only simulation forced by identical atmospheric observation (3 atmospheric forcings × 4 models)

Runoff sensitivity: quantifying land process representation

✓ Inter-annual runoff sensitivity can be measured by multiple linear regression.

$$\delta Q \approx \delta Q_p = a\delta P + b\delta T + c\delta P\delta T$$

δ: Inter-annual variation
Q_p: prediction by runoff sensitivity

$$a = \frac{\partial(\delta Q)}{\partial(\delta P)} \qquad b = \frac{\partial(\delta Q)}{\partial(\delta T)}$$

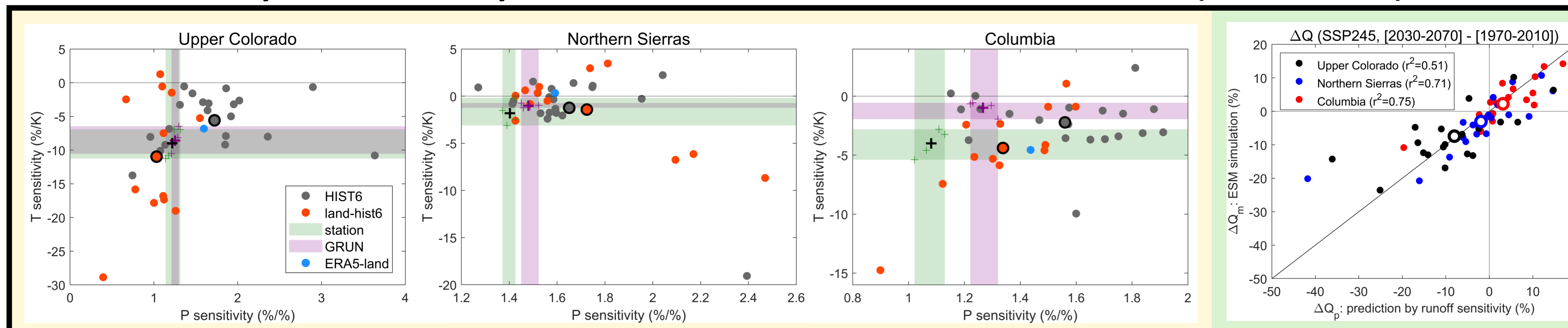
P sensitivity | T sensitivity

- P sensitivity: Q increase [%] per unit P increase [%]
- T sensitivity: Q [%] per unit T increase [K]
- Training period: 1940-2010 (Present-day)
- Runoff sensitivity quantifies land processes, enabling comparison between ESMs and OBS.

Summary and Discussion

- ✓ The land process representation in ESMs is biased. The runoff decrease due to temperature increase is generally too weak in ESMs, implying a drier future than currently projected.
- ✓ However, the bias estimation is contingent on the observational runoff datasets used. While machine-learning based dataset (GRUN) offers a reasonable proxy, its reliability requires validation against station river discharge measurements. Furthermore, the causes of sensitivity biases need further investigation.

Present-day sensitivity biases and future corrections (for WUS)



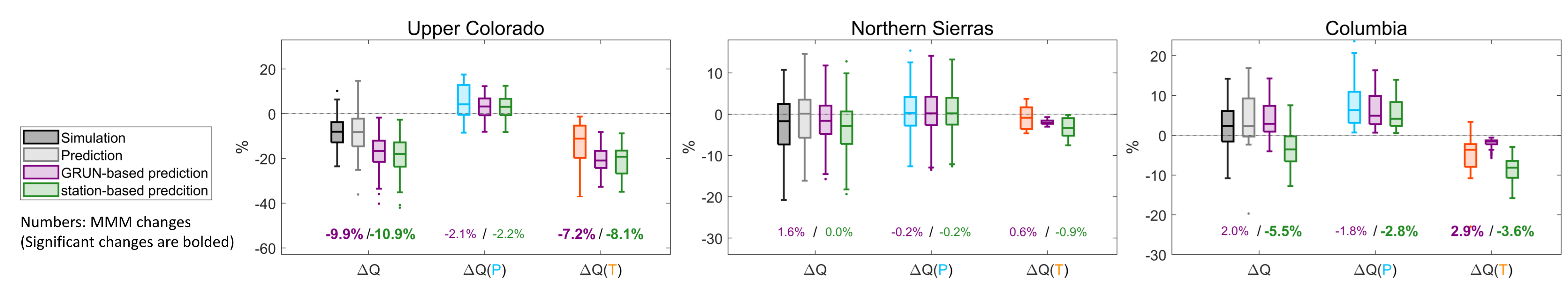
Inter-model spread of land-hist6 is comparable to HIST6. → Land process representations widely differ even when the same mean state is enforced. A substantial portion of these biases is thus inherent to land models themselves.

Compared to station-based estimate, ESMs (HIST6) generally exhibit more positive P sensitivity and less negative T sensitivity; however, the extent of this bias depends on the basins and observational datasets.

