Improving Continuous Estimates of Global River Discharge with Satellites

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Key Points

1) River widths and water surface elevation (WSE) measured by satellites (e.g., Landsat and SWOT) provide essential information for river discharge estimation.
2) We developed a physics-based modeling-data assimilation framework to assimilate satellite–derived discharge into hydrological model simulations, which significantly improved the accuracy of the discharge estimates.
3) We also developed a deep learning framework to directly integrate SWOT WSE data for discharge estimation. The results show that SWOT WSE observations can help improve discharge estimation for the Arctic rivers
4) Through the integration of satellite data with physics-based or data-driven models, we can produce continuous (every day, every river reach) discharge estimates for pan-Arctic rivers with improved accuracy. This product provides essential data for tracking freshwater discharge from rivers to the oceans.

Methods

Improve discharge estimation using Landsat-derived river widths

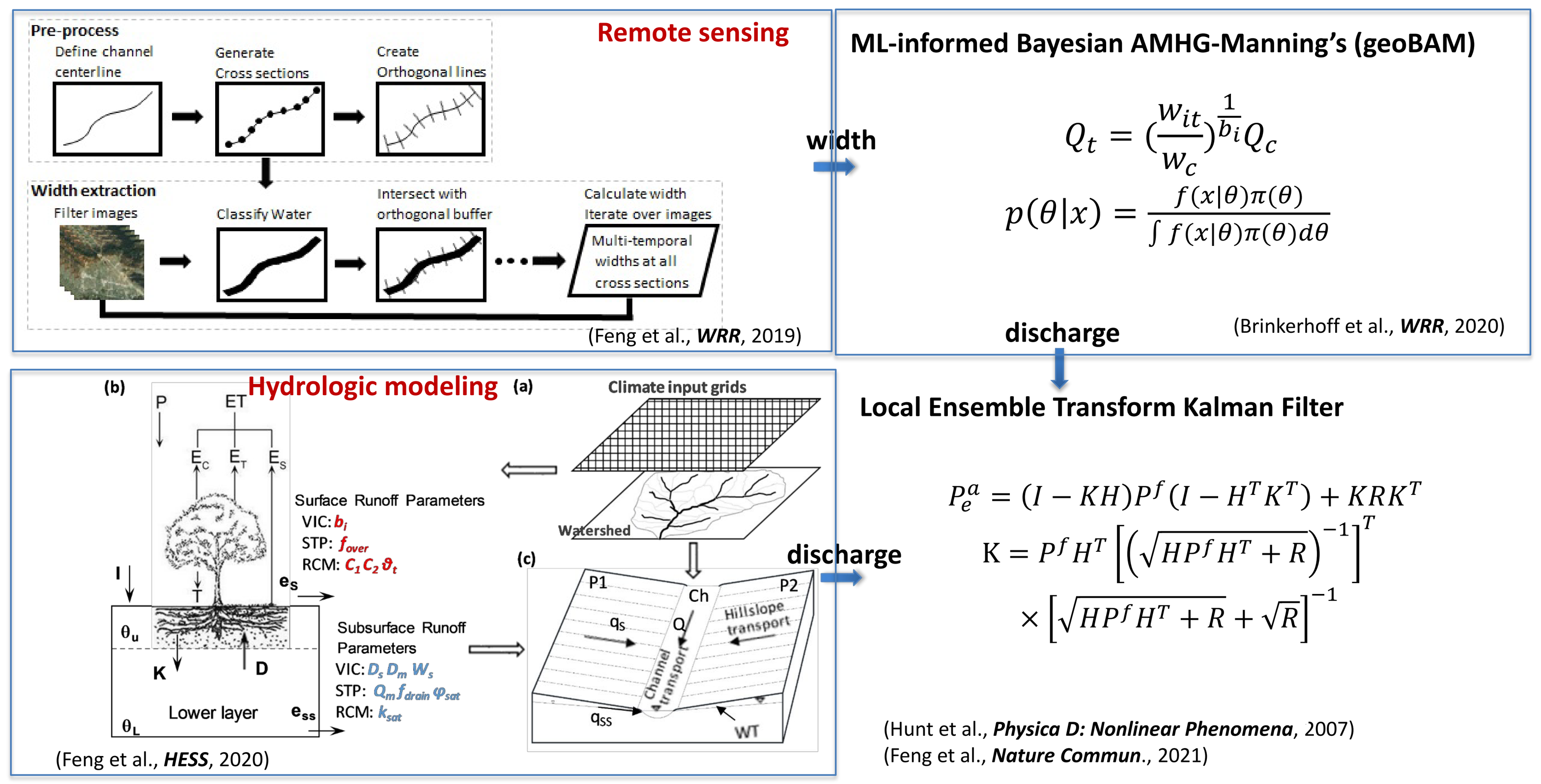


Figure 1: Overview of the data assimilation scheme that assimilates satellite-derived discharge into hydrological model simulations

