Supplemental Material for Online Publication Only for:

A Wavelet-Based Approach to Streamflow Event Identification and Modeled Timing Error Evaluation

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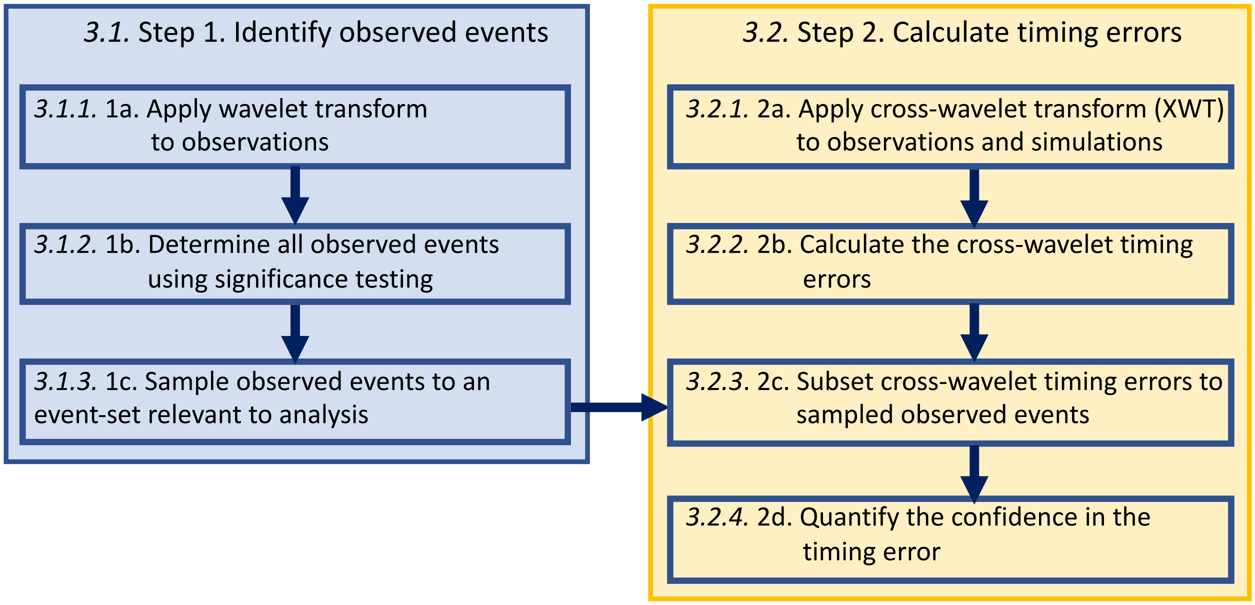
Nomenclature Table

Supplemental Table 1. Nomenclature table of terms used in the manuscript.