An opportunity to correct runoff projections

Runoff sensitivity successfully emulates runoff projections. Thus, we can substitute the sensitivity of ESMs with observations

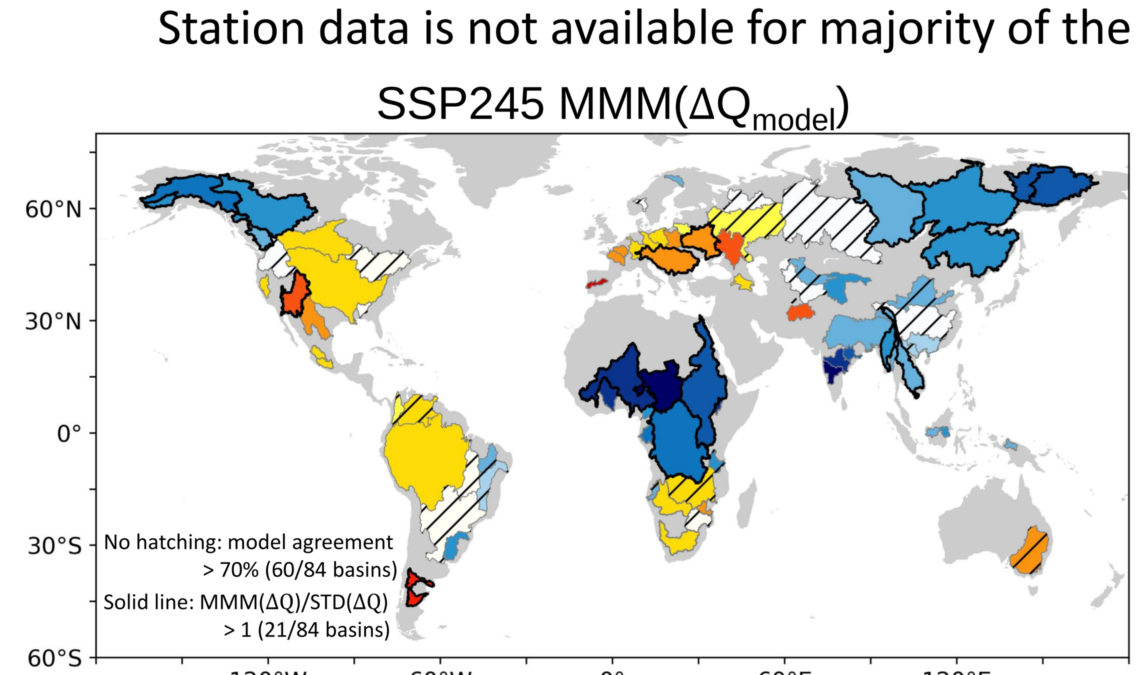
$$\Delta Q_p = a_m \Delta P_m + b_m \Delta T_m == \Delta Q_{model} \longrightarrow (a_{obs}, b_{obs}) \longrightarrow \Delta Q_{obs} = a_{obs}\Delta P_m + b_{obs}\Delta T_m$$

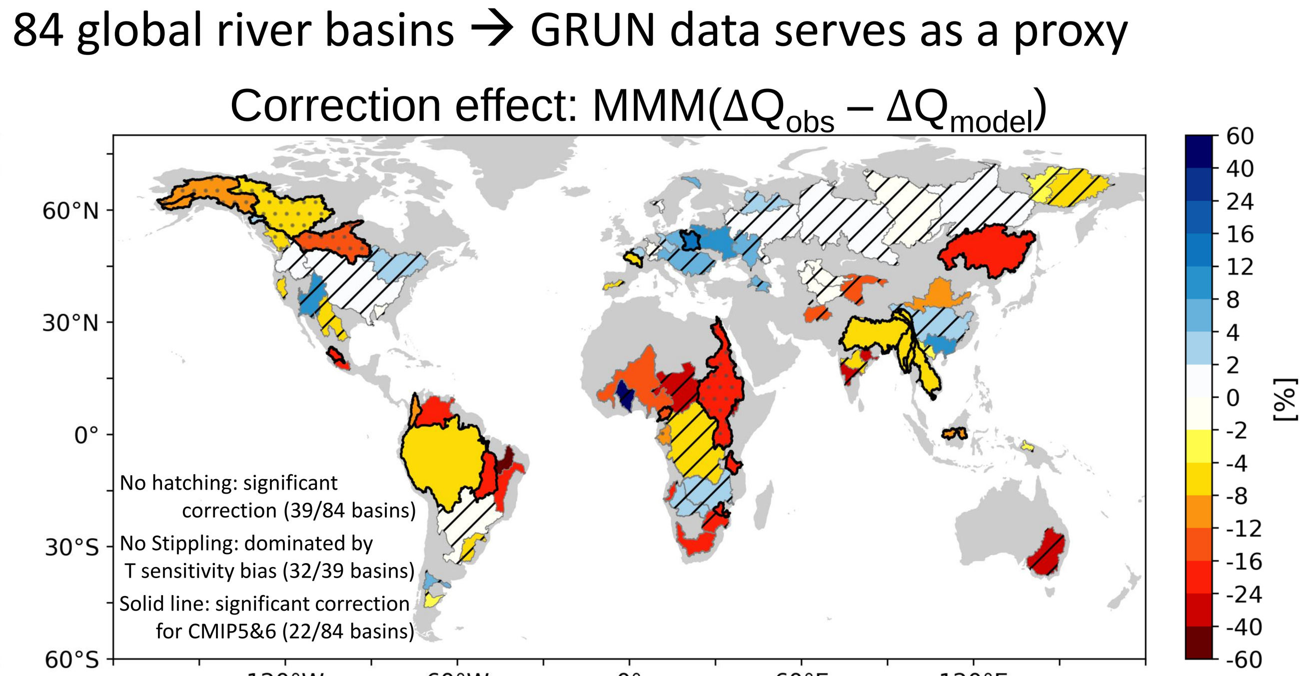


Future runoff in Upper Colorado and Columbia basins would be drier than model projections.

Global application

Station data is not available for majority of the 84 global river basins → GRUN data serves as a proxy





- ✓ As in WUS, runoff sensitivity in most global basins emulates the future runoff changes successfully (not shown).
- ✓ T sensitivity is typically less negative in ESMs, suggesting a drier real-world future, except in Eastern Europe.

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