Improve discharge estimation using SWOT water surface elevation (WSE) data

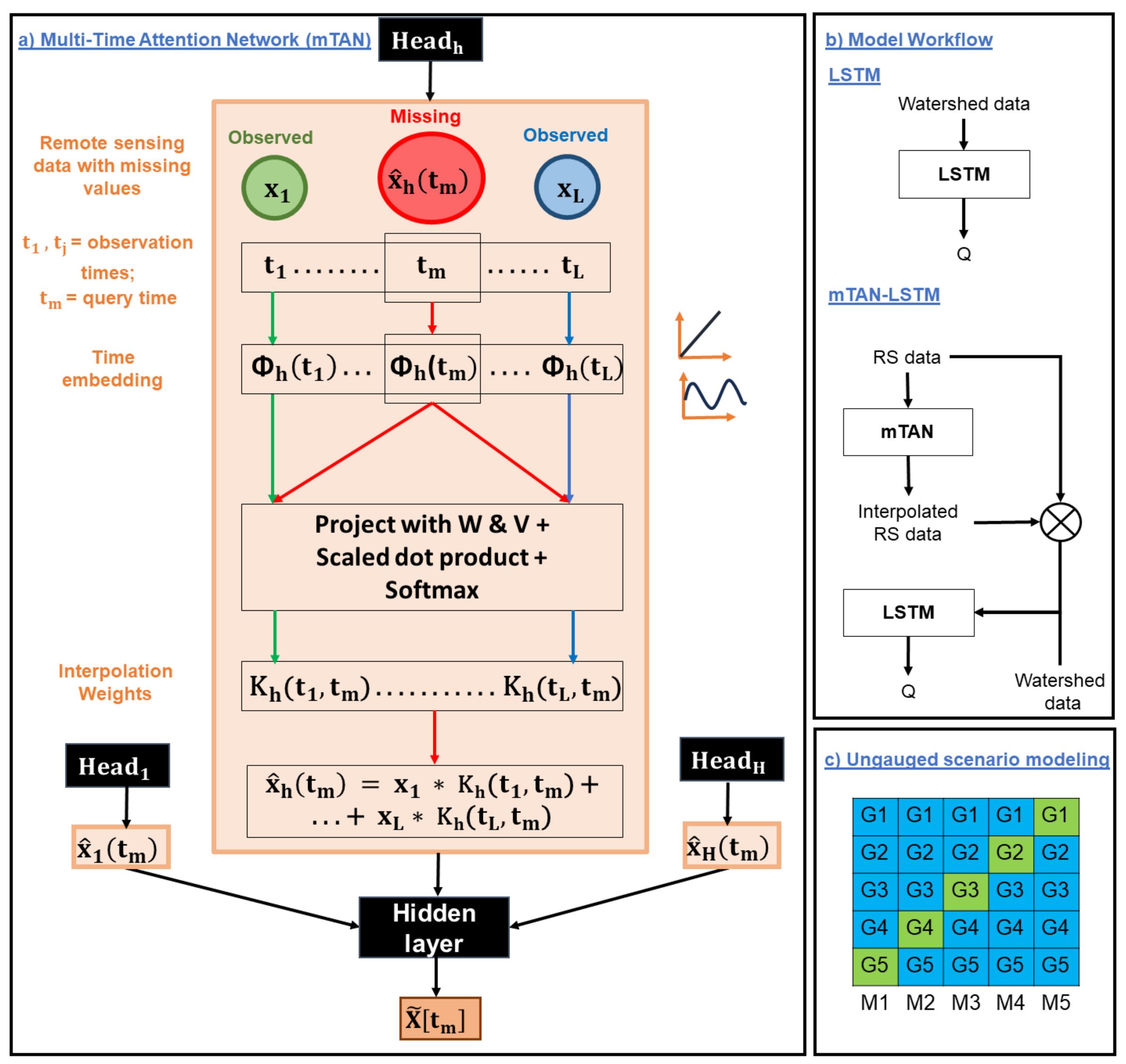
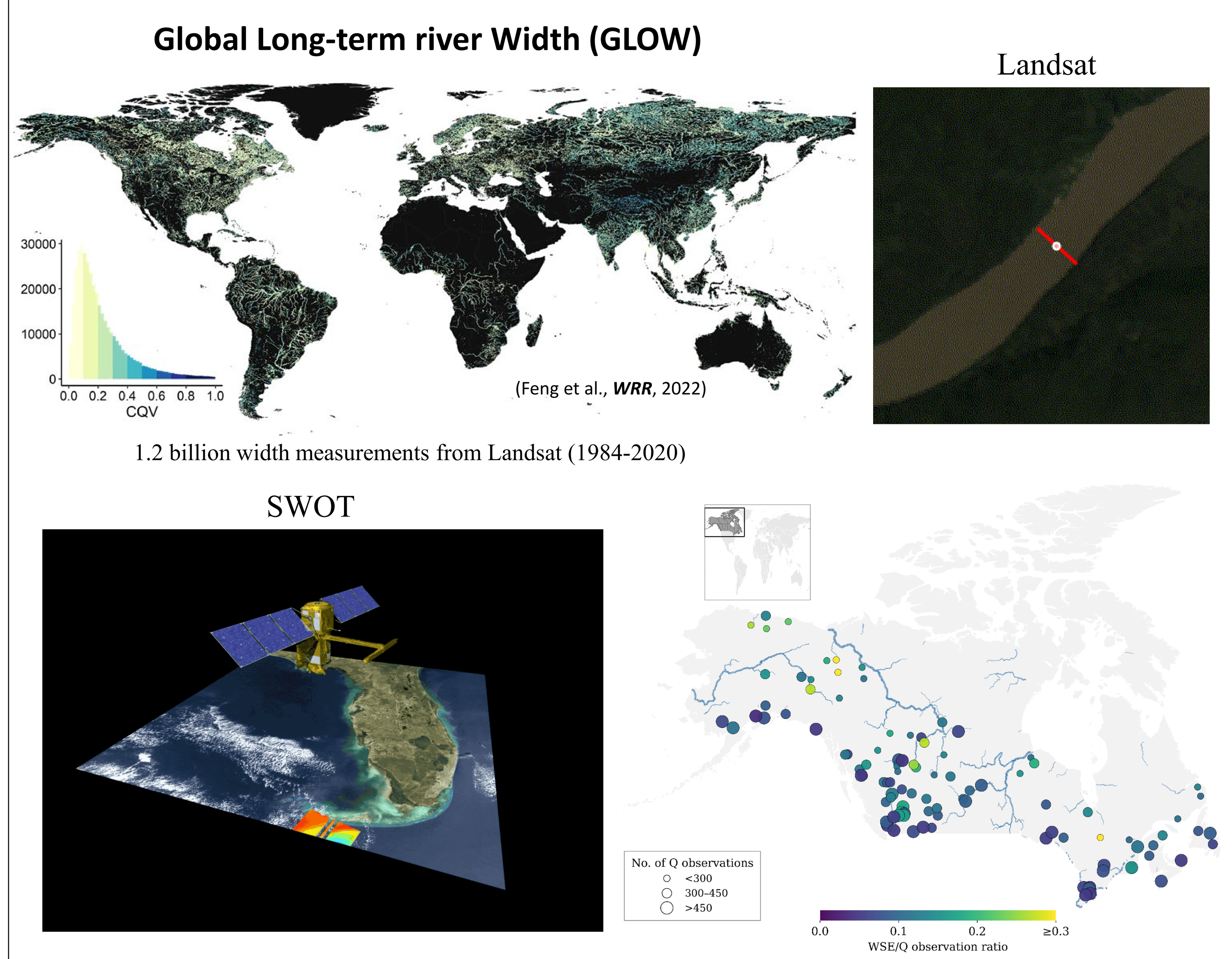


