Response

Anonymous Referee #1

This paper presents a novel approach to investigate the performance of GloFAS streamflow reanalysis from the perspective of the time-frequency domain. The results provide interesting insights into the performance of global streamflow reanalysis datasets and attribution analysis. The paper is well-structured and well-written. Below are some comments for consideration.

We appreciate the positive comments.

1. Abstract - The significance of evaluating global streamflow reanalysis in the time-frequency is in demand, which helps clarify the contribution of this paper.

Thank you for the insightful comment. The abstract has been improved to highlight the significance of evaluating global streamflow reanalysis in the time-frequency domain:

"While global streamflow reanalysis has been evaluated at different spatial scales to facilitate practical applications, its local performance in the time-frequency domain is yet to be investigated. This paper presents a novel decomposition approach to evaluating streamflow reanalysis by combining wavelet transform with machine learning. Specifically, the time series of streamflow reanalysis and observation are respectively decomposed and then the approximation components of reanalysis are compared to those of observed streamflow. Furthermore, the accumulated local effects are derived to showcase the influences of catchment attributes on the performance of streamflow reanalysis at different scales. For streamflow reanalysis generated by the Global Flood Awareness System, a case study is devised based on streamflow observations from the Catchment Attributes and Meteorology for Large-sample Studies. The results highlight that the reanalysis tends to be more effective in characterizing seasonal, annual and multi-annual features than daily, weekly and monthly features. The Kling-Gupta Efficiency (KGE) values of original time series and approximation components are primarily influenced by precipitation seasonality. High values of KGE tend to be observed in catchments where there is more precipitation in winter, which can be due to low evaporation that results in reasonable simulations of soil moisture and baseflow processes. The longitude, mean precipitation and mean slope also influence the local performance of approximation components. On the other hand, attributes on geology, soils and vegetation appear to play a relatively small part in the performance of approximation components. Overall, this paper provides useful information for practical applications of global streamflow reanalysis." (Page 1, Lines 9 to 24)

2. Lines 110 to 120 – Consider adding some diagnostic plots about the clustering results in the supplementary material, as the existence of outliers also indicates the variability of global streamflow reanalysis.

Thank you for the valuable suggestion. We have added four boxplots in Figure S1 in the supplementary material to illustrate the difference between the performance of inliers and outliers using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN). The KGEs of outliers are generally lower than those of inliers:

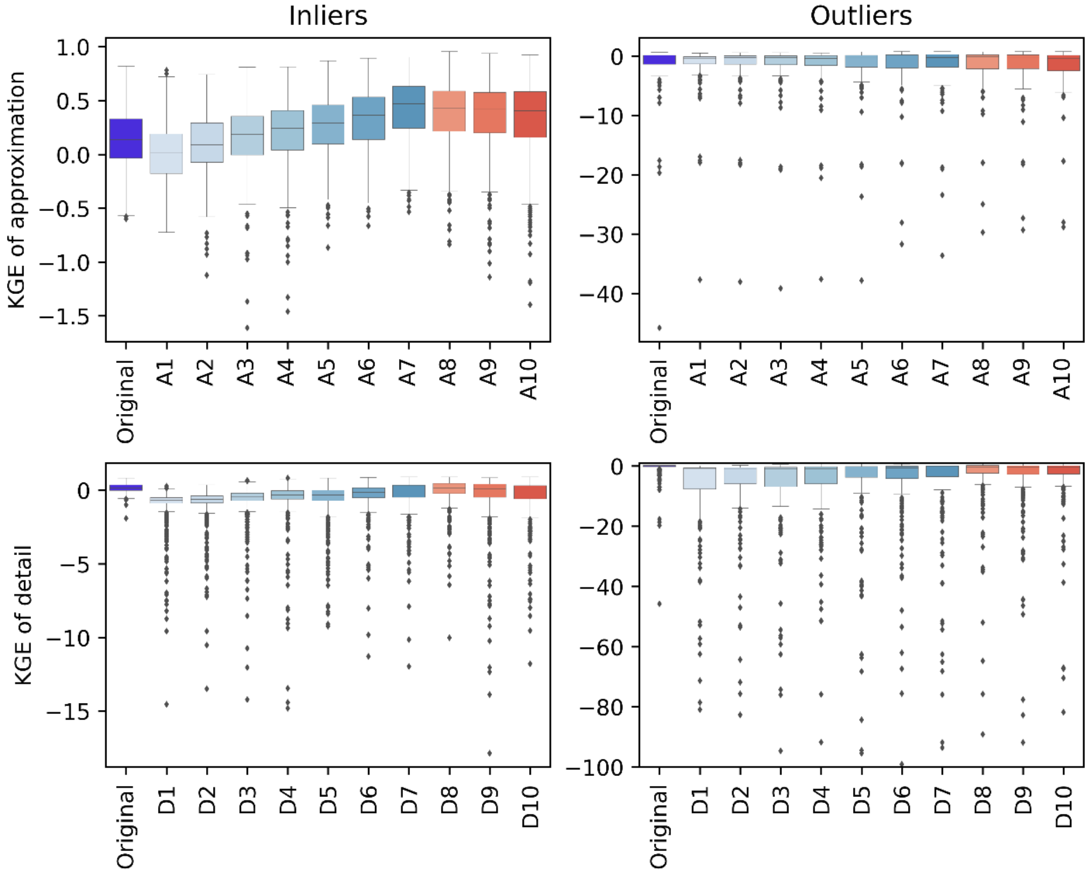

Figure S1. The KGEs of inliers and outliers for approximation and detail components using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN).

3. (11) – Two KGE terms are used in this equation. For clarity, I suggest adding subscripts to differentiate between the observed KGE and the predicted KGE by RF.

Thank you for the constructive suggestion. To clarify Equation (11), p and o are respectively used as subscripts for KGE to represent the predicted KGE by the random forest model and the observed KGE:

"Taking the KGE of original time series as an example, the prediction of the performance of approximation components for reanalysis using the random forest model is denoted as:

$$KGE_p = RF\left(X\right) \tag{11}$$

in which KGE_p is the predicted KGE using the random forest model, $RF(\cdot)$ is the random forest model and X is the catchment attributes. The R^2 between the predicted KGE_p and the calculated KGE_o is denoted by:

$$R^2 = \left(\frac{\sum_{i=1}^{N}\left(KGE_{p,i} - \mu_{KGE_p}\right)\left(KGE_{o,i} - \mu_{KGE_o}\right)}{\sqrt{\sum_{i=1}^{N}\left(KGE_{p,i} - \mu_{KGE_p}\right)^2}\sqrt{\sum_{i=1}^{N}\left(KGE_{o,i} - \mu_{KGE_o}\right)^2}} \right)^2 \tag{12}$$

in which μ is the mean KGE. The KGE_p and KGE_o represent the predicted KGE of the random forest model and the calculated KGE between reanalysis and observed streamflow, respectively." (Page 6, Lines 145 to 150)

4. Results – The correspondence between approximation level (e.g., A1, A2) and time scale (e.g., daily, monthly) is mentioned in Lines 255 to 260. To improve readability, consider moving this information to Section 4.1.

Thank you for the valuable suggestion. We have added information about the correspondence between approximation level and time scale in Sections 2.2 and 4.1:

"The DWT captures time series information at multiple scales in the time-frequency domain, with each scale corresponding to a specific period (Joo and Kim, 2015; Manikanta and Vema, 2022). Specifically, the approximation and detail components at decomposition level l correspond to the time scale 2^l days (Nalley et al., 2012)." (Page 4, Lines 104 to 106)

"The time series of streamflow reanalysis and observation along with their approximation and detail components are presented in Figure 1. The plots are for the station 6224000 in which streamflow reanalysis tends to exhibit the highest KGE value of 0.82. The approximation and detail components at the level l correspond to the time scale of 2^l days. For example, A1 and A8 correspond to the periods of 2 and 256 days, respectively. It can be observed that the original time series of reanalysis generally captures the primary features of the observed streamflow. Under the stepwise decomposition of the streamflow time series, the KGE tends to increase from 0.48 for A1 to 0.62 for A8 and increase from -4.57 for D1 to 0.48 for D8. This result indicates that streamflow reanalysis tends to capture seasonal and annual information more effectively than daily, weekly and monthly information. At higher decomposition levels, the series of approximation and detail components becomes smoother. As the decomposition level increases, the reanalysis becomes more able to capture the information in the observation." (Page 9, Lines 203 to 212)

5. Results - The varying number of stations under investigation in this paper may raise concerns about the robustness of the results. In Line 185, it is demonstrated that there are 661 stations, while 554 stations are used in Figure 4. If the reduction is due to the use of clustering, please include a description in the paper to clarify this point.

