Reviewer 2: Dr. Sandhya Patidar

The paper presents a continuous wavelet-based phase randomisation approach for the stochastic generation of streamflow time series. This is an interesting paper that substantially extends the original techniques developed in [1] for stochastic simulation of streamflow using Fourier transformation based phase randomisation. The original method, presented in [1] is associated with certain limitations such as application of Fourier transformation does not account for the non-stationarities in time series and resulted in an underestimation of spatial dependencies (e.g. cross-correlation) in both daily discharge and extreme events across the multiple sites. The present paper address some of the limitations observed in [1] by replacing Fourier transformation with a complex wavelet-based approach.
The efficiency of original method has been evaluated to generate realistic series for distributional and temporal correlation characteristics and is validate through the application across four catchments in Switzerland. The proposed model is applied to a large dataset of 671 catchments in the contiguous United States and the efficiency of the model has been evaluated by assessing its ability to capture distributional and temporal characteristics at individual sites along with the spatial dependencies across the multiple sites, and extreme events (floods) including duration and volume.

Some general comments
Section 1 - Considering the theme of paper that signifies the application of wavelet approach, the Introduction section presents an interesting critical review on recently developed/applied modelling schematics that involves wavelet-based phase randomization as a key approach.
Line 70-73: To add clarity it would be helpful if the authors' team add some brief explanation on how data normalisation procedure and back transformation impacts the spatial dependencies.
Reply: *Thank you for pointing out the need for clarification. We specify that 'This weakening is because phase randomization preserves the cross-correlation in the normal domain but not necessarily in the domain of the original distribution as linear correlation is not invariant under non-linear strictly increasing transformations.'*
Modification: p.3, l.71-73

Line 87-88: Please add some clarity on how continuous wavelet transform is more effective than a discrete wavelet transforms in minimising/overcoming issues around the long-term periodicities and/or non-stationarities. Is there any specific studies carried out to investigate such issues.
Reply: *The discrete wavelet transform only allows for real wavelet functions while the continuous transform allows for complex wavelet functions. Stochastic approaches randomizing only real-valued amplitudes have been shown to have problems with the reproduction of non-stationarities* [*Breakspear et al.*, 2003]*. Chavez and Cazelles* (2019) *show that the randomization of phases (information stored in the complex-valued coefficients) allows for the generation of non-stationary time series. We rephrased the whole paragraph to clarify that the advantage of using a continuous instead of a discrete transform comes from the additional phase information gained when using complex wavelet functions which are only available for the continuous transform.*
Modification: p.3, l.83-83 and l.89-93

Section 2 - Theoretical background section provides suffiecient details on the wavelet decomposition approach.
Reply: *We are glad that you consider the background section to provide sufficient detail.*

Section 3 Data – For illustration and validation purposes, dataset are organised in three different region based on the general hydrological characteristics. It is not clear which specific properties has been used and how rigorously they have been appied. I think, this work could have benefitted if Authors' have considered using some form of clustering approaches (e.g. K-mean) based on key characterisetic for clustering the sites.

Reply: *Thank you very much for this suggestion. We indeed applied a clustering procedure to define these regions which are similar in terms of their flood characteristics. The clustering was applied on a distance matrix computed from the F-madogram, which is a measure of extremal dependence, between pairs of stations. The clustering was applied to the 671 catchments and resulted in 15 clusters among which we selected 3 for illustration purposes. Our manuscript, where we describe this clustering procedure and the resulting clusters, is currently under review and we will include its reference here if it receives a DOI before this manuscript eventually goes into press.*

Section 3 Method - It seems that the model interconnect different site only as part of step 1 (phase randomisation/perturbation applied throught the medium of white noise). All the remaing steps (1-4 steps) are applied independently across all the sites. I think the approach is appropriate. A separate Kappa distribution is fitted for each day for a 30-day window to factor in seasonal differences. I have a minor concern here, What is the motivation for the selection of a 30 day window, how does it effect data with different seasonal periods across different sites (e.g. may be one site having monthly seasonality but other having weekly seasonal characteristics or say over a three months period).
Reply: *Thank you for acknowledging the appropriateness of our approach. We chose a window of 30 days to temporally pool data prior to the estimation of the daily parameters of the kappa distribution. The idea of the smoothing is to reduce the effect of sampling uncertainty and to reduce day-to-day variability in parameters under the assumption that the distribution of flow on day x is unlikely to be substantially different from the one on day x+1. A value of 30 days was chosen for the moving window to enable sufficient smoothing in the parameter space and to ensure a sufficient sample size for the estimation of the four parameters. The moving-window nature of the approach allows for capturing seasonal and partly also weekly variations. We clarified in the method description that this approach corresponds to a moving window approach.*
Modification: p.8, l.165

Section 4
A robust evaluation has been conducted that includes careful seletion of sites (distinct and representative). Statistics used for comparision are appropriate and results are well explained.
Reply: *Thank you for appreciating the representativeness of our evaluation.*

Some minor comments
Figure 9 – Visually observed and simulated looks in good agreement for occurance of POT events but for a robust comparision some measurements should bave been used in parallel.
Reply: *We computed differences in the mean inter-event duration (i.e. time elapsing between two successive events) of observed and simulated series and the standard deviation of inter-event duration for events where 1, 2, and 3 stations were jointly affected, respectively. We find that over all three regions, relative differences in mean and standard deviation of inter-event duration lie mostly below 10%. However, we find that a visual comparison is most effective here to demonstrate the value of the simulation approach.*

Figure 10 gives a good illustration of how spatial dependencies could be effected among th sites with respect ot the Euclidean distance. However, for the readers benefit it would be appreciate if Authors' consider to provide few sentences to explain F-madograms plots, specifically, what should a relative difference of 0.05 in observed and simulated values should be interpreted.
Reply: *We specified in the figure caption that the F-madogram is a measure of extremal dependence. We also state that an overestimation of spatial dependence means that a pair of stations co-experiences more joint floods than in the observations. What a difference of 0.05 means in terms of differences in regional hazard estimates is hard to say and would need to be investigated in a proper study where the stochastic simulations are used to estimate regional flood hazard.*
Modification: p.17, caption of Figure 10

Section 5 and 6 – Overall good and capture key aspects of the paper.
Reply: *Thank you.*

Reference
[1] Manuela I. Brunner, András Bárdossy, and Reinhard Furrer, Technical note: Stochastic simulation of streamflow time series using phase randomization, Hydrol. Earth Syst. Sci., 23, 3175–3187, 2019.

References used in this response to the reviewer

Breakspear, M., M. Brammer, and P. A. Robinson (2003), Construction of multivariate surrogate sets from nonlinear data using the wavelet transform, *Phys. D Nonlinear Phenom.*, *182*(1–2), 1–22, doi:10.1016/S0167-2789(03)00136-2.

Chavez, M., and B. Cazelles (2019), Detecting dynamic spatial correlation patterns with generalized wavelet coherence and non-stationary surrogate data, *Sci. Rep.*, *9*(1), 1–9, doi:10.1038/s41598-019-43571-2.