Forecasting in-stream turbidity using machine learning and a high-frequency sensor network

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RESEARCH ARTICLE OPEN ACCESS

Leveraging High-Frequency Sensor Data and U.S. National Water Model Output to Forecast Turbidity in a Drinking Water Supply Basin

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Overall objective: Forecasting turbidity in Upper Esopus Creek

How? Using streamflow forecasts

- National Water Model
- Northeast River Forecast Center

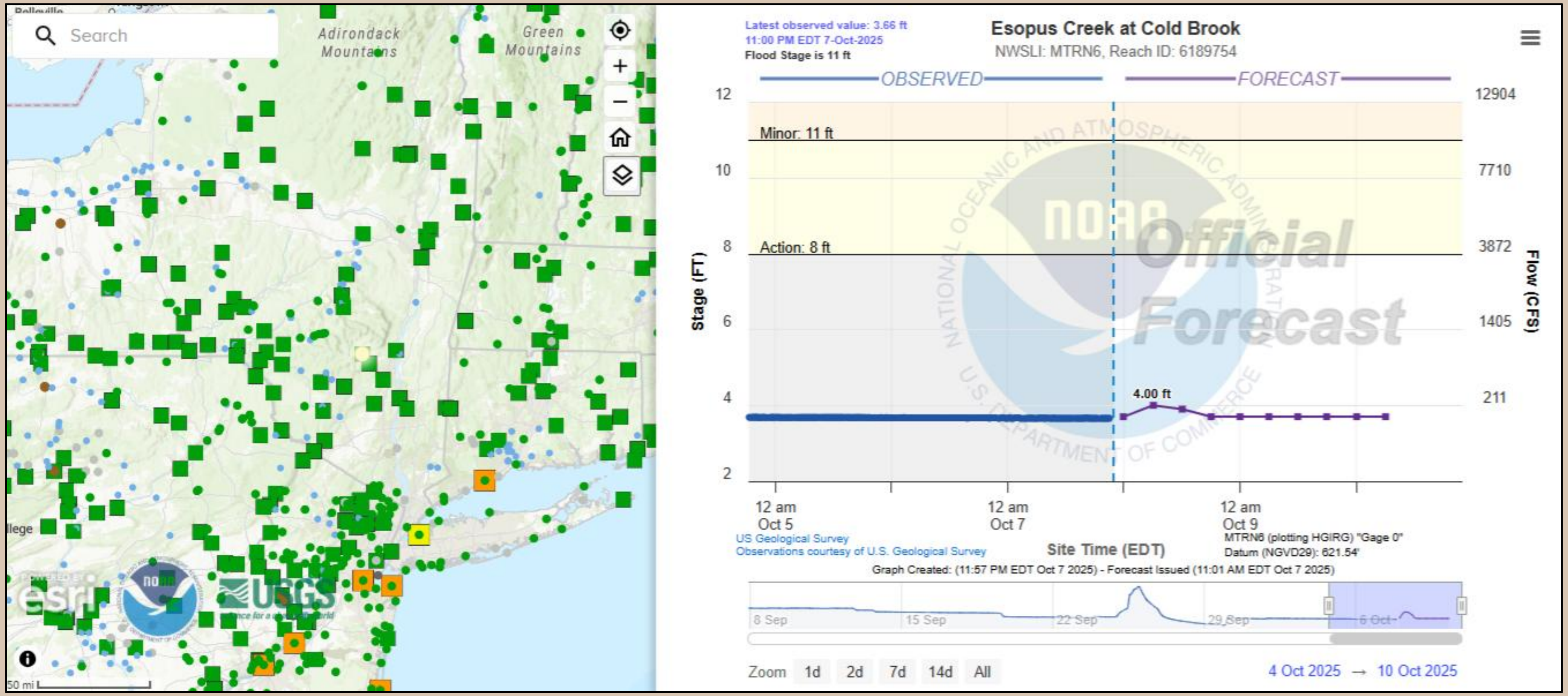
Overall objective: Forecasting turbidity in Upper Esopus Creek

- First, what is the National Water Model (NWM)?
  - Physically-based model built on WRF-Hydro that provides streamflow forecasts at more than 2.7 million river reaches
  - Three “types” of forecasts:
    1. Short-term
    2. **Medium-term**
       - Initialized & issued every 6 hrs; hourly forecast timestep
       - Seven-member ensemble out to 8.5 & 10 days
    3. Long-term

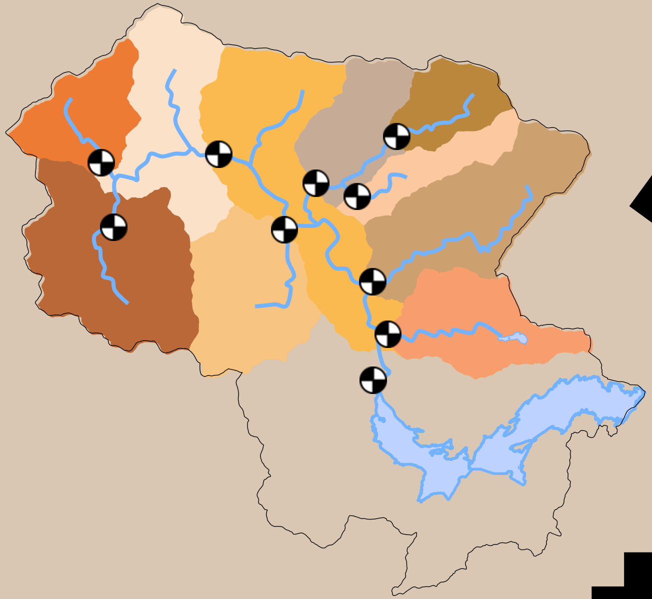
Overall objective: Forecasting turbidity in Upper Esopus Creek

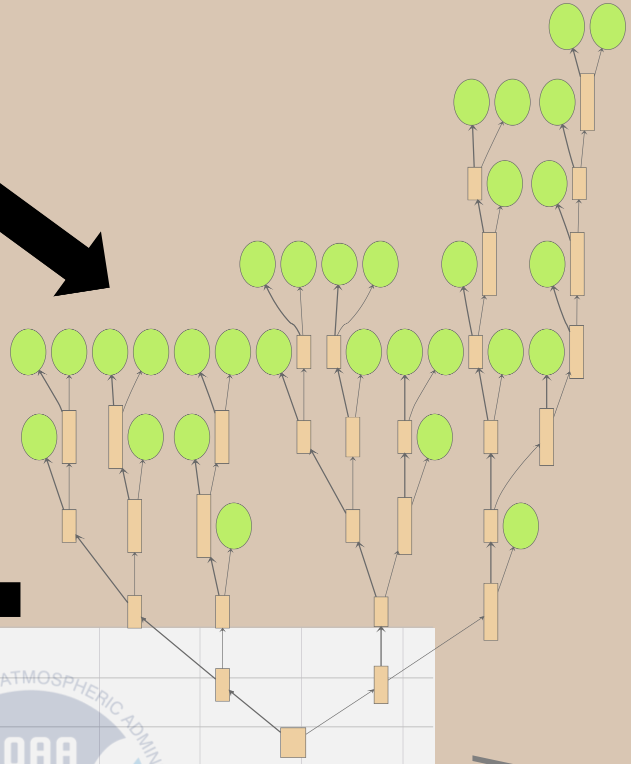
- Second, what are Northeast River Center Forecasts (NERFC)?
  - Conceptual model built on the Sacramento Soil Moisture model that provides streamflow forecasts at ~236 locations
  - Official forecasts of the US Govt.

- Forecasts are generally issued ~11 am local time unless event is underway, at which point they are more frequent
  - 72 hr look-ahead
  - 6 hr timestep

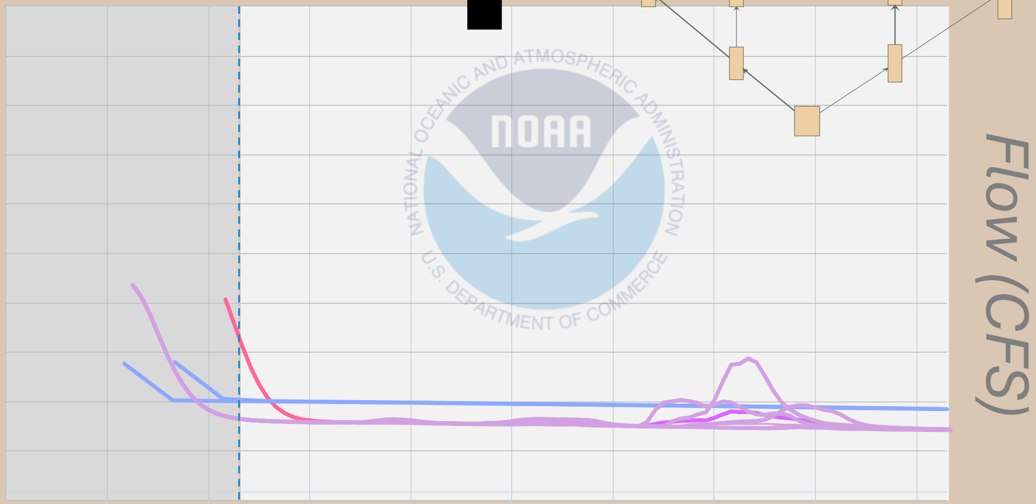


And how can we turn these into water quality forecasts?