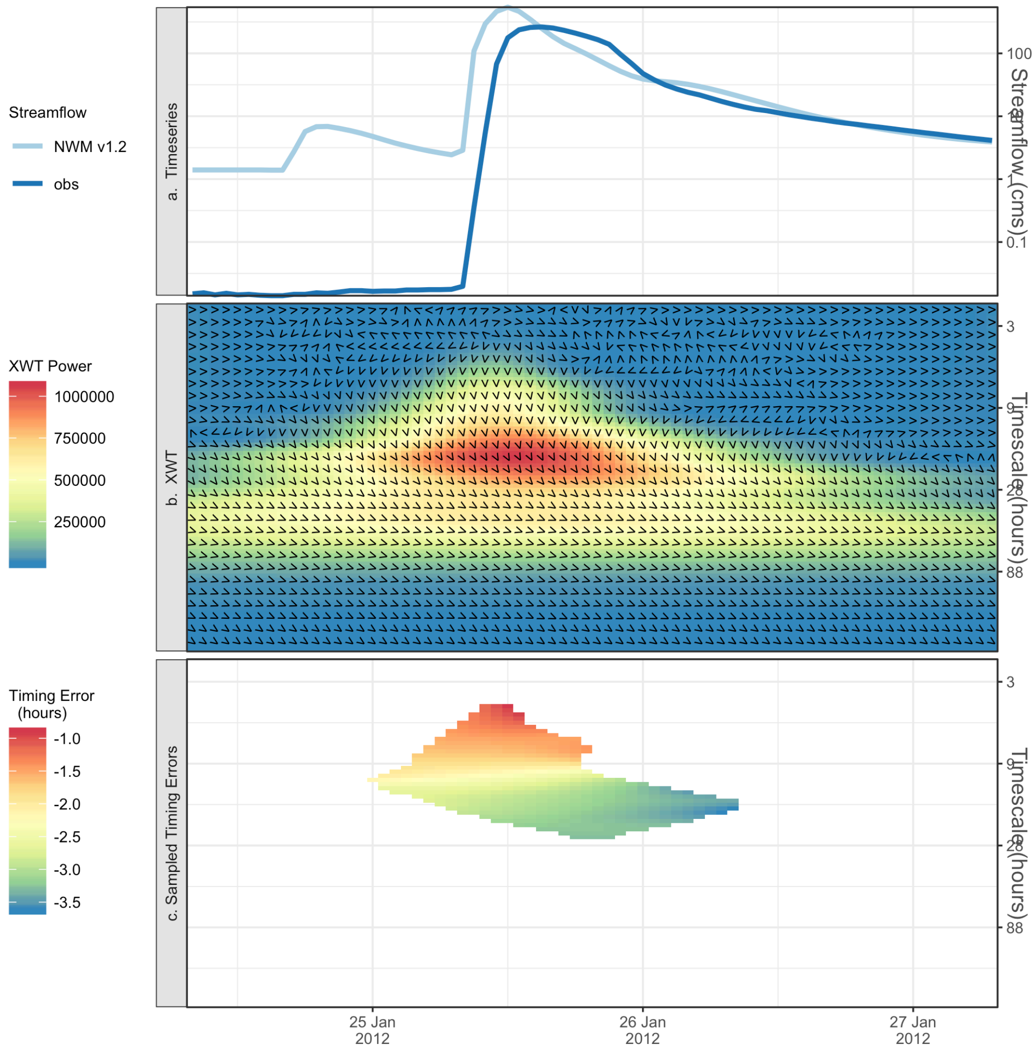
Term, Acronym	Synonyms	Units	Comments
time series	Input data	m^3/s for streamflow	We analyze streamflow observations and simulations, which are ordered by the time dimension (Figure 1a)
time		hours	Dimension of the input timeseries (x-axis on all Figure 1 panels).
timescale	period	hours	Dimension introduced at each time by the WT (y-axis on Figure 1b-d)
wavelet transform (WT)	wavelet power spectrum (result of the transform)	m^6/s^2	In this paper, we employ the continuous WT (Figure 1b) with scale normalized energy (Liu et al, 2007)
cone of influence (COI)	COI		Where wavelet analysis is affected by the wavelet extending beyond the time domain of the input (muted colors in Figure 1b)
event			We define events in terms of both time and timescales that are significant in the WT and outside the COI (Figure 1c)
characteristic timescale	dominant timescale	hours	We define characteristic timescales by local maxima in time-averaged, significant wavelet power (e.g. over events) (Figure 1d)
event cluster			For a single (e.g. characteristic) timescale, contiguous events in time (Figure 1d)
cross wavelet transform (XWT)	cross wavelet power spectrum (result of the transform)	Power: m^6/s^2 Phase: radians	The complex, cross-wavelet transform has properties of power and phase. Significance of the XWT can also be computed (e.g. Torrence and Compo, 1998) and are used in this work but not shown on the plots. Figure 2b.
timing error		hours	Timing errors are calculated from the phase offset of the XWT (e.g. Liu, 2011) and have dimensions of both time and timescale. Several statistics of timing errors (over time) for characteristic timescales can be computed (Figure 2c).

