Response to the comments of Reviewer #1:

This paper applies the autocorrelation process and a harvested population model as well as network analysis for the early warning signals of transition in the hydrological system at the global and CONUS city scale.
Overall, the paper is well-written and certainly contains many novel ideas potentially helpful for the boarder community.

We thank the reviewer for the constructive feedback and help in improving the quality of this manuscript. Below are detailed responses to the comments. All changes and clarifications were included in the revised manuscript.

I see the paper will be strengthened by:

1. Line 50: important role
We have the typo corrected.

2. Line 219 – 222: discussion about the relative magnitudes of AR1 and s.d. I agree that visually figures 1b and d are quite distinct, but the authors may want to provide more information about whether any objective measures of high and low exist or any reference state exists in AR1 and s.d. in gauging the state of the system regarding how far away from the tipping point.
The quantification of threshold values of AR1 and s.d. to determine how far the system is from the tipping point varies from case to case. The particular case presented in Fig. 1 only shows the increasing *trend* of AR1 and s.d., when the system is approaching the tipping point. The asymptotes of both measures, to the best of our knowledge, have not been worked out; it will be interesting, though challenging, to quantify the values of AR1 and s.d. at the tipping point by casting this practical problem in the analytical framework of Scheffer et al. (2009), e.g. Eqs. (2) & (3).

3. In addition, it appears unclear to the reviewer whether Figure 1 is an example toy problem to illustrate the concepts or related to the main finding.
It is true that the benchmark problem show in Figure 1 is not directly related to the subsequent applications to precipitation and PET in the study. Nevertheless, we think it is a good example for illustrating the concept of critical transition, especially the increasing trends of AR1 and s.d. Figure 1 is based on a classic harvest model in which the stability of population can be controlled by the parameter harvesting rate E. The increasing AR_1 and s.d. in population time series due to increasing E as shown in Figure 1 signify that the population is approaching the tipping point, and these characteristics can serve as early-warning signals. Similar characteristics will be used in the following sections to determine how the hydrological systems evolve approaching critical transitions. We clarified this in the context.

4. 2.3: the beginning few sentences seem to be repetitive of part of the introduction – therefore, may be better to combine with the introduction or shorten it.
Thanks for the comment. We removed first two sentences in this section to make the presentation more concise.

5. Line 253-254: single-plural mismatch

Corrected in the revision.

6. "The year of critical transition was determined based on the abrupt change of slopes in each cumulative time series. We then divided each original precipitation (or PET) time series into two (quasi)stationary parts using this critical transition year" – maybe good to provide in the appendix, since this is quite important. Also, may want to give more explanation for what you mean by the two parts being quasi-stationary.

Thanks for the comment. Below we demonstrate in Fig. R1, using the example of Miami, how the year of transition (1998) was determined. We bisected the cumulative precipitation data (scatters) and fitted each segment using linear regression (thus each being *quasi-stationary* with a constant slope). The year of transition is determined as the intersection of two trend lines (solid red: prior to transition, and dash red: after transition) with different slopes. In addition, Fig. R1b shows the annual (not cumulative) precipitation, where the two different means (prior to and after the transition year) are subtracted. The precipitation anomalies are then used for subsequent statistical analysis to determine the two statistical metrices (AR_1 and s.d.). We clarified the meaning of quasi-stationary in the revision.

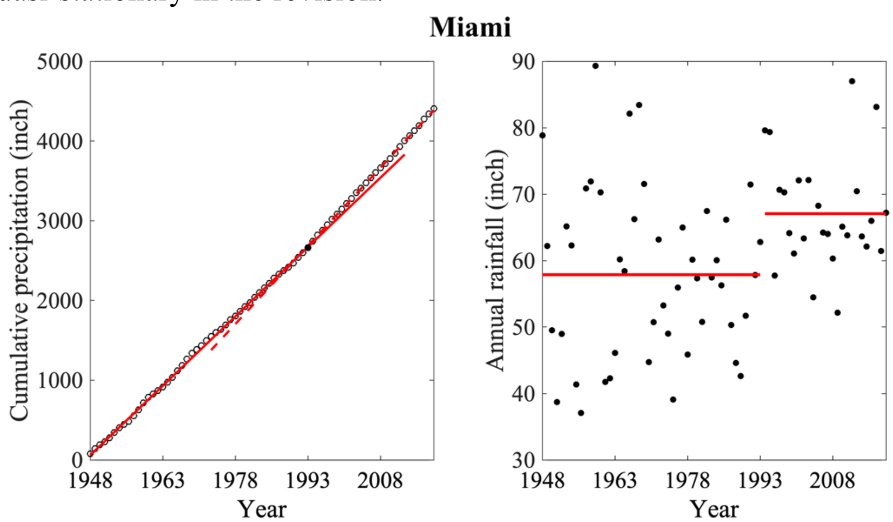

Figure R1. The statistics of precipitation in Miami (1948-2019): (a) the solid and dashed red line denotes the fitted lines before and after the critical transition year (solid black dot) (b) the two different solid red line are the mean values for each parts spilt by the critical transition year.