Figure 2: (a) Schematic of the multi-time attention network (mTAN) used to interpolate irregular remote-sensing observations (SWOT WSE in this study) at a query time using multiple temporal embedding heads. Here, $t_1, \ldots, t_L$ denote the irregular observation times, t_m denotes the query time, $x_1, \ldots, x_L$ denote the observed values, $\phi_h(t)$ denotes the embedding vector of time t for temporal embedding head h, $\kappa_h(t_i, t_m)$ denotes the attention weight assigned to the observation at time t_i when interpolating at query time t_m for head h, and $\hat{x}_h(t_m)$ denotes the intermediate attention-based estimate at query time t_m under head h, and $\tilde{X}[t_m]$ denotes the final interpolated value at query time t_m

Remote sensing data



Results

Remotely-sensed Arctic Discharge Reanalysis(RADR)

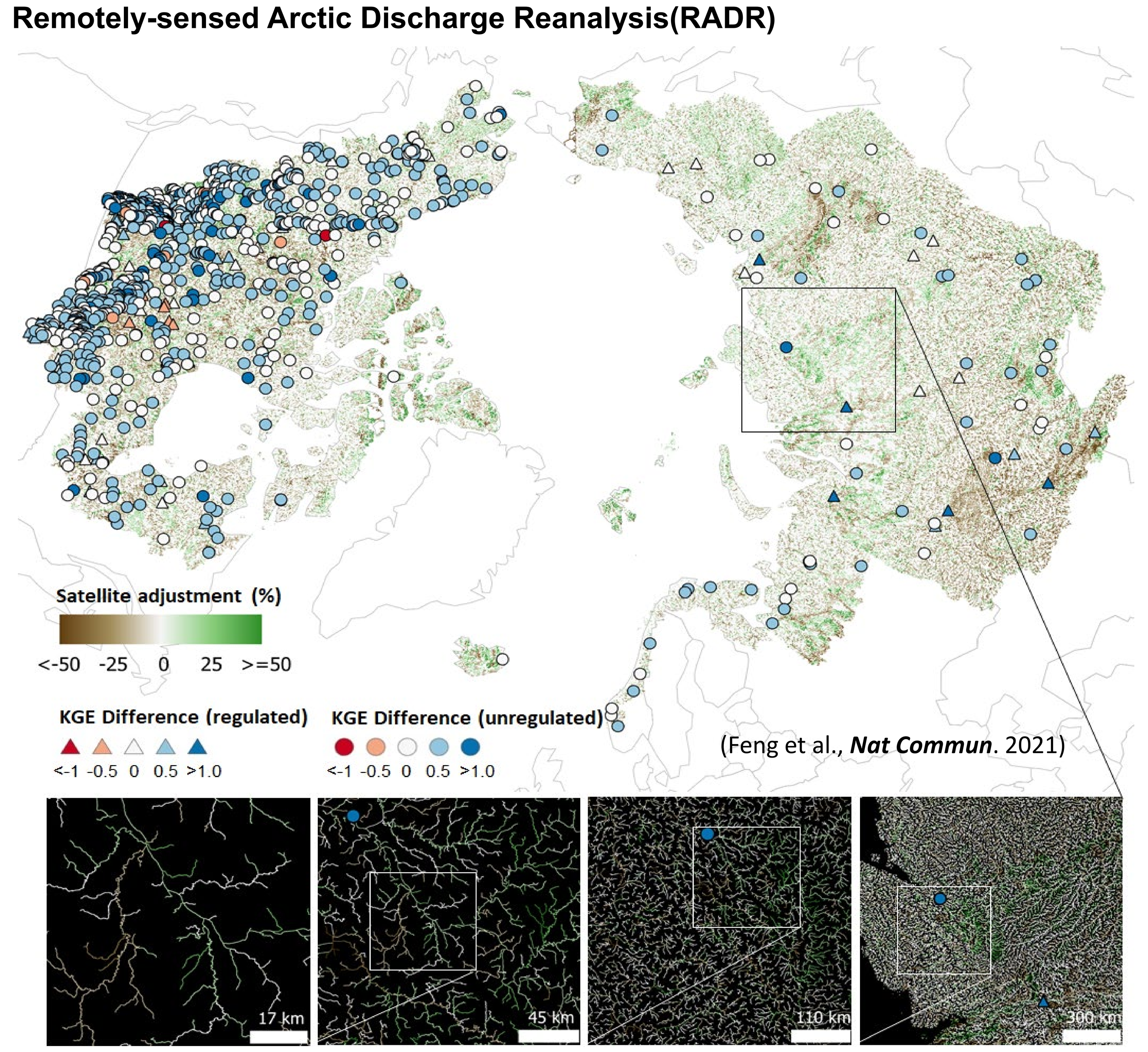


Figure 3: The satellite adjustment (relative difference, %) between RADR and baseline models in the annual mean discharge at each of 486,493 reaches is shown in a color gradient from brown (less water) to green (more water). Colored circles (for unregulated reaches) and triangles (for regulated reaches) indicate the difference in KGE (Kling-Gupta efficiency, a standard error metric, positive difference indicates improvement) of daily discharge between RADR and baseline model simulations evaluated against 1,079 gauges at the daily scale