Methodology Overview



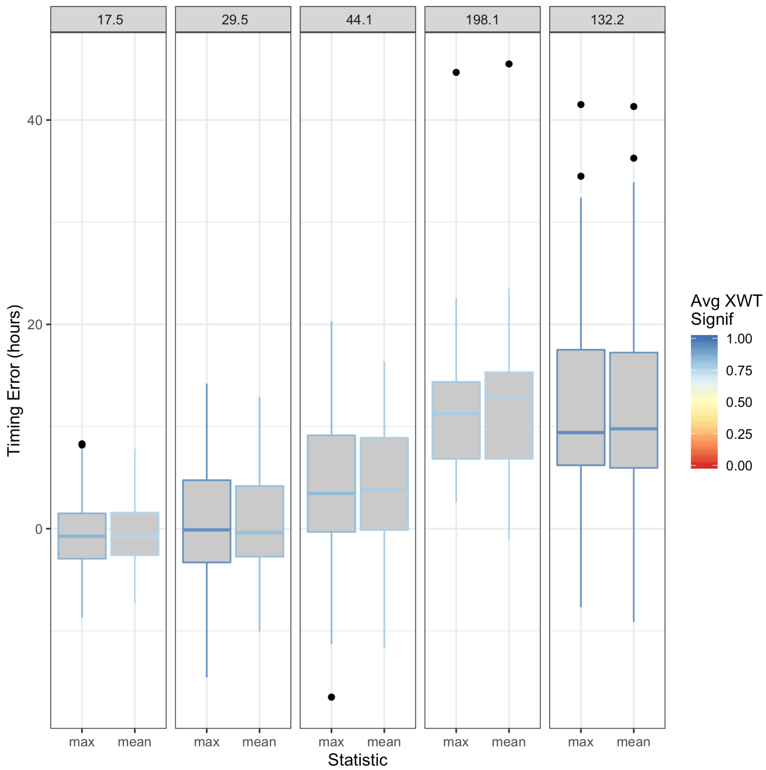
Supplemental Figure 1. Flow chart of steps in the methodology; although Steps 1a-1b and Steps 2a-2b can happen in parallel, Step 2c needs to be preceded by Step 1c.