- Use **monitoring data** (high-frequency turbidity & flow sensors) and **geospatial information** (land cover, topography, etc.) to **build data-driven models**
  - Feed models streamflow projections
  - **Outcome**: water quality forecasts for constituent of interest (in this case, ***turbidity***)



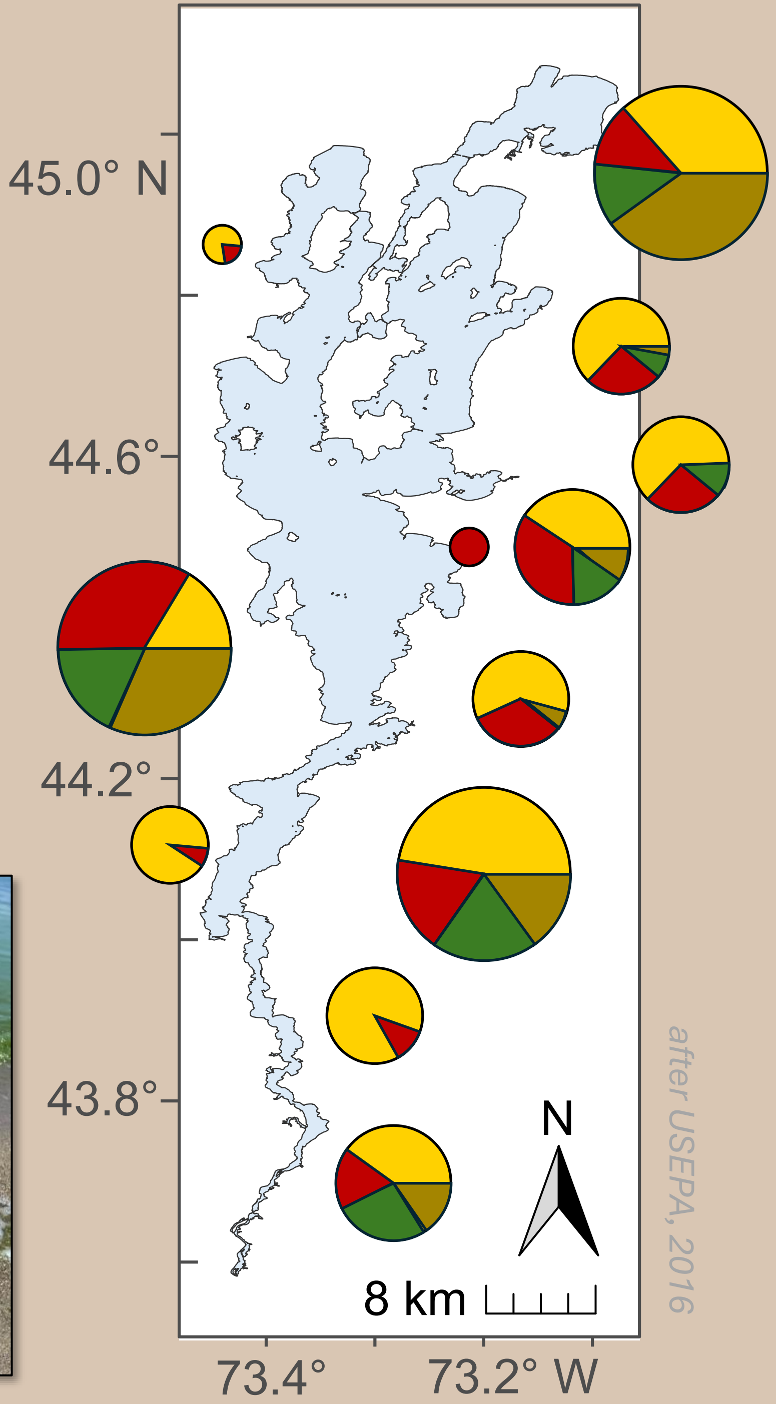
Uses? Why does it matter?

Anticipating high loading events

- Improve anticipation of sediment/turbidity loading in drinking water reservoirs (e.g., Ashokan Reservoir)
- Proactive reservoir management

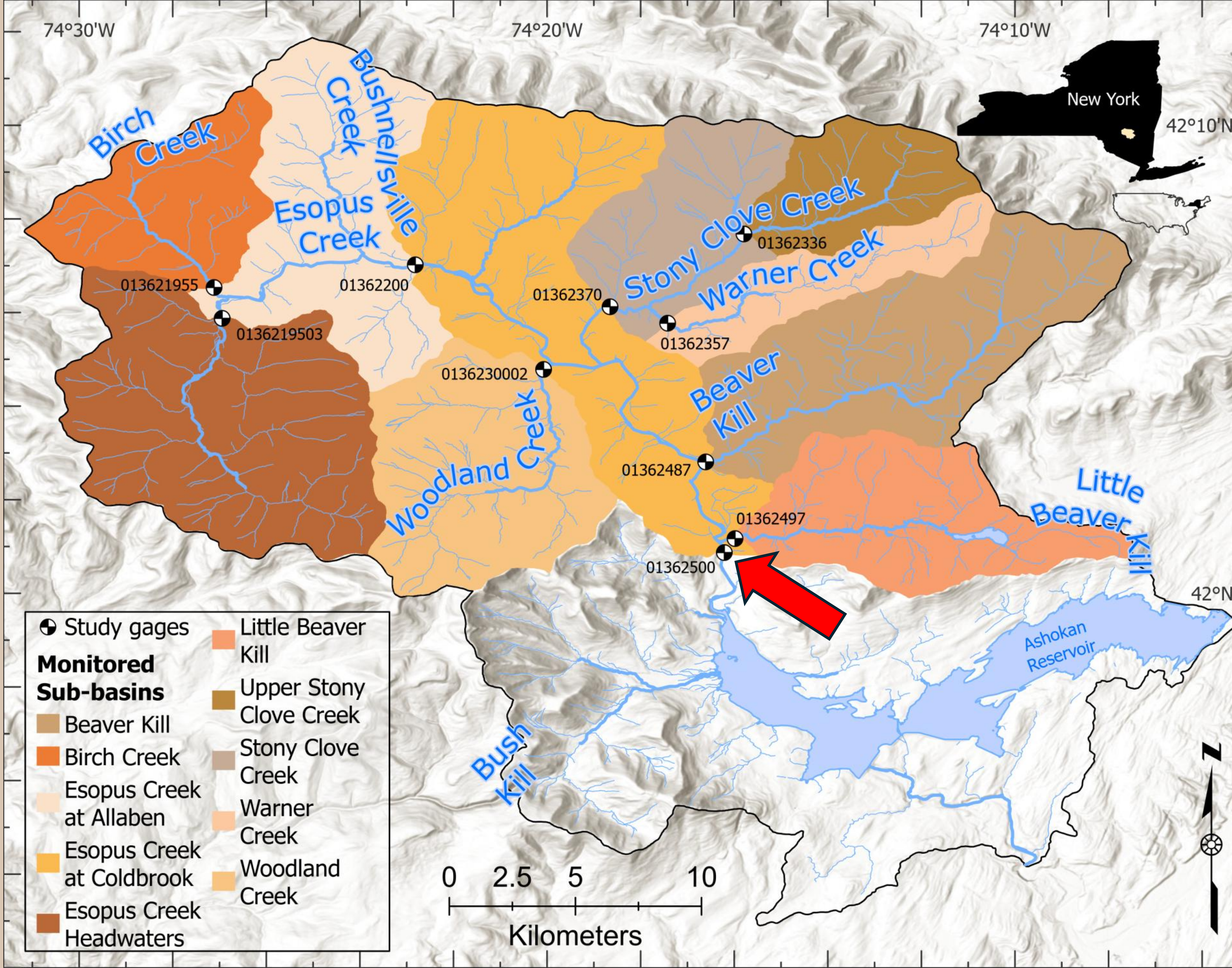
Anticipating high loading events & regulatory compliance

- Predict events in receiving water bodies e.g., harmful algal blooms
- Help ensure TMDL compliance e.g., P in Lake Champlain

