

Interactive comment on “Technical note: Fourier approach for estimating the thermal attributes of streams” by M. Ryo et al.

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Received and published: 21 June 2016

Reply to RC1

1. Page 2, line 5–6: “Progress in understanding response patterns have been delayed partially because the quantification of thermal attributes is difficult for running waters.” The introduction stresses that understanding of thermal attributes in lotic ecosystems is hindered by scarce temporal observations, which certainly is a limitation in current research. However, this method hinges on a reference hydrologic station (i.e. a site that is not data-scarce) to elucidate thermal attributes at a data-scarce site. The manuscript’s current focus seems to lie in extrapolating within a basin where there is abundant data from at least one location, and it may be helpful to state this explicitly because the de-

C1

scription of the limitations in currently available methods/research that are mentioned in the introduction may signal to readers that the proposed method will be rooted solely in spot measurements.

—[Our reply]—

As the reviewer has clarified, our approach for temperature estimation based on extrapolation cannot be applied where no monitoring station exists along the streamline. To avoid misleading readers, we would have modified the last two sentences in this paragraph and a sentence in the next paragraph according to the reviewer’s comment as follows:

Before (p.2, line 10-): Often in these cases, researchers rely on spot-measures of temperature at study sites and thus lack time-series temperature, thereby limiting understanding of the ecological consequences of thermal attributes in freshwaters. Clearly, an estimate of the thermal attributes at spot-measured sites would benefit this understanding.

After: Often in these cases, researchers rely on spot-measures of temperature at study sites although lacking time-series temperature or, otherwise refer to temperature time-series monitored at a near hydrological station along the streamline although likely being biased in thermal attributes. Either one has the problem, thereby limiting understanding of the ecological consequences in freshwaters. Estimating thermal stream attributes from both spot-measurements at study sites and time-series at the nearest hydrological station would allow more robust estimates.

Before (p.2, line 15): For instance, regression models employ correlative relationships with air temperature (e.g., Pilgrim et al., 1998) and streamflow (Webb et al., 2003).

After: For instance, regression models employ correlative relationships with air temperature (e.g., Pilgrim et al., 1998) and streamflow (Webb et al., 2003), while a correlative approach considering water temperature at a near hydrological station along the

C2

streamline have not been implemented yet.

2. Page 3, line 5: The authors consider external factors such as weather conditions as part of the irregularity component. However, in other climates, these meteorological conditions would likely factor into the diel (sun) and seasonal (rain) periodicity patterns as well. For better clarification we would have modified the description as follows:

—[Our reply]—

We assume that hourly stream temperature $T(t)$ at a given time t is generally composed of the average value \bar{T} , seasonal periodicity pattern $S(t)$, and diel periodicity pattern $D(t)$. The seasonal and diel periodicity patterns can be driven by meteorological (e.g., solar radiation and precipitation) and hydrological (e.g., discharge and snow-/ice-melt) conditions. The remaining component, which is unexplained by these three components, results from multiple external factors such as stochastic sub-daily changes in weather conditions (sunshine, rain, wind, etc.): we call this component an irregularity $\varepsilon(t)$.

Before (p.3, line 4): We assume that hourly stream temperature $T(t)$ at a given time t is generally composed of the average value \bar{T} , seasonal periodicity pattern $S(t)$, and diel periodicity pattern $D(t)$. The remaining component, which is unexplained by these three components, results from multiple external factors such as weather conditions (sunshine, rain, wind, etc.): we call this component an irregularity $\varepsilon(t)$.

After: We assume that hourly stream temperature $T(t)$ at a given time t is generally composed of the average value \bar{T} , seasonal periodicity pattern $S(t)$, and diel periodicity pattern $D(t)$. The seasonal and diel periodicity patterns can be driven by meteorological (e.g., solar radiation and precipitation) and hydrological (e.g., discharge and snow-/ice-melt) conditions. The remaining component, which is unexplained by these three components, results from multiple external factors such as stochastic sub-daily

C3

changes in weather conditions: we call this component an irregularity $\varepsilon(t)$.

3. Page 6, line 5: Are the r^2 values (0.66 vs. 0.6) significantly different to state that the proposed method works better than linear regression? It might make more sense to first stress that the method can successfully recreate extremes (cf. linear regression), and then state that it is better at estimating temperatures at site A.

—[Our reply]—

We fully agree with the reviewer's suggestion. We would have modified the text to better stress out the success in our primary aim recreating extremes: "This result indicates that our approach can accurately estimate periodic components and extremes including the variability in irregularity, that cannot be represented by linear regression focusing on an average estimate." Inserted in p. 5 line 2 just before the sentence starting from "At site B, ..."

4. Page 7, line 16: Is the threshold value specific to the system in question? How was this value chosen, and what implications might this have?

—[Our reply]—

Yes, it would be system-dependent. The paragraph would have been modified accordingly to clearly indicate how we selected the threshold (p. 7, line 15). See also new supplement figure S1:

First, the analysis connecting Eqs. (1) and (7) is threshold dependent. We firstly estimated an appropriate range of threshold value visually so as to capture a handful of trigonometric curves (i.e., the three major peaks were focused in Figure 3). Then, we compared the patterns modeled based on some threshold values. Too low threshold value results in too sensitive to noises, while too high threshold value results in too in-

C4

sensitive to periodic patterns. We compared the performance of the models based on a set of threshold values (0.05, 0.1, and 0.2°C etc.) and determined graphically as the value 0.1°C clearly separated periodicity patterns and irregularities (Figure S1). Therefore, a threshold value must be carefully chosen and needs to be evaluated whether the irregularity attribute is unbiased.

5. Below is a list of technical corrections: 1. "Thermal attributes" should be explicitly described earlier in the introduction. The full description is currently on page 2, line 21, but "thermal attributes" are first mentioned well before this line. 2. Page 2, line 26–27: "...multiple scales in time-series data, and water temperature in particular." 3. Page 2, line 33: "...sites along the same stream..."

—[Our reply]—

We would have modified technical corrections 1–3 suggested by the reviewer accordingly.

Please also note the supplement to this comment:

<http://www.hydrol-earth-syst-sci-discuss.net/hess-2016-238/hess-2016-238-AC1-supplement.pdf>

Interactive comment on Hydrol. Earth Syst. Sci. Discuss., doi:10.5194/hess-2016-238, 2016.

C5

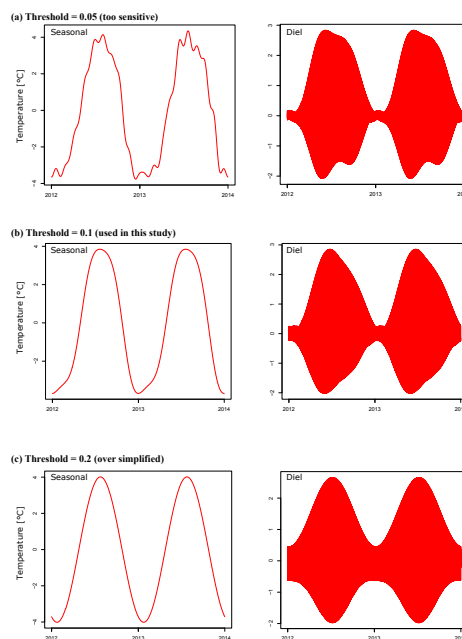


Fig. 1. Figure S1 The relationships of the threshold selection to extracted seasonal and diel periodic patterns in temperature (also see Figure 2)

C6