Riverine Discharge Changepoint Detection

An exploration of Sequential Bayesian Onlince Change Point Detection (BOCPD)

Mae Hutchison

School of Economics Political and Policy Sciences, UT Dallas

December 2, 2025

Table of Contents

USGS riverine gage data

The U.S. Geological Survey (USGS) river gage data provides continuous monitoring of streamflow conditions.

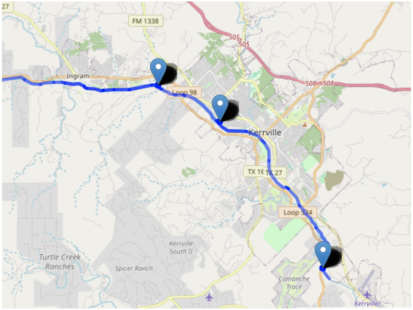

Figure 1: Three hydrologically connected gages in Kerr County, TX

Distribution

The Log-Pearson Type III distribution is widely used in hydrology to model peak streamflows (England et al., 2018). It applies a Pearson Type III distribution to the log-transformed discharge data. Let Q be the daily peak discharge. Define:

$$X = \log_{10}(Q)$$

$$X \sim \text{PearsonIII}(\kappa, \theta, \tau)$$

Bayesian Framework

For this solution, we use a simplified model where $X \sim \Gamma(\alpha, \beta)$ with shape parameter α and rate parameter β (inverse of scale). With a Gamma-Gamma conjugage prior, the likelihood is Gamma and the conjugate prior for the rate parameter β (given α) is also Gamma.

- Prior: $\beta \sim \Gamma(a_0, b_0)$
- Likelihood: $x_i|\beta \sim \Gamma(\alpha, \beta)$
- Analytical posterior (with n observed data points): $\beta|x_{1:n} \sim \Gamma(a_0 + n\alpha, b_0 + \sum_{i=1}^{n} x_i)$

Analytical Results

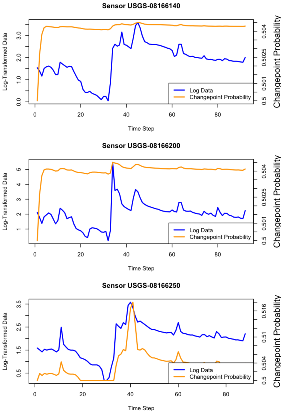

Figure 2: Results of analytical solution on Kerr County streamgage data

Sampler

For each time step:

- sample for each run length before current timestep
- calculate the predictive probability of the observed posterior
- calculate the run length probability
- calculate changepoint probability

$$P(r_t = 0 \mid x_{1:t}) \propto \sum_{r_{t-1}} P(r_t = 0 \mid r_{t-1}) \cdot P(x_t \mid r_{t-1}, x_{1:t-1}) \cdot P(r_{t-1}, x_{1:t-1})$$

Numerical Results (simplified version)

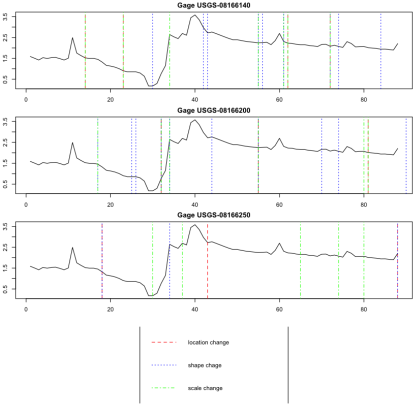

Figure 3: Change in parameter points on Kerr County streamgage data

Rbeast

Rbeast is an R package that uses Bayesian Estimator of Abrupt change, Seasonal change, and Trend (BEAST) (Zhao et al., 2019)
Combines:

- Bayesian changepoint detection for time series.
- Ensemble modeling to improve robustness and uncertainty quantification.

EA Results

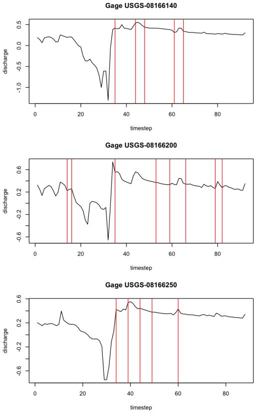

Figure 4: Rbeast calculated changepoints on Kerr County streamgage data

Future Work

Improve numerical solution with particle filtering

- Save samples from previous run lengths
- Each particle represents the current rung length, segment parameters, and weight
- Compute likelihood of new observation under particle's parameters
- Update and normalize weights
- Resample particles after certain metrics are triggered (e.g., effective sample size drops).

References I

Adams, R. P. and MacKay, D. J. C. (2007). Bayesian online changepoint detection. *arXiv preprint arXiv:0710.3742*. Accessed October 2025.

DeCicco, L., Lorenz, D., Read, J., and Johnson, M. (2023). *dataRetrieval: R packages for discovering and retrieving water data available from U.S. federal hydrologic web services*. U.S. Geological Survey. R package version 2.7.8.

England, J. F. J., Cohn, T. A., Faber, B. A., Stedinger, J. R., Thomas, W. J., Veilleux, A. G., Kiang, J. E., and Mason, R. R. J. (2018). Guidelines for determining flood flow frequency—bulletin 17c. Techniques and Methods Book 4, Chapter B5, U.S. Geological Survey.

References II

Zhao, K., Wulder, M. A., Hu, T., Bright, R., Wu, Q., Qin, H., Li, Y., Toman, E., Mallick, B., Zhang, X., and Brown, M. (2019). Detecting change-point, trend, and seasonality in satellite time series data to track abrupt changes and nonlinear dynamics: A bayesian ensemble algorithm. *Remote Sensing of Environment*, 232:111181.