Onion Creek, Single Event



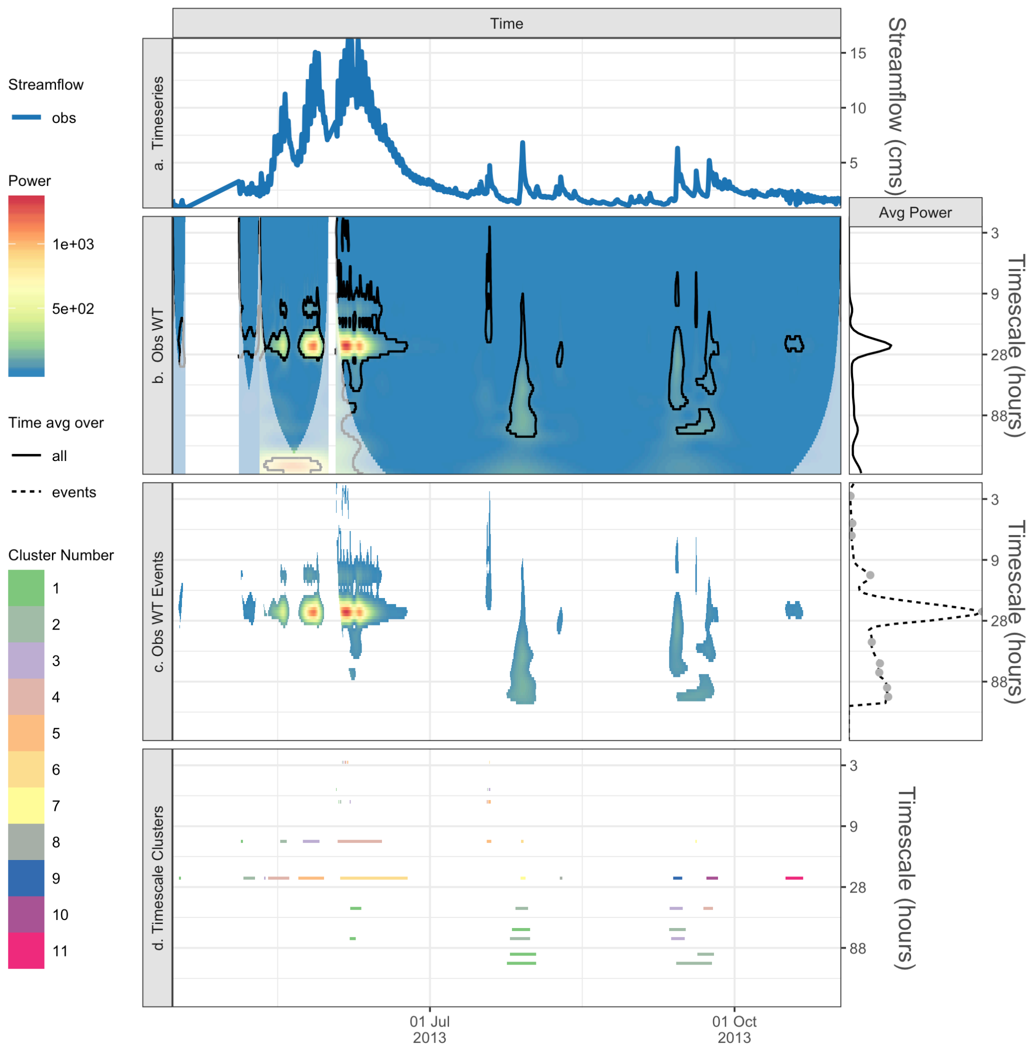
Supplemental Figure 2. An isolated peak from Onion Creek, TX and simulated NWM data: (a) observed and simulated time series, (b) cross wavelet (XWT) power spectrum and phase angles (arrows), (c) sampled timing errors for observed events.

Pemigewasset River, Five Years



Supplemental Figure 3. Five year run from Pemigewasset River, NH: For NWM V1.2, cluster max and mean timing errors by characteristic timescales (see panel title); outline shading shows average significance in the cross wavelet transform (XWT).

