Re: Manuscript #hess-2024-118 entitled "Exploring the Potential Processes Controls for Changes of Precipitation-Runoff Relationships in Non-stationary Environments".

RC2: 'Comment on hess-2024-118', Anonymous Referee #2

1. Lines 75-82 the author wrote that hydrological models regionalize the PRR over a specific period, assuming minimal anthropogenic disturbance to simulate hydrologic processes. However, several hydrological models already consider anthropogenic effects on hydrological processes, such as WEP-L, watergap, and PCR-GLOBWB, which effectively incorporate anthropogenic impacts on hydrological processes into their simulations. So the statement "Hence, they may not be suitable for non-stationary hydrological processes" is inappropriate. Meanwhile, the list of PRR identification methods is not comprehensive. The author should highlight the similarities and differences between this study and these previous methods (hydrological model, machine learning, etc.), i.e., the research gaps, and emphasize the real advantages of the method in this study over the hydrological model, which has a physical mechanism, otherwise, it will be hard to be convincing.

Reply: We appreciate the reviewer's comment and agree with their suggestion. The statement "Hence, they may not be suitable for non-stationary hydrological processes" has been revised. Additionally, we have delineated the similarities and differences between this study and previous methods (hydrological model, machine learning, etc.), i.e., the research gaps, and emphasized the real advantages of the method in this study over the hydrological model, thereby addressing the identified research gaps.

Compared to traditional data-driven and process-driven approaches, the primary advantages of the method (DPRR index) proposed in this study are as follows: Continuous simulation of the PRR is accomplished through the application of data-driven hydrological models or process-based models with intricate model structures (Sikorska-Senoner and Quilty, 2021; Nayak et al., 2013). **Data-driven models** such as Artificial Neural Networks (ANN) and Linear Perturbation Model (LPM) rely on empirical analysis to produce corresponding outputs based on specific input data (Tanty and Desmukh, 2015; Nash and Barsi, 1983). **These models are heavily dependent on the characteristics of existing data and provide a relatively vague description of the hydrological cycle processes, failing to explicitly reflect the impact of individual factors within these processes.**

On the other hand, **process-based hydrological models** such as TOPMODEL and SWAT can reveal more details and mechanisms of physical processes (Beven et al., 2021; Krysanova and White, 2015). However, **these models involve complex modeling processes and require careful selection based on adequate prior knowledge** (Reichl et al., 2009). Furthermore, **many traditional hydrological models regionalize the PRR over a specific period in stationary climatic and catchment conditions, assuming minimal human interference** (Yang et al., 2022; Westra et al., 2014). **As a result, they may not be suitable for non-stationary hydrological processes.**

With the advancement of hydrological models, the impact of human activities is increasingly incorporated into the simulation of hydrological processes. **Models such as WEP-**

L, WaterGAP, PCR-GLOBWB, and CWatM not only simulate natural hydrological cycles but also effectively incorporate the influence of anthropogenic factors into their simulations (Jia et al., 2006; Müller Schmied et al., 2021; Sutanudjaja et al., 2018; Burek et al., 2020). However, **it is crucial to recognize that such hydrological models have high data requirements, limiting their application in regions lacking sufficient observational data** (Clark et al., 2016). For instance, **long-term, high-quality data on human activities are often difficult to obtain comprehensively**, and remote sensing datasets emerge as vital tools for the global analysis of human impacts on hydrological regimes. However, the **impact of human activities on streamflow represented by these data is complex and cannot be directly used as model input**.