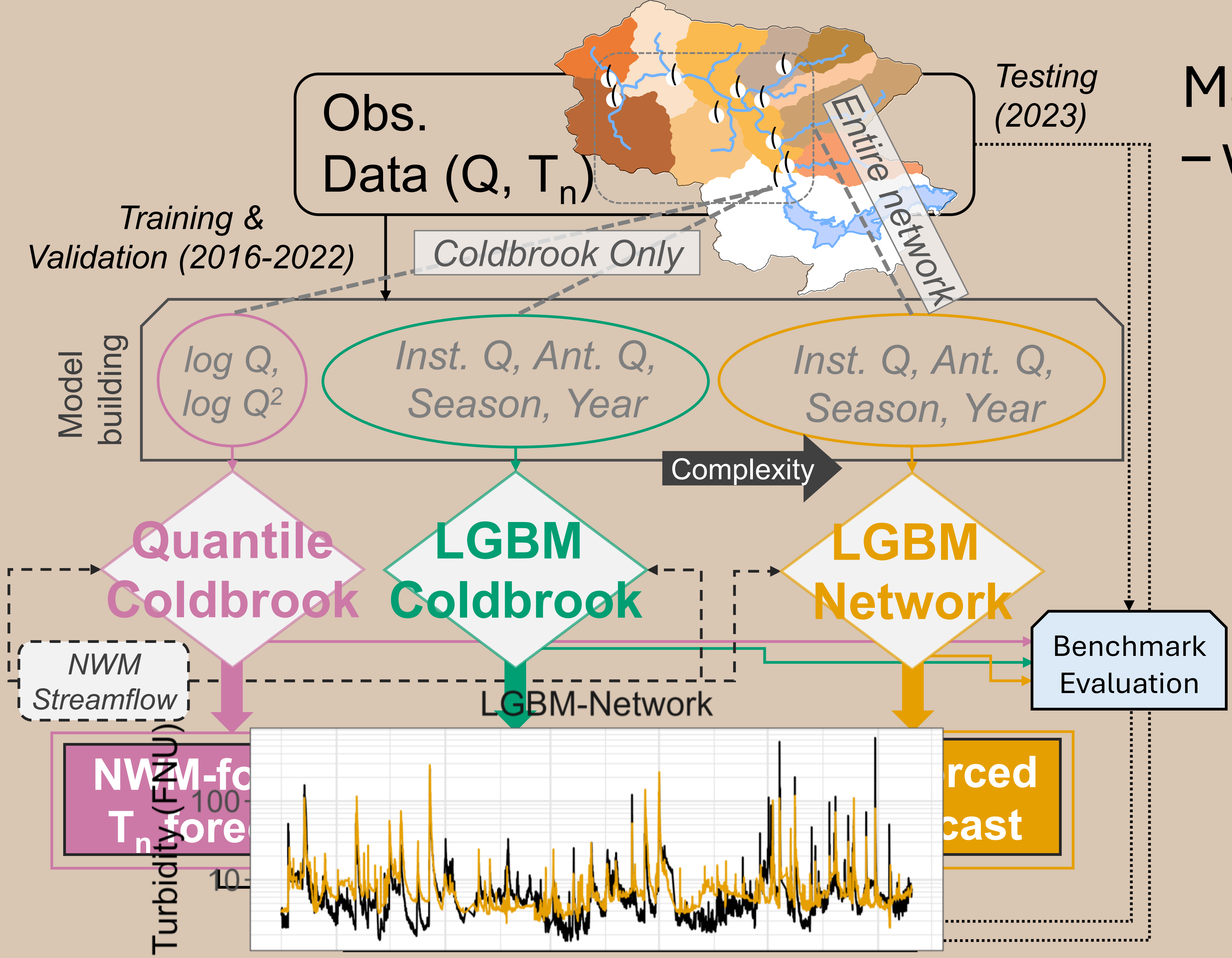


Making the forecasts – observational data

- 10 stations
- High frequency (15-min) in-situ sensors for 5+ yrs

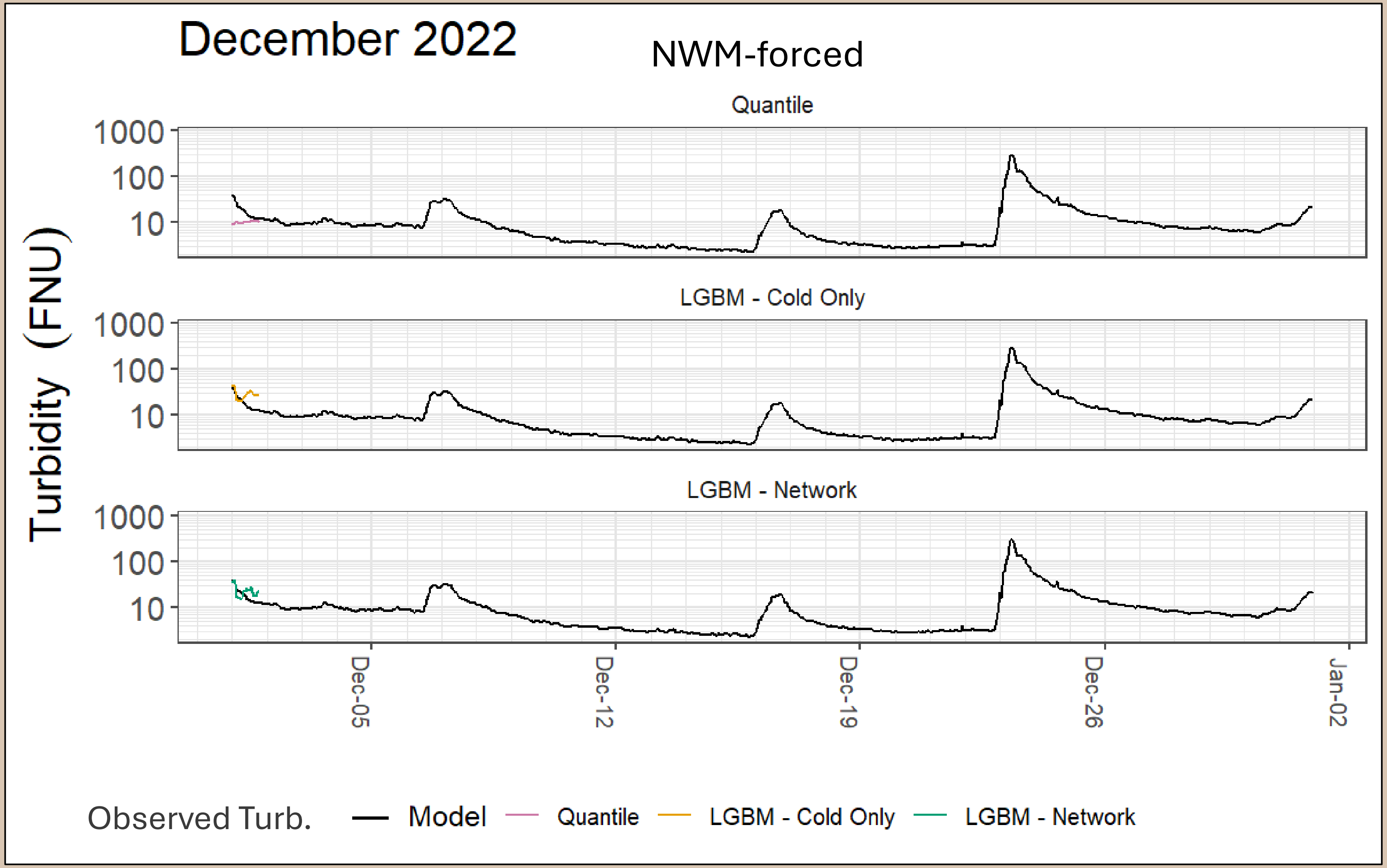


Making the forecasts – workflow

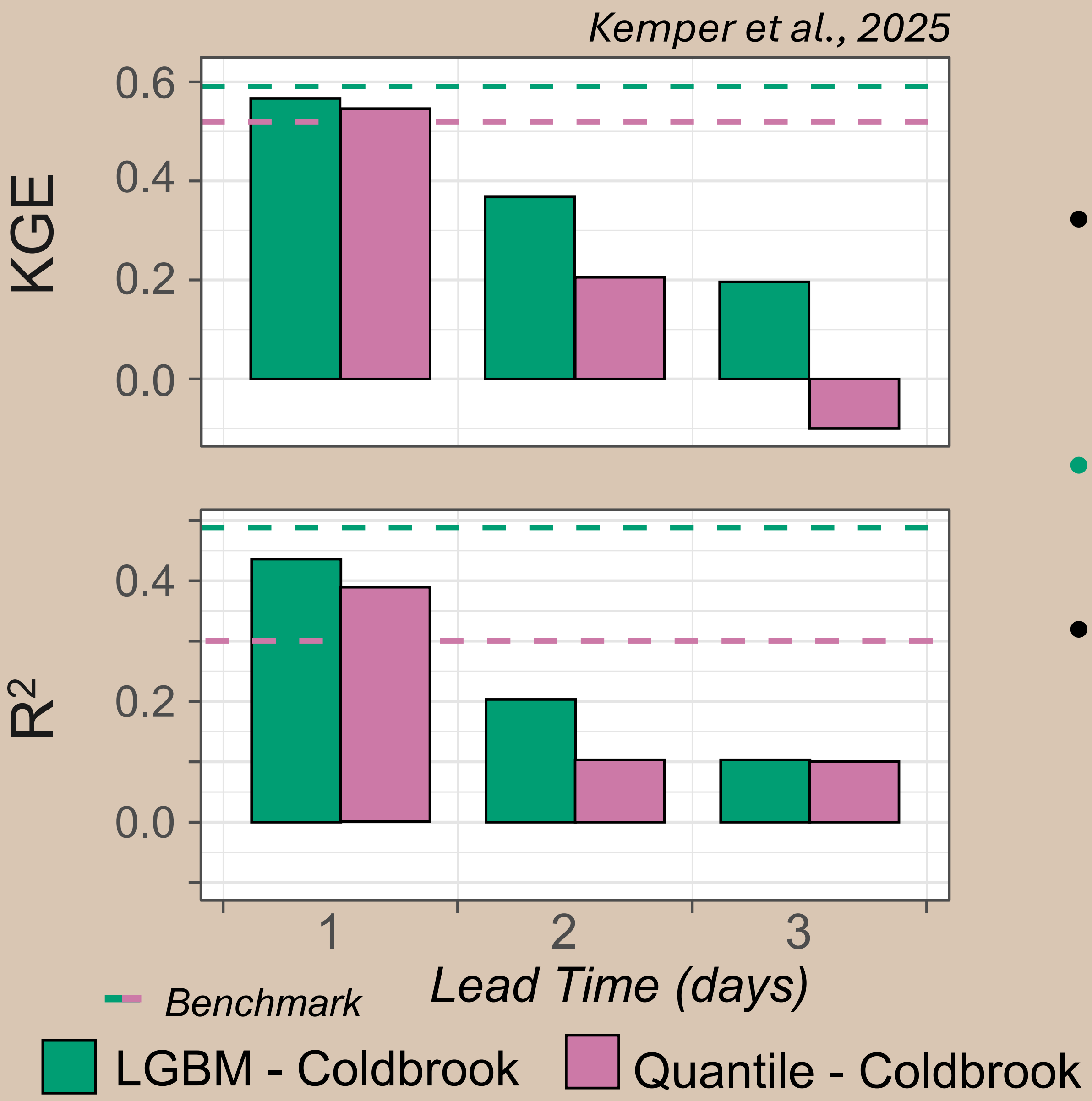


1. Build three models for turbidity from obs.
   I. Quantile model – (Mukundan et al., 2014; Wang et al., 2021)
   II. LightGBM (LGBM) – Coldbrook Only
   III. LGBM – Network
2. Evaluate benchmark
3. Feed forecasts from NERFC and NWM