Thank you for the valuable comment. The 554 stations shown in Figure 4 are due to the use of clustering. We have added a description in the paper for clarification:

"The KGE values of original time series and its approximation components for the 554 catchments after removing the outliers are presented in Figure 3. In total, there are 11 spatial plots for original time series and its components after decomposition. It can be observed that the original time series tends to exhibit relatively high KGEs in the western United States and relatively low KGEs in the central United States. This observation is consistent with those of Addor et al. (2017), which found poor performances in the high plains and desert southwest. In the meantime, the approximation components from A1 to A10 tend to exhibit high KGEs in the western United States and low KGEs in the central United States. This finding indicates that the KGE values of approximation components are related to the KGE values of original time series. Moreover, as the scale increases from A1 to A10, the performance of approximation components tends to improve. The KGEs in the central United States change from negative values in A1 to positive values in A10. That is, seasonal, annual and multi-annual features tend to be better represented by streamflow reanalysis than daily, weekly and monthly features." (Page 11, Lines 230 to 239)

6. Results – While the Results section is well-written, it would benefit from further interpretations. Overall, similar analyses are conducted for both raw reanalysis and the decomposition. Consider adding further illustrations to highlight the added value or new findings that cannot be directly found based on raw data but are derived from the novel approach.

Thank you for the constructive comment. We have replaced Figures 1 and 2. The new figures demonstrate that the approximation and detail components reveal features of the time series that are not directly found in the original time series. The results indicate that streamflow reanalysis captures seasonal and annual information more effectively than daily, weekly, and monthly information:

"The time series of streamflow reanalysis and observation along with their approximation and detail components are presented in Figure 1. The plots are for the station 6224000 in which streamflow reanalysis tends to exhibit the highest KGE value of 0.82. The approximation and detail components at the level l correspond to the time scale of 2l days. For example, A1 and A8 correspond to the periods of 2 and 256 days, respectively. It can be observed that the original time series of reanalysis generally captures the primary features of the observed streamflow. Under the stepwise decomposition of the streamflow time series, the KGE tends to increase from 0.48 for A1 to 0.62 for A8 and increase from -4.57 for D1 to 0.48 for D8. This result indicates that streamflow reanalysis tends to capture seasonal and annual information more effectively than daily, weekly and monthly information. At higher decomposition levels, the series of approximation and detail components becomes smoother. As the decomposition level increases, the reanalysis becomes more able to capture the information in the observation." (Page 9, Lines 203 to 212)