7. Was the critical transition year 1994 identified a priori from the method described in point 6?

Yes, the critical transition year(s) were all determined prior to statistical and network analysis, as illustrated in the response above.

8. Line 326 – 332: how is the claim supported? Maybe an additional figure or if not important may choose not to mention. The reviewer is confused.

This was only to show that our result is consistent to prior findings. We removed this part for better clarity.

9. For city-scale analysis, is each transition year for each city identified using the same method as that for global scale?

Yes, the same method (as illustrated in Fig. R1) was applied when identifying the transition year for each city.

10. Why is CONUS PET not analyzed? Is it due to a lack of data?
Right. The dataset we used for CONUS precipitation analysis does not contain PET data.

11.Figure 4a, is it possible to indicate region number 1-9 corresponding to the adjacency matrix in a? This will facilitate the readers to connect the meaning of b to the spatial pattern of the network in a.
Thanks for the advice. We replaced the original Fig. 4 with Fig. R2 shown below, where cities (nodes) are colored based on their corresponding climate region.

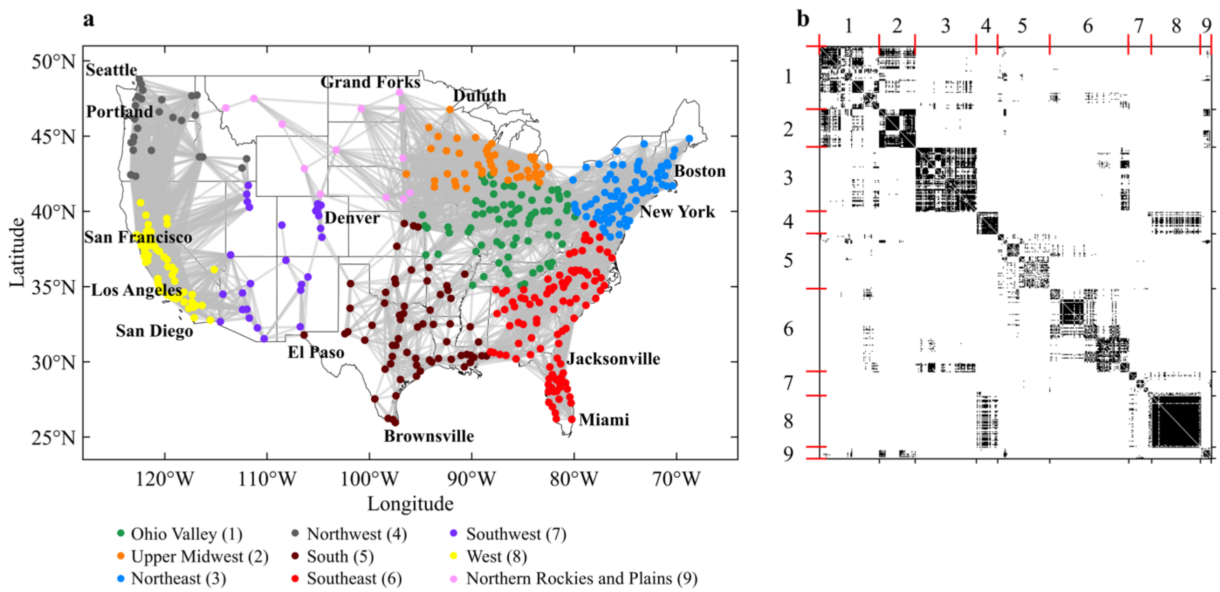

Figure R2. The precipitation network of CONUS cities: (a) the geographic map of connectivity and (b) the adjacency matrix, with $A_{ij} = 1$ in black (connected), $A_{ij} = 0$ in white, and red lines marking the division of nine geographic regions as shown in (a).