4. Evaluate forecasts for each model
   i. Full series
   ii. Event based

What do we get? Forecasts of turbidity for 2-3 models across 1-8 day lead times (for WY 2023)



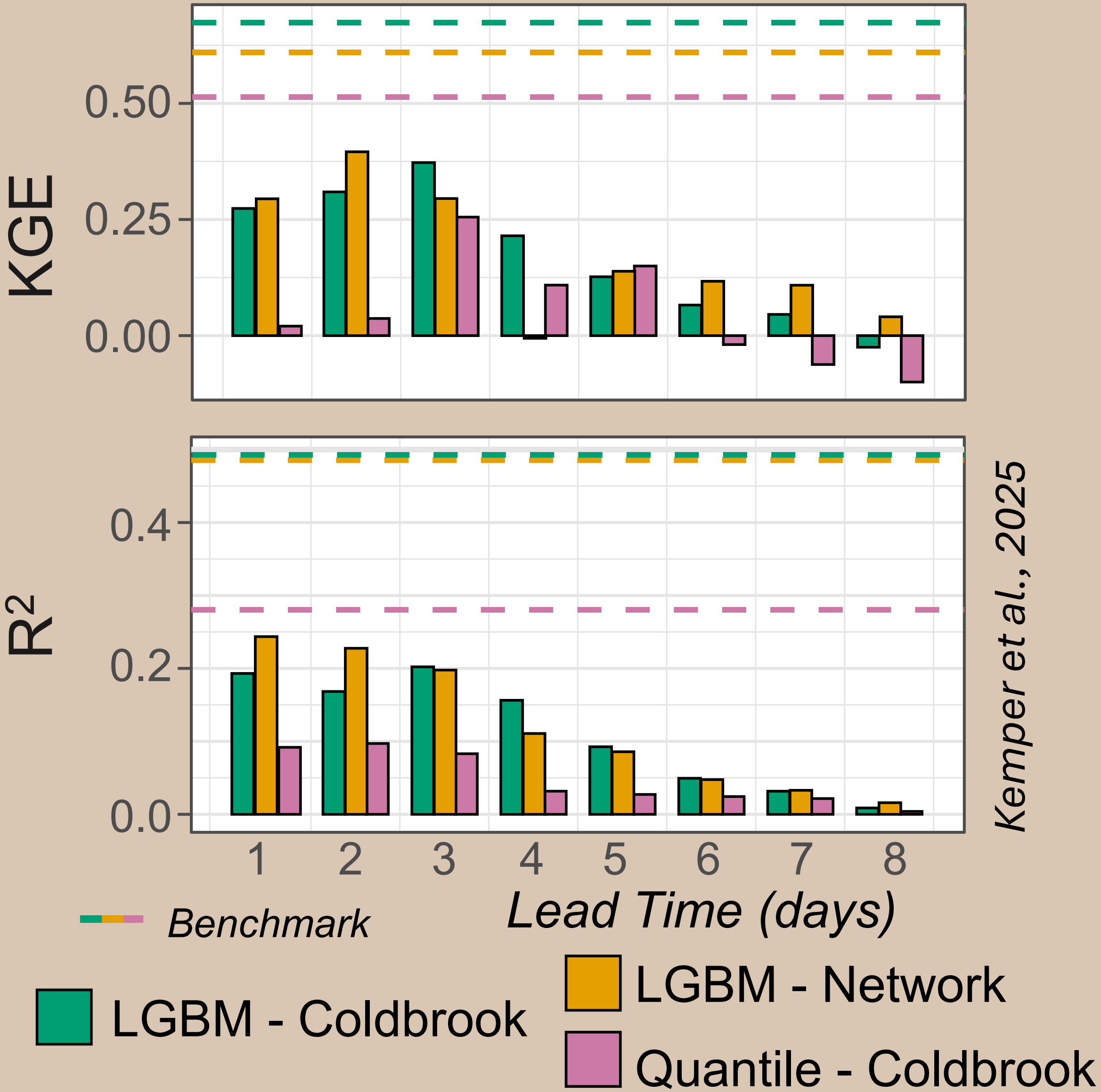
Performance of **NERFC-driven** turbidity forecasts



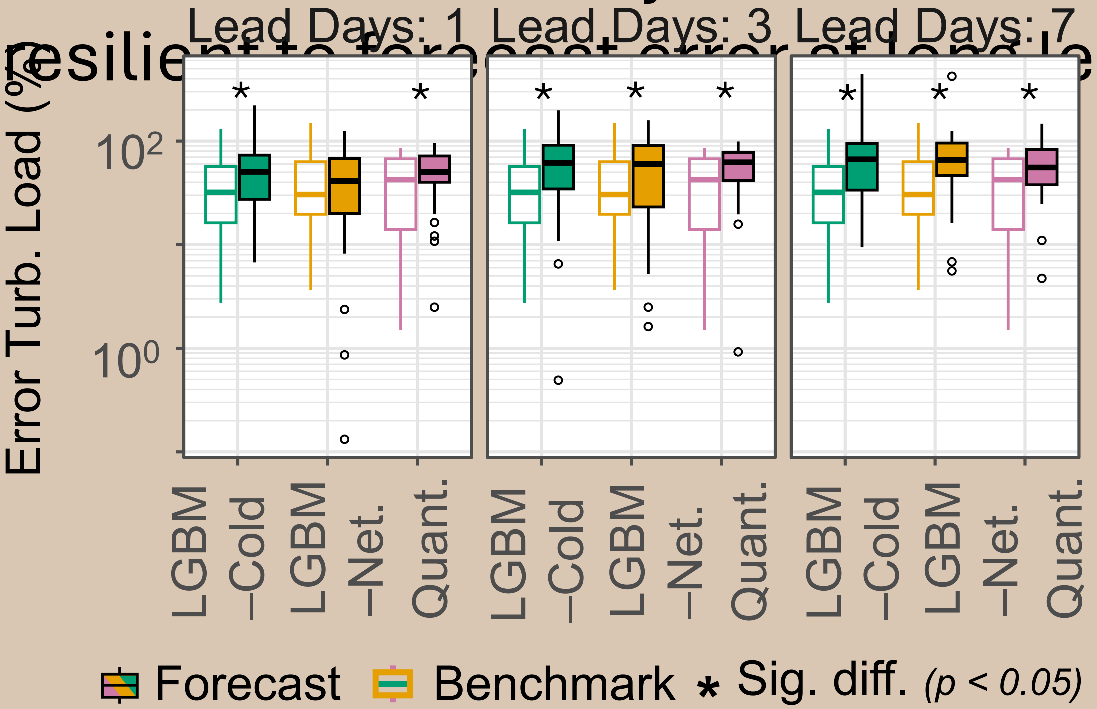
- Performance is relatively robust at short lead time(s), declines w/ increasing lead time
- **LGBM model** may be more resilient to forecast error at long lead
- Room for improvement