Results

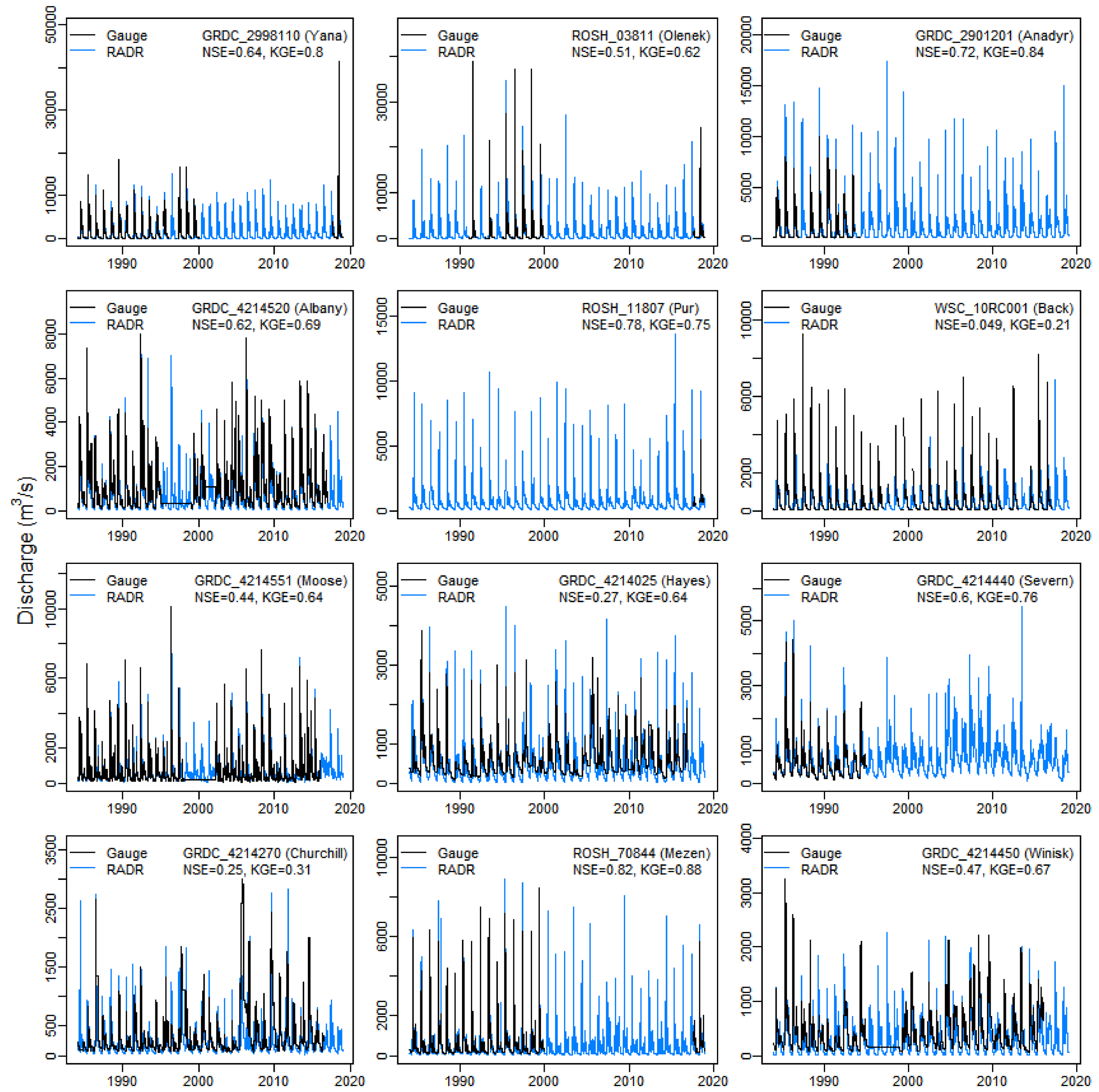


Figure 4: Hydrographs of RADR compared with gauge observations for 24 large basins in the pan-Arctic region. Error metrics (KGE and NSE), station IDs, and river names are shown in the figure. Station IDs are labeled in the format of 'Agency_Station Number.' WSC: Water Survey of Canada; GRDC: Global Runoff Dataset