Taylor River, One Year

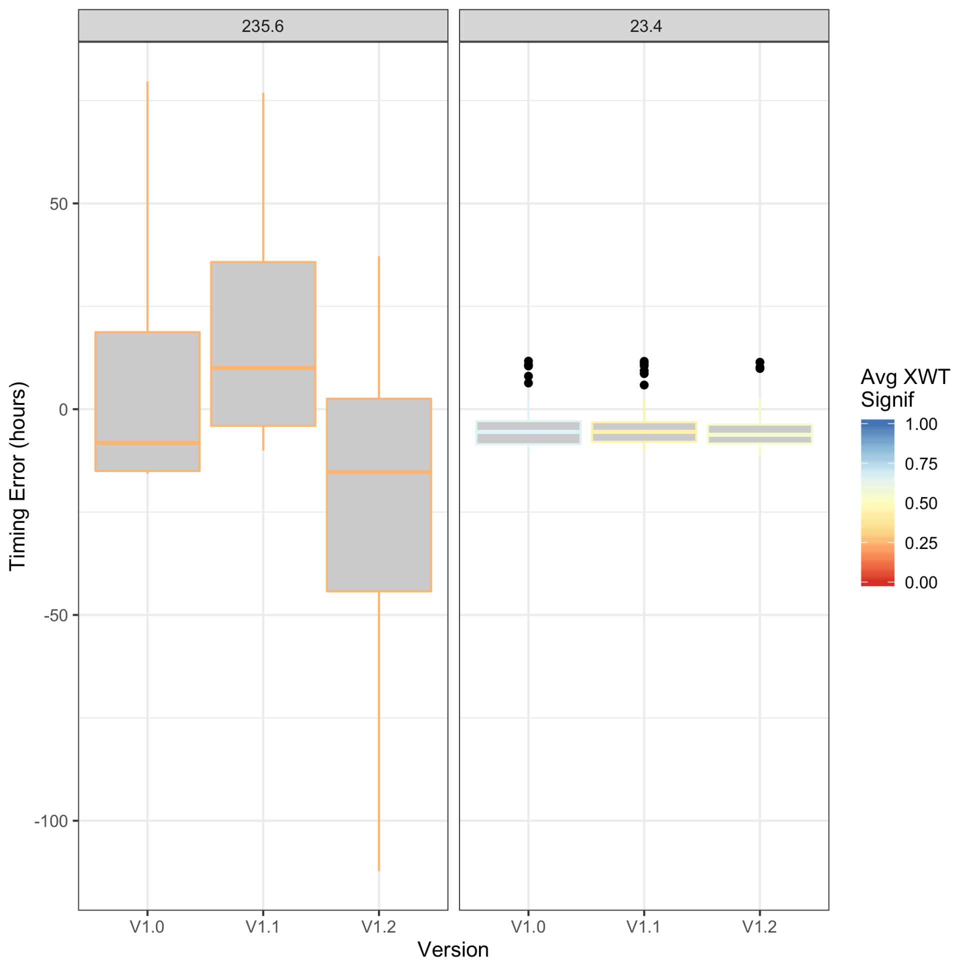


Supplemental Figure 4. Taylor River, CO: (a) observed time series, (b) observed wavelet power spectrum (left) and average power by timescale for all points (right); (c) statistically significant wavelet power spectrum or events (left) and average power by time scale for all events with maxima shown by grey dots (right); (d) Characteristic scales event clusters (horizontal lines).

Taylor River, Five Year

Supplemental Table 2. Summary of timing errors using cluster max for 5-years from Taylor River, CO.

NWM Version	Characteristic Timescale (hr)	Number of Clusters	Avg WT Power	Median Timing Error (hr)	Avg % Significance in XWT
v1.0	23.4	39	249	-5.52	67%
v1.1	23.4	39	249	-5.50	44%
v1.2	23.4	39	249	-6.22	54%
v1.0	236	4	220	-8.19	25%
v1.1	236	4	220	10.01	25%
v1.2	236	4	220	-15.28	25%



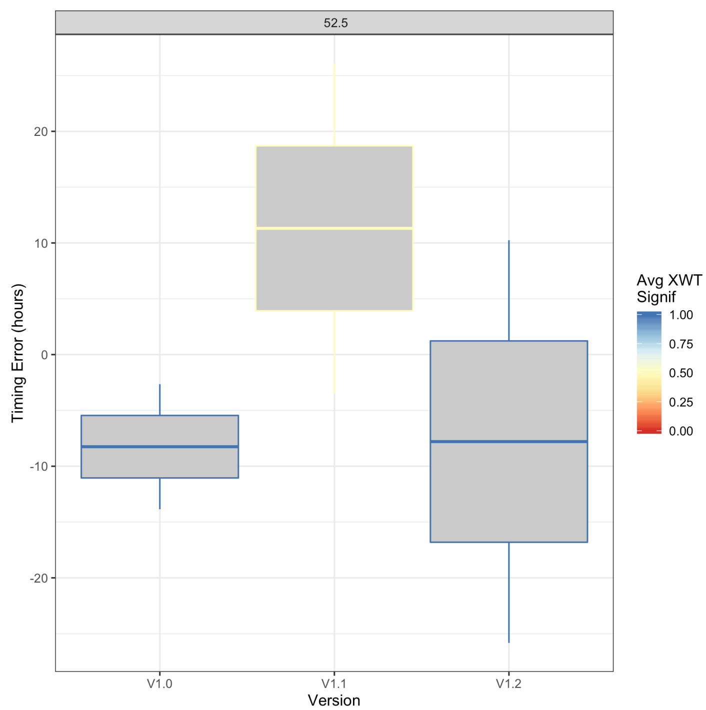
Supplemental Figure 5. Five year run from Taylor River, CO: Comparing cluster max timing error distributions for top two characteristic timescales (see panel title) across NWM versions; outline shading shows average significance in the cross wavelet transform (XWT).