Performance of **NWM-driven** turbidity forecasts

- Performance is relatively robust at short lead time(s), declines w/ increasing lead time
- **Room for improvement** – models substantially underperform perf. Q benchmarks across all lead times
- **Network model** may be more resilient to forecast error at long lead

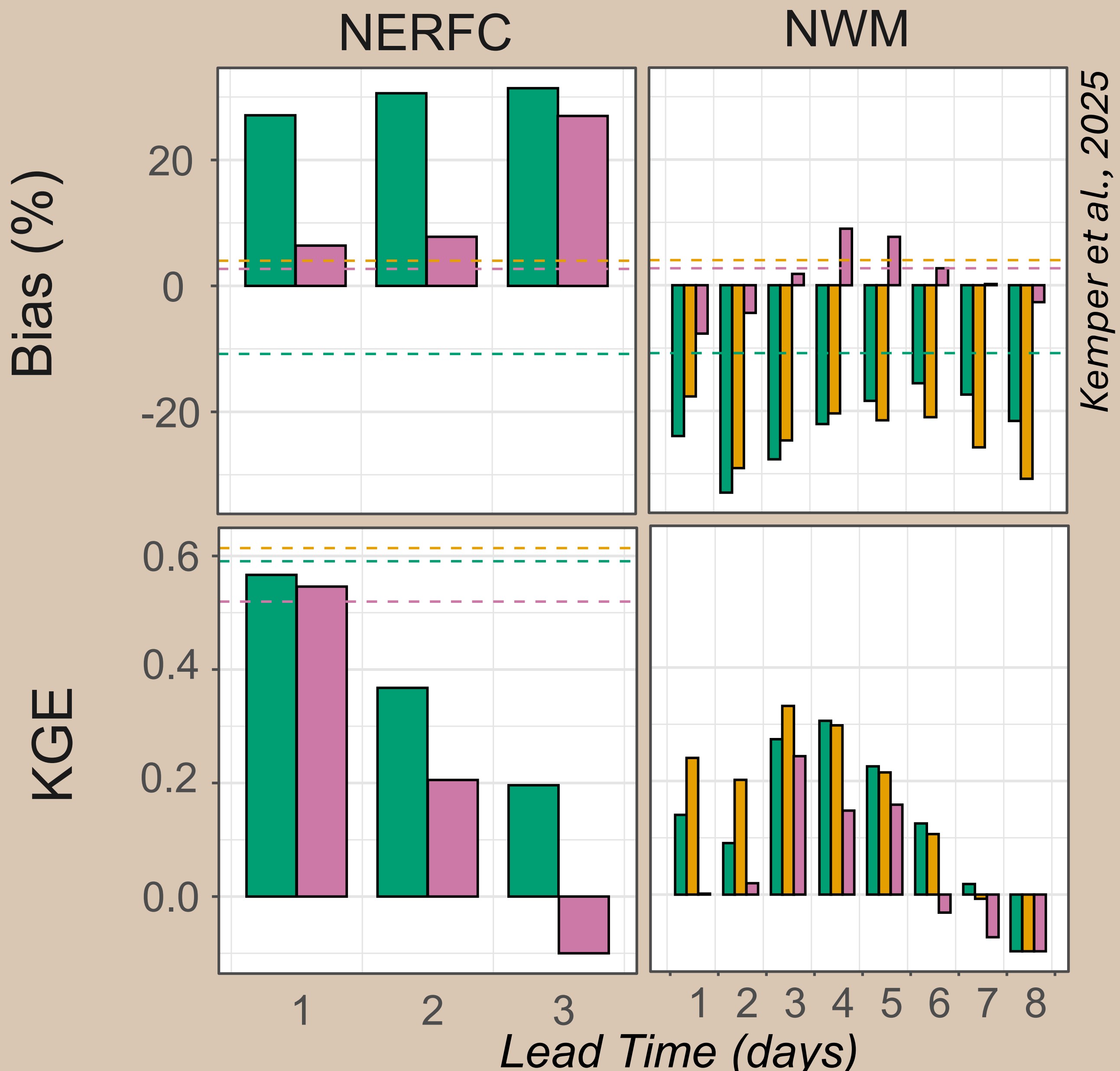


Kemper et al., 2025



How might we use these forecasts together?

- Ensemble forecast
  - NERFC is positive biased, NWM is negative
  - Breaking down KGE: α is better for NERFC, r is better for KGE – NERFC hits peaks better, NWM mimics the timing and shape better
- NWM for longer forecast horizon



So where does ML help us?