Center; ROSH: Roshydromet; and USGS: U.S. Geological Survey

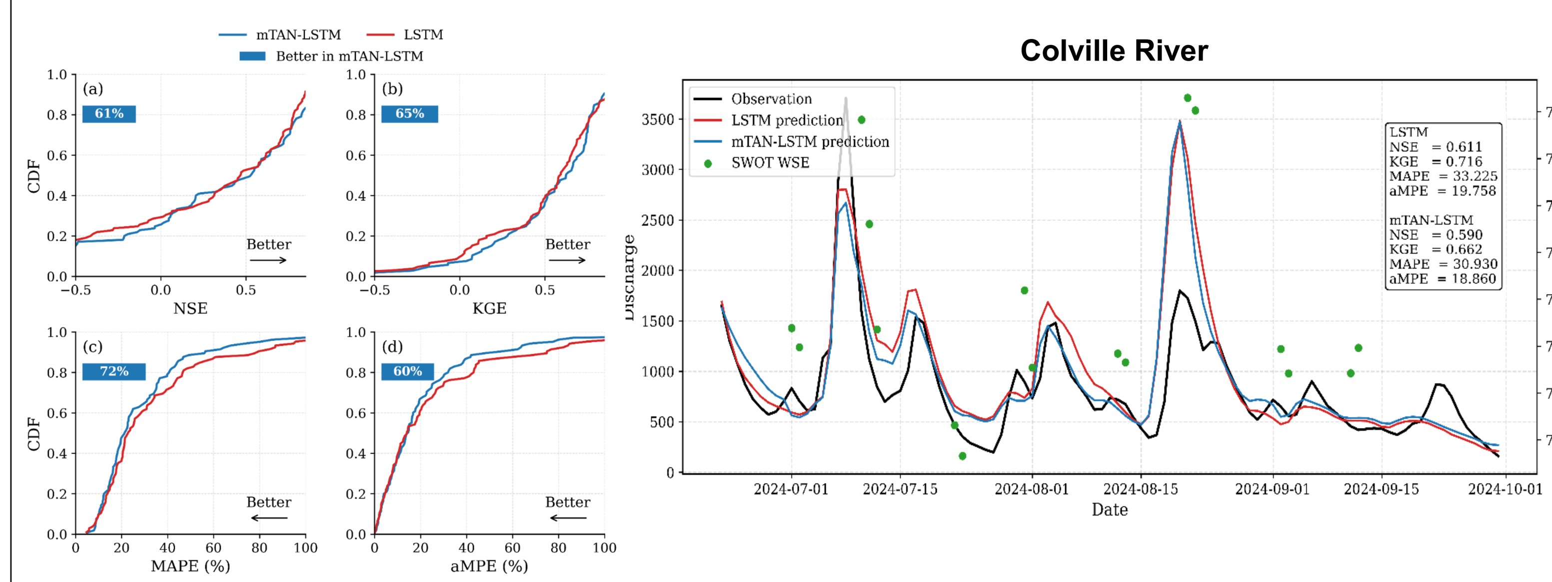


Figure 5: (a-d) Station-wise performance metrics for the LSTM and mTAN-LSTM models in the gauged scenario; right: Colville River discharge estimated by LSTM and mTAN-LSTM, compared with gauge observations

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