Bad River, One Year

Supplemental Table 3 and Supplemental Figure 6 show that for the characteristic scale of 52.5 hours, the model is early and confident for V1.0 and V1.2; V1.1 shows a late timing error, but confidence is lower (~50%). However, results were only based on 2 event clusters.

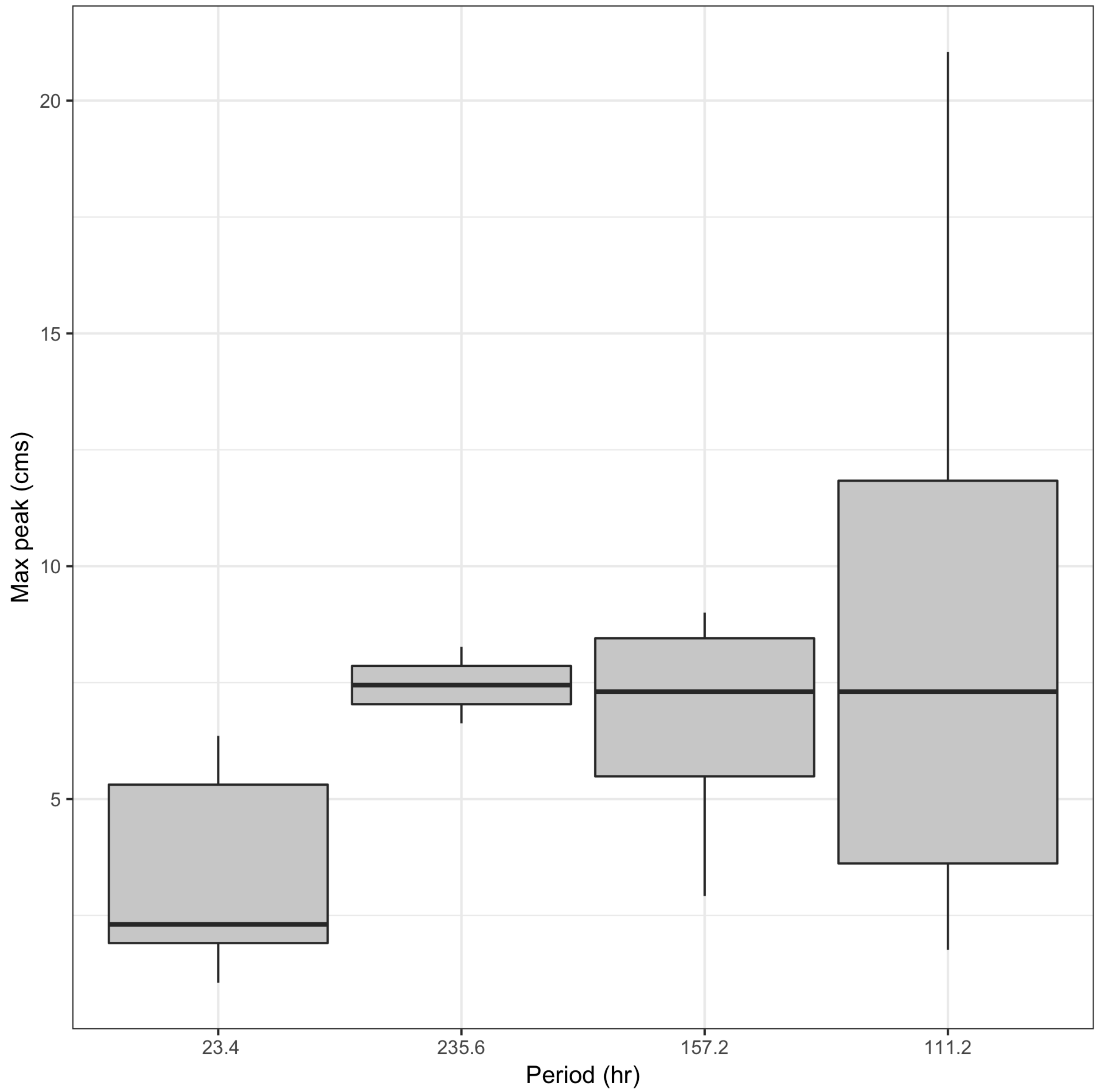
Supplemental Table 3. Summary of timing errors using cluster max for 1-year from Bad River, SD.