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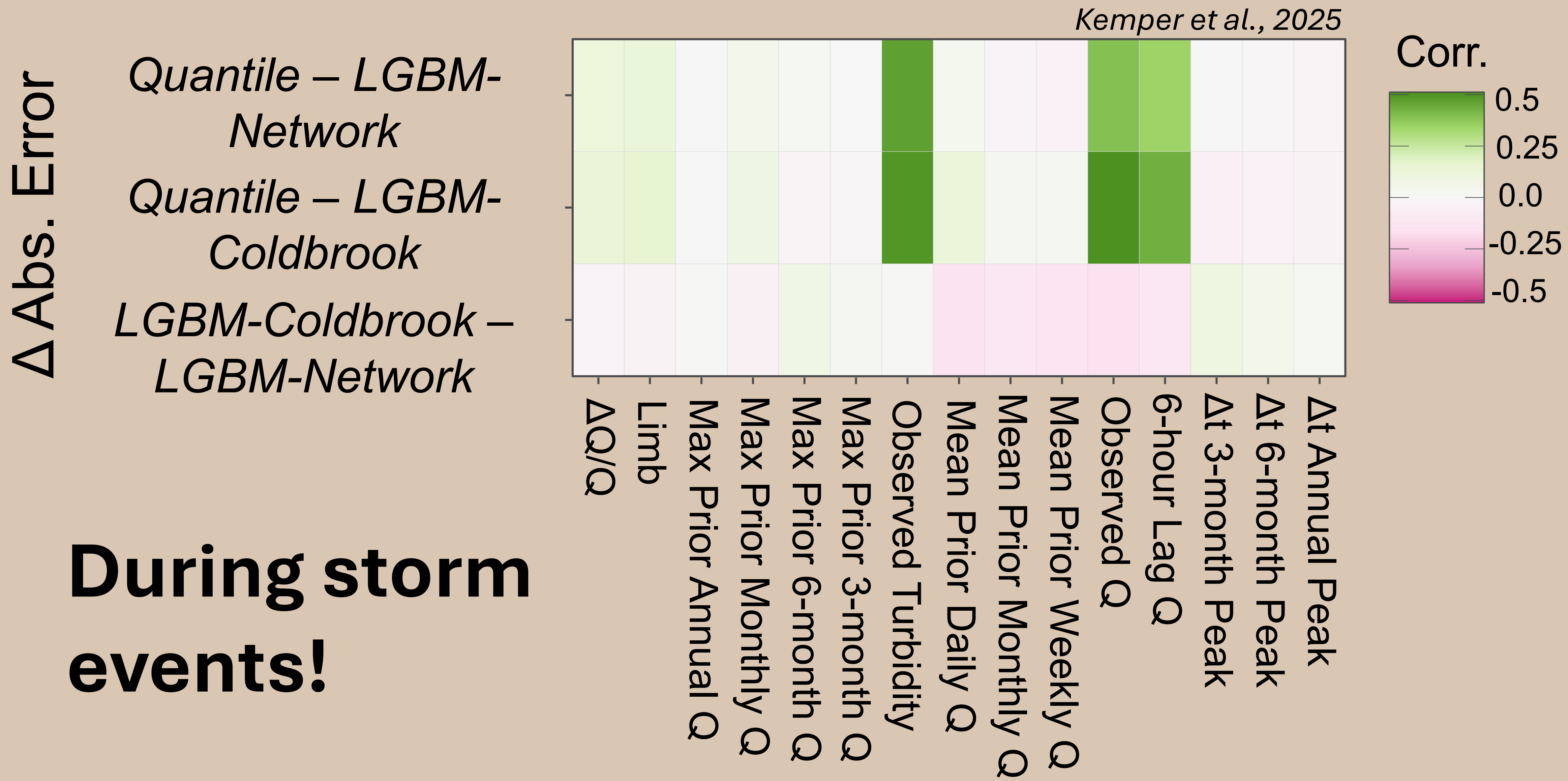
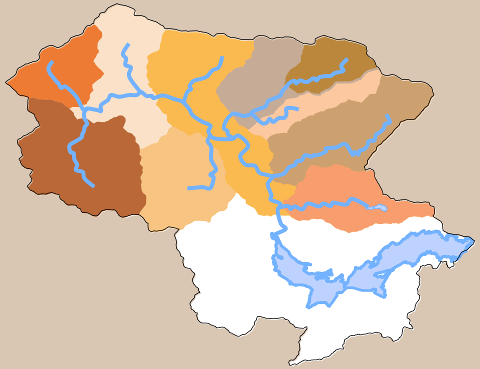
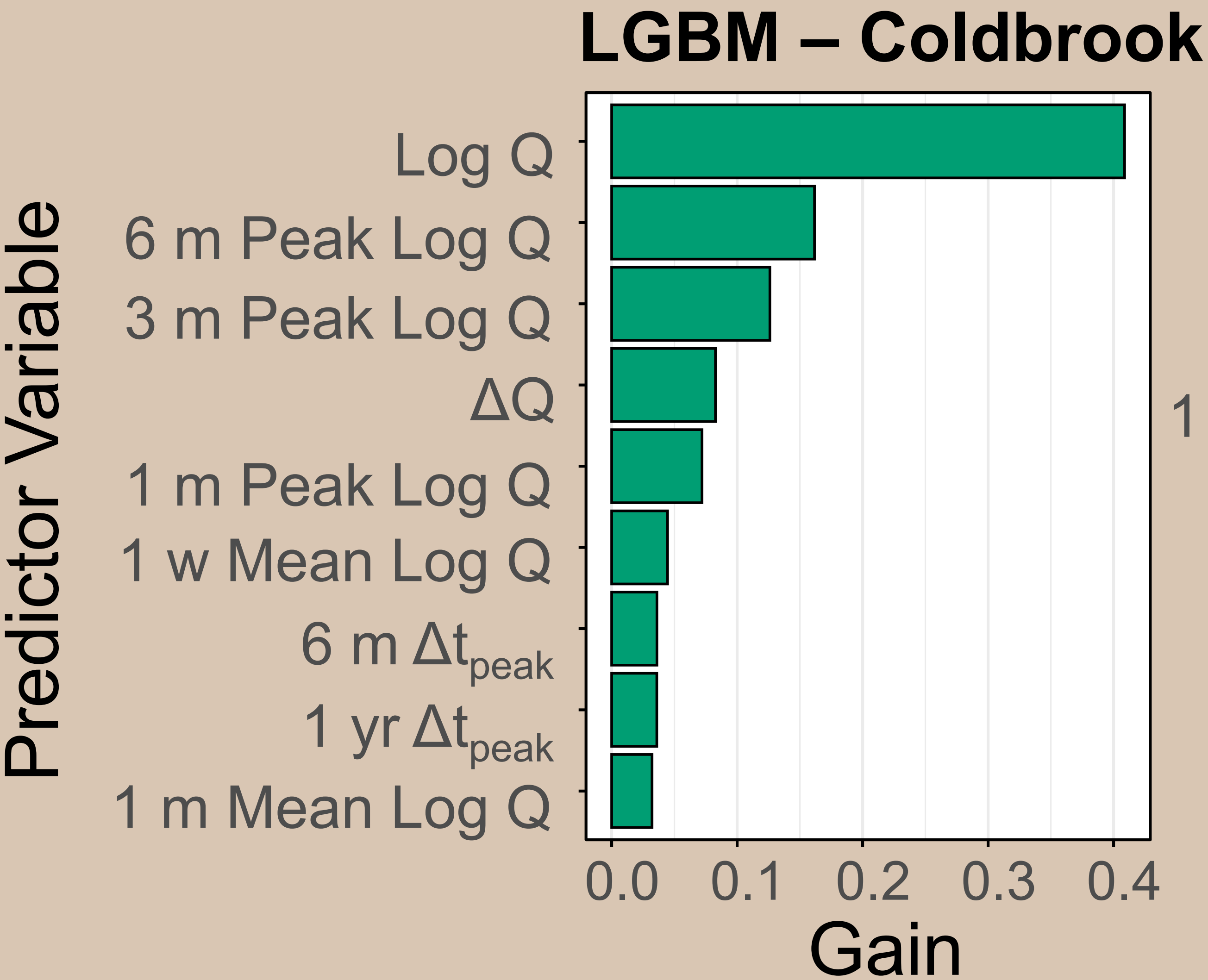
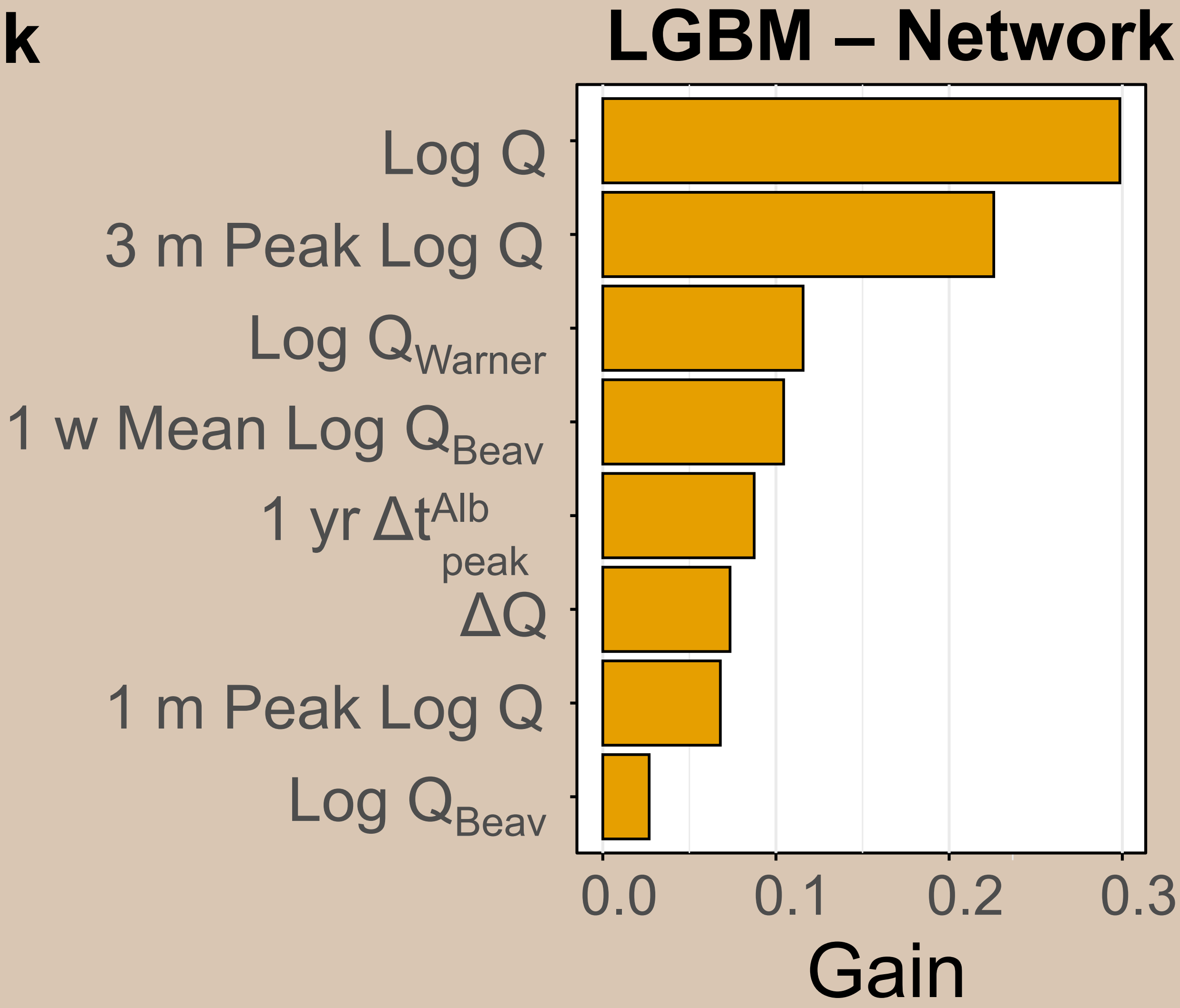


During storm events!