Therefore, there is a need for a flexible and effective PRR technique that has lower data requirements while being able to explore the impact of individual or specific driving factors on PRR under non-stationary conditions. Compared with the above methods, **the DPRR index proposed in this study has the following advantages**: (1) the DPRR index has lower data requirements and offers a simple and flexible technique for identifying the potential impacts of driving factors on PRR. (2) The inputs are not strictly restricted by temporal and spatial constraints or by format, especially when assessing the impacts of anthropogenic activities on streamflow. (3) It also addresses the limitations of traditional process-driven hydrological models with the assumption of stationarity in the run, which assume stationary conditions (Ammann et al., 2019; Jehanzaib et al., 2020). Hence, the proposed index offers crucial information for the hydrological cycle process driven by climate change or anthropogenic disturbances, which guides the construction of more robust hydrological models and the development of water resource management and allocation. (4) Considering the elimination of trends is a crucial step in accurately analyzing the relationships between complex non-stationary systems (Zhao et al., 2012), the DPRR removes the non-stationary effects by subtracting local trends with appropriate polynomial orders, ensuring the normality of input signals for cross-correlation analysis (Zebende, 2011). (5) The effect of external factors on PRR may lead to spurious cross-correlation estimations (Yuan et al., 2015). Hence, the developed index applies the theoretical foundations of the DPCCA technique to reveal the "intrinsic" relations between precipitation and runoff time series with potential influences of other factors removed, such as evapotranspiration, groundwater, land cover, and anthropogenic interference. (6) The DPRR index characterizes the potential driving mechanisms influencing PRR on different time scales, which can improve our understanding of hydrological responses to climate forcing and anthropogenic activities at various time scales. (7) The DPRR index provides the driving level and direction and allows for comparisons of the index values among different driving factors with inconsistent data-sequence lengths and across various types of catchments. The relevant content has been supplemented in the *Introduction* and *Methods* section.

2. The author described the catchment response conceptual model with a very detailed relational network in Fig.2, Fig.6, and Fig.7. use a slightly more concise presentation? It might be more reader-friendly.

Reply: Thank you for the comment. We have removed the symbols representing feedback types from Figures 2, 6, and 7 and eliminated some minor relationship lines to emphasize the primary relationships and structures. The detailed figures have been moved to the *Supporting Information*.

3. How to validate the effectiveness of the constructed methods in the study for the identification of non-stationary hydrological processes and their drivers? It seems unconvincing to describe its advantages over hydrological modeling only through text. There have been many studies analyzing the non-stationary hydrological processes in the Weihe River, and there is a need to compare with them to enhance the reliability of the results, as well as to quantify the uncertainties.

Reply: We agree with the comment of the Referee. Mutual information theory and techniques have been further applied to quantitatively validate the effectiveness of the constructed methods in the study. In addition, various studies on the impact of various factors on runoff changes in the Wei River basin are investigated and compared.

The method based on mutual information theory for validating the proposed index in this study is as follows. Entropy is a fundamental concept with wide-ranging applications across engineering and scientific disciplines (Mishra and Ayyub, 2019). It serves as a quantifiable metric for assessing signal uncertainty, simultaneously enabling the computation of mutual information between signal pairs. Mutual information (MI) is a measure of interdependence between variables (Cover, 1999). In these regards, we applied MI to develop an index for identifying the possible driving mechanisms in PRR using a nonlinear theory approach. By calculating mutual information between driving factors and precipitation (runoff), a Driving index for Precipitation-Runoff links with the nonlinear theory approach (DPRL) is developed and quantifies the nonlinear nature of their associations. Higher mutual information values signify stronger associations or interdependencies. The calculation procedure for the DPRL index is as follows.

Step 1: Involve three time series: the runoff time series denoted as X_t, the precipitation time series denoted as Y_t, and an influencing factor denoted as Z_t, where $t = 1,2,\ldots,n$, and n signifies the length of the time series. The initial computation entails deriving the cumulative frequency for each time series. Subsequently, the runoff time series is transformed into the following time series Q_t:

$$Q_t = \begin{cases} 1, & X_t \leq X^{20} \\ 2, & X^{20} < X_t \leq X^{40} \\ 3, & X^{40} < X_t \leq X^{60} \\ 4, & X^{60} < X_t \leq X^{80} \\ 5, & X_t > X^{80} \end{cases} \tag{1}$$

where X^{20}, X^{40}, X^{60}, and X^{80} correspond to X_t when the cumulative frequencies are 20%, 40%, 60%, and 80%, respectively. Similar processing is applied to the precipitation time series X_t and the influencing factor Z_t, resulting in the updated time series W_t and F_t. These time series are discretized into five equidistant intervals to reduce the impact of noise while capturing a wider range of time series values across various magnitudes. Notably, the division into five equidistant boxes is a deduced outcome derived from rigorous comparative analyses and verifications (Franzen et al., 2020).