12. The trend of AR1 within the moving window prior to transition year: in figures showing this metric, the non-monotonic trend can make it less useful as an indicator.
In analyses of the behavior of real dynamic system, both AR1 and s.d. often exhibit non-monotonic trend, deviating from the theoretically increasing trends. This phenomenon has been consistently found in prior studies (e.g. Scheffer et al., 2009; C. Wang et al., 2020), and must involve the complex interactions of multiple determinants of the system (e.g. North Atlantic Oscillation, ENSO, and other low frequency variabilities for annal precipitation in CONUS). Because of this, caveats need to be taken using a singular indicator. It is also the very motivation behind this study that we look for more usable indicators (from statistical to network structure) so the critical transition can be more firmly determined by cross examine multiple indicators.

13.Another question the reviewer is wondering about: I understand the paper's network analysis focuses on the network topology structure prior to transition, but will the network structure end up being different after the transition? i.e. will the enhanced network connectivity stay or *gradually 'relax' towards some 'climatological equilibrium state'?*

Thanks for the very insightful comment. We illustrate the trend of changes before and after the transition for CONUS precipitation, using s.d. and clustering coefficient (as they appear more reliable than other measures). The results are shown below in Fig. R3. Apparently, both trends relaxed after the transition. Yet, there are time lags (potential hysteresis) for different indicators (e.g. the clustering coefficient plateaued slightly after the transition year and gradually relaxed). This is somehow expected as the network parameters represented the "concatenated" system behavior, and should experience some lag in response and relaxation to the critical transition.

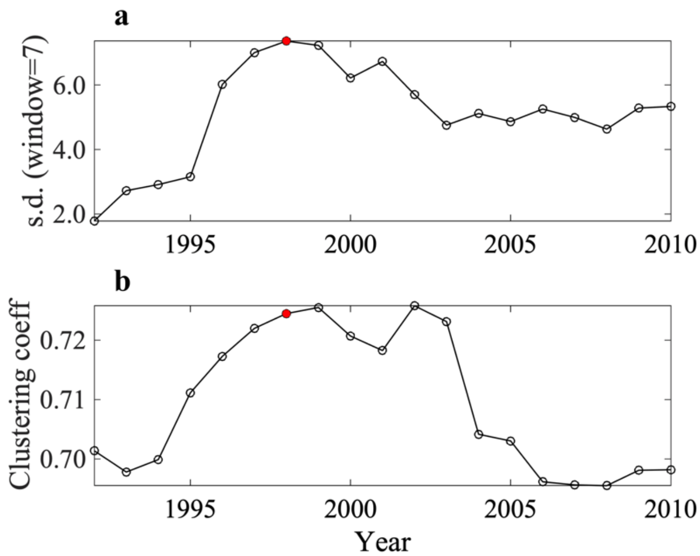

Figure R3. Two different metrices of CONUS precipitation: (a) the conventional s.d., and (b) the network clustering coefficient.

14. The phrase potentially catastrophic transition may be less emphasized: the mean precipitation anomalies (for CONUS cities) are analyzed. If another variable like the maximum precipitation or number of days exceeding historical summer mean (just arbitrary examples of more catastrophic flavor), the reviewers will be more convinced.

We agree that the phrase "catastrophic" is too strong for transitions in precipitation. We rephrased using "critical transition" throughout the manuscript.

In this study, we are focused on long-term (climatological) transition in precipitation (and PET), so annual means are good for this purpose. For maximum precipitation (or PET, or drought), it will be more natural to shift the focus to extreme events at meteorological scales. Theoretically, the concept of critical transition and the methodology developed in this study should be applicable. But practical difficulties will arise, such as the length of dataset (number of days for extreme precipitation) might be inadequate to discern the dynamic evolution of the network structure. Nevertheless, we have this in mind for our future research endeavor.

15. The reviewer thinks that making more efforts to connect the global scale to the city scale will make the paper more coherent. For example, results in Fig. 3 are partially tied to global climates. Figure 5 and Figure 2 also seem to have some connections. In the introduction, the motivation for city-scale analysis may allude to some of these findings. E.g. city-scale responses are embedded in global hydrologic cycle changes but form systemic coherent structures/patterns – highly appealing to system-based network analysis.

We thank the reviewer for this constructive comment. Yes, from the results of the study, we speculate that there is a positive correlation between the dynamics of precipitation in individual cities and regional/global trends, especially as we focus on the precipitation climatology. On the other hand, as we switch the spatial scale from local city to regional, the active determinants for precipitation are expected to change as well. For example, anthropogenic emissions of heat and aerosols are expected to have strong influence on local precipitation, whereas their impact on global scale might be diluted or replace by larger scale (and low-frequency) oscillations (e.g. ENSO). Future research along the line suggested by the reviewer will be promising, albeit we are refrained to make too strong assertion or speculation in the current study given the limited scope and results available at this stage.