Management implications: Feature importance reflects the influence of large storm events and network dynamics

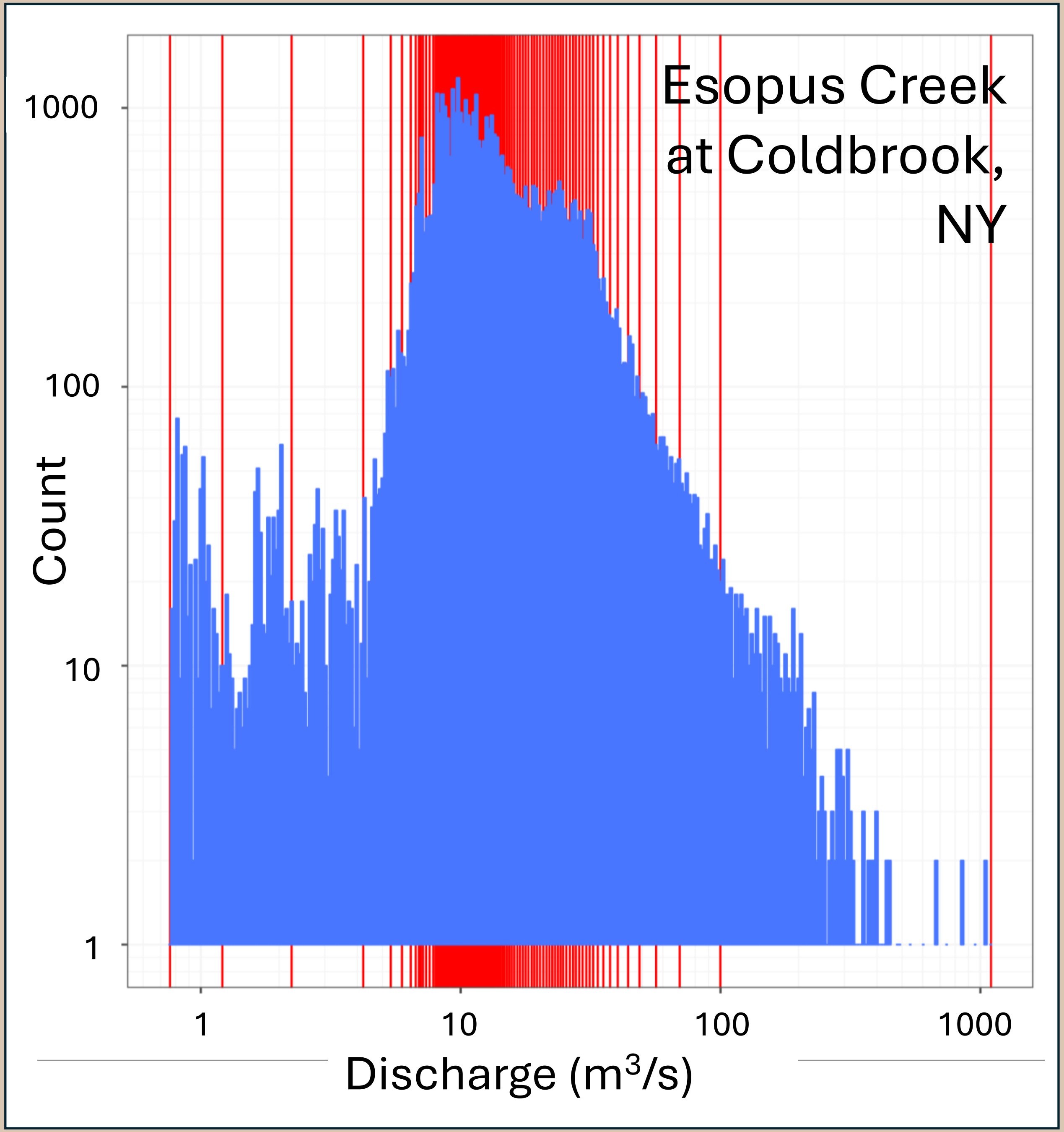




Take home points

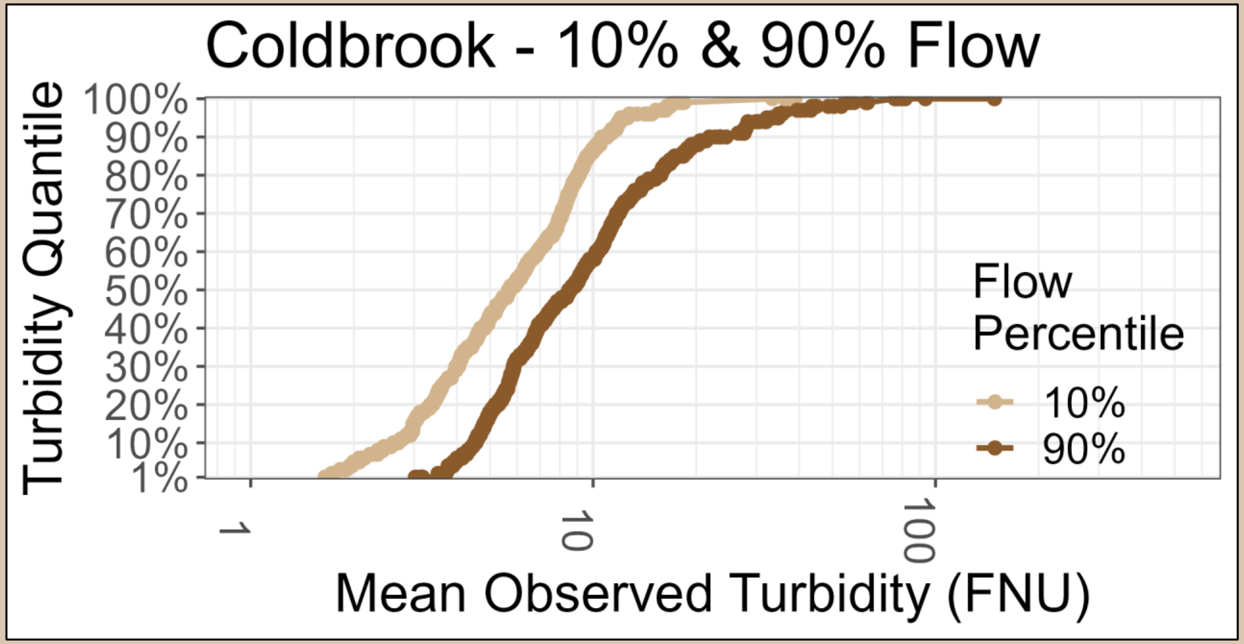
- ML models learned **spatially & temporally complex dynamics** (turbidity in Esopus)
- Different streamflow forecasts can be used in an **ensemble format** to provide bounds and range of possibilities
- ML can improve predictions during high flow scenarios
- **Flexible, interpretable, and efficient models** like LightGBM offer opportunities to **gain process insight** (explainableAI) and **provide skillful predictions**
- When combined with monitoring data, **the NWM can be employed as a relatively robust water forecasting tool** → potential to greatly expand the capacity of WQ forecasting across the country

Examining the impact of large storms - if & how & for how long storm occurrence elevates turbidity

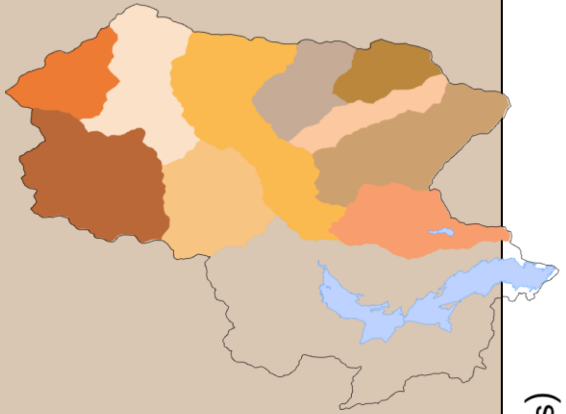


(Kemper et al., in review)

- Because flow & turbidity interact, we need to control for discharge magnitude
  - Bin flow into single percentiles (1%)
  - For each flow percentile, calculate turbidity distribution

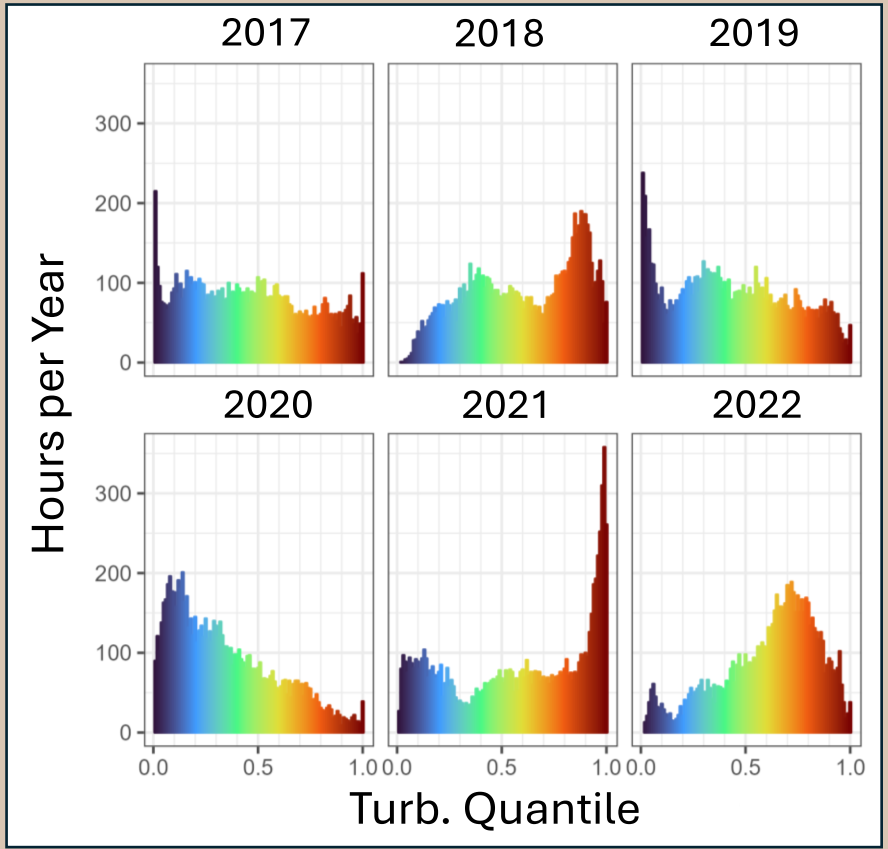


Starting at the Coldbrook (mouth) station



- Turbidity stays elevated across the hydrograph after Nov. 2018 & Christmas 2020 storm