Step 2: Calculate the probability distribution functions for the time series:

$$\begin{cases} p(q_i) = \dfrac{\text{count}(q_i)}{n} \\ p(w_j) = \dfrac{\text{count}(w_j)}{n} \\ p(f_k) = \dfrac{\text{count}(f_k)}{n} \end{cases} \tag{2}$$

where $p(q_i)$, $p(w_j)$ and $p(f_k)$ are the probability distribution functions of Q_t, W_t and F_t respectively; $\text{count}(q_i)$, $\text{count}(w_j)$ and $\text{count}(f_k)$ represent the occurrences of numerical values in Q_t, W_t and F_t, respectively; $i = 1,2,\dots,5$; $j = 1,2,\dots,5$; $k = 1,2,\dots,5$.

Step 3: The Shannon entropy of time series is calculated as follows:

$$H(Q_t) = -\sum_{i=1}^{5} p(q_i)\log_2 p(q_i) \tag{3}$$

where $H(Q_t)$ is the Shannon entropy of Q_t. Here, entropy with a logarithm of base 2 is considered, such that entropy and related IT measures are in units of bits.

Step 4: Calculate the joint distribution functions as follows:

$$\begin{cases} p(q_i, f_k) = \dfrac{\text{count}(Q_t = q_i, F_t = f_k)}{n} \\ p(q_i, w_j) = \dfrac{\text{count}(Q_t = q_i, W_t = w_j)}{n} \end{cases} \tag{4}$$

where $p(q_i, f_k)$ is the joint distribution function of Q_t and F_t; $p(q_i, w_j)$ is the joint distribution function of Q_t and W_t; $\text{count}(Q_t = q_i, F_t = f_k)$ is the number of simultaneous occurrences of $Q_t = q_i$ and $F_t = f_k$; $\text{count}(Q_t = q_i, W_t = w_j)$ is the number of simultaneous occurrences of $Q_t = q_i$ and $F_t = f_k$.

Step 5: Given the influencing factor, the quantification of uncertainty within the sequence becomes feasible through the utilization of conditional entropy. This measure is computed as follows:

$$\begin{cases} H(Q_t|F_t) = \sum_{i=1}^{5}\sum_{k=1}^{5} p(q_i, f_k)\log_2 \dfrac{p(q_i, f_k)}{p(f_k)} \\ H(Q_t|W_t) = \sum_{i=1}^{5}\sum_{j=1}^{5} p(q_i, w_j)\log_2 \dfrac{p(q_i, w_j)}{p(w_j)} \end{cases} \tag{5}$$

where $H(Q_t|F_t)$ is the conditional entropy of Q_t given F_t; $H(Q_t|W_t)$ is the conditional entropy of Q_t given W_t.

Step 6: Mutual information $I(Q_t; F_t)$, quantifies the reduction in uncertainty of one variable when another variable is known. It is the difference between entropy and conditional entropy. The calculation for mutual information is as follows:

$$I(Q_t; F_t) = H(Q_t) - H(Q_t|F_t) = \sum p(q_t, f_t)\log_2 \frac{p(q_t, f_t)}{p(q_t)p(f_t)} \quad (6)$$

Step 7: The DPRL index is further updated as follows:

$$\text{DPRL}(t) = \frac{I(Q_t; F_t)}{H(Q_t|W_t) + 1} \quad (7)$$

where $I(Q_t; F_t)$ represents the mutual information between Q_t and F_t. It quantifies the reduction in the uncertainty of Q_t when F_t is given, providing insights into their interdependence. With regard to the impact of precipitation on runoff, this index introduces the concept of conditional entropy $H(Q_t|W_t)$, accounting for the conditional uncertainty within runoff given precipitation. Furthermore, incorporating the notion of relative error, a modification is applied to the denominator by adding +1. This adjustment prevents the denominator from becoming exceedingly small, which may lead to anomalous metric values of the index.

The validation results from DPRL index (Figure R1b) illustrate that baseflow is the primary driving force influencing the PRR in the five sub-basins. The driving levels of baseflow are all greater than 0.4 in the five sub-basins, while the driving levels of other factors are all below 0.1. Baseflow is an important component of the Wei River Basin's runoff, particularly during the dry season (Miao et al., 2020), primarily contributing to runoff generation. Therefore, the driving