NWM Version	Characteristic Timescale (hr)	Number of Clusters	Avg WT Power	Median Timing Error (hr)	Avg (%) Significance in XWT
v1.0	52.5	2	37524	-8.3	100%
v1.1	52.5	2	37524	11.3	50%
v1.2	52.5	2	37524	-7.8	100%



Supplemental Figure 6. One year run from Bad River, SD: Comparing timing error distributions for top characteristic timescale (see panel title) across NWM versions.

Taylor River, Five Year



Supplemental Figure 7. Five year run from Taylor River, CO: for top four characteristic timescales (periods), maximum streamflow distributions for each event (using cluster max) in cubic meters per second (cms). This figures shows that all events identified by the algorithm are not necessarily flood events, the highest maximum streamflow value occurs at a timescale of 111.2 hours. To compare with traditional peak-over-threshold approaches, this event-set could be filtered to include only events above a given threshold.

Example Code and Runtime Profile

The code for reproducing the figures in this paper and extended vignettes/notebooks are provided in public github repository https://github.com/NCAR/wavelet_timing. The core code is provided in the "rwrfhydro" R package https://github.com/NCAR/rwrfhydro and the specific analyses are contained in the first repository. The installation of rwrfhydro requires having the devtools package installed.

Installation

```
install.packages(devtools)
devtools::install_github("https://github.com/NCAR/rwrfhydro")
```

Example: Three Basic Figures

After the installation of rwrfhydro, there a two more packages are required as show below to run the examples. This example (adapted from the vignettes and the code to reproduce the figures in the paper) plots the equivalent of figures 1, 2 and

```
library(rwrfhydro)
if(!require("relayer")) {
  devtools::install_github("https://github.com/clauswilke/relayer")
  library(relayer)}
if(!require("grid")) {
  install.packages(grid); library(grid)}

location = 'pemigewasset_river'
time_period <- 'small_event'

data <- WtGetEventData(location, time_period)

wt_event = WtEventTiming(
  POSIXct=data$POSIXct,
  obs=data$q_cms_obs,
  mod=list('NWM v1.2'=data$`NWM v1.2`),
  min_ts_length=24,
  max.scale=256,
  rm_chunks_warn=FALSE
)

figure1 = step1_figure(wt_event)
grid.draw(figure1)


figure2 = step2_figure(wt_event)
grid.draw(figure2)


figure3 = event_cluster_timing_by_period(wt_event, n_period=5)
plot(figure3)
```

Example: Performance Profiling

If the wavelet timing error method is suitable for use in a calibration strategy partially depends on the time required to calculate the timing errors. The following code provides a measure of the time required.

```
if(!require("microbenchmark")) {
  install.packages("microbenchmark"); library(microbenchmark)}

location = 'pemigewasset_river'
time_period <- 'five_years'
data = WtGetEventData(location, time_period)

get_wt_stats = function() {
  wt_event = WtEventTiming(
```

```
    POSIXct=data$POSIXct,
    obs=data$q_cms_obs,
    mod=list('NWM v1.2'=data$`NWM v1.2`),
    min_ts_length=24,
    max.scale=256,
    rm_chunks_warn=FALSE
  )
  return(we_hydro_stats(wt_event))
}

# Runtime profile – using observations.
suppressWarnings(
  print(microbenchmark(get_wt_stats(), times=10), unit='s'))
```

On an iMac desktop, the mean time to get the stats was 8.7 seconds.