- Change in hysteresis as well? High turbs on falling limbs in 2021 and 2022 contrast with what is seen previously



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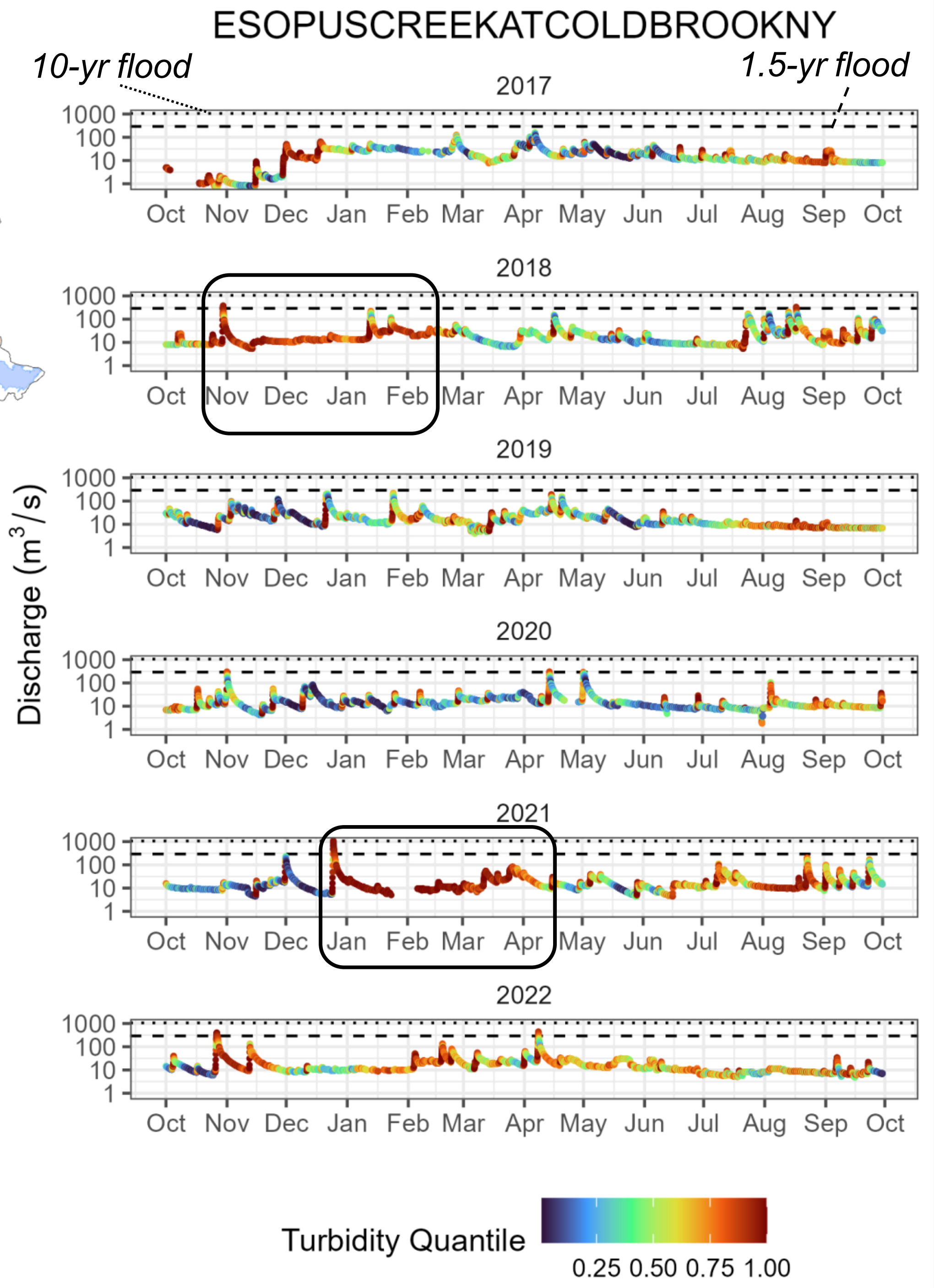
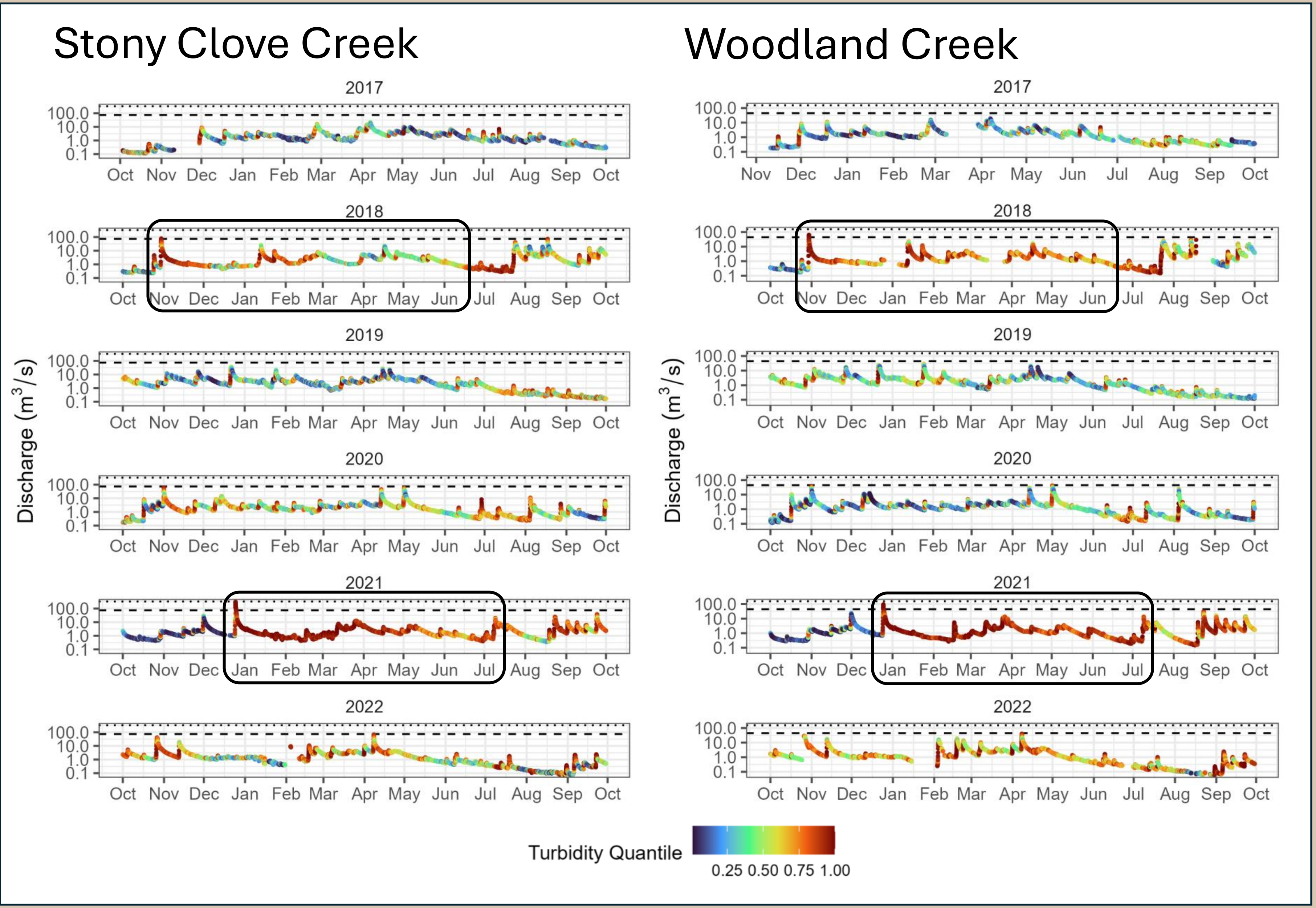


Woodland Creek & Stony Clove



- Similar response to 2021 storm
- Observably different to 2018 storm