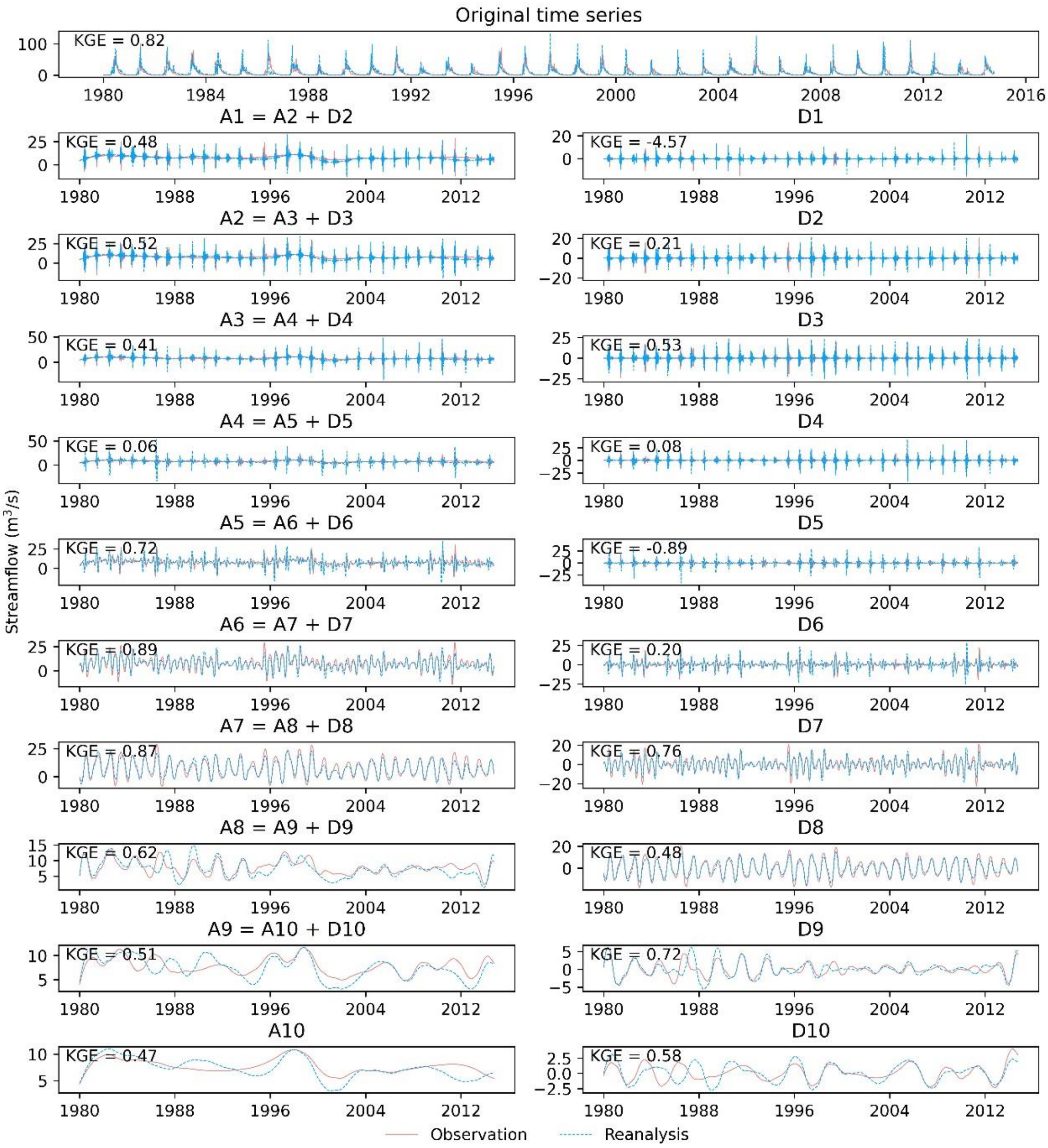

Figure 1: Time series plots of original time series and its approximation and detail components for the station 6224000.

"The KGEs of approximation and detail components across the CONUS are illustrated in Figure 2. There are respectively 554 and 417 catchments for the approximation and detail components by removing outliers. It can be observed that the KGEs of the approximation components tend to increase from A1 to A10 and that by contrast, the KGEs of the detail components exhibit considerable fluctuations from D1 to D10. The comparison between the left and right parts of Figure 2 indicates that the detail components are more difficult to be characterized than the approximation components. This outcome is attributable to the presence of environmental noises in the original time series (Freire et al., 2019). Given that the KGEs of the detail components can drop below -2.5 in some catchments, the attention is paid to the approximation components in the subsequent analysis." (Page 11, Lines 217 to 224)

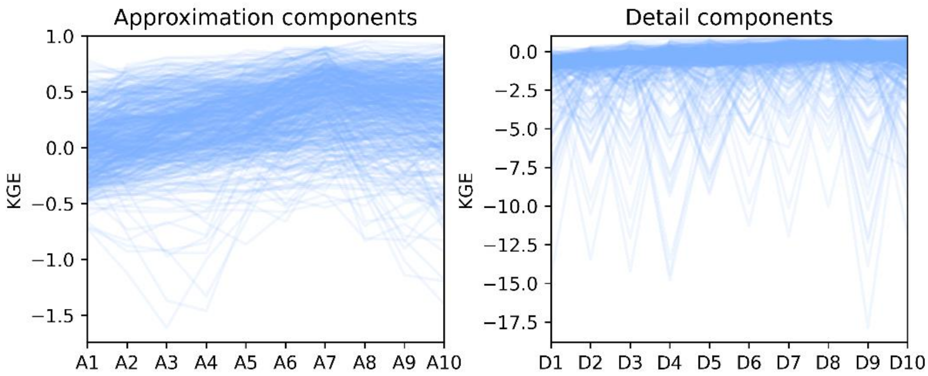

Figure 2: The KGEs of approximation and detail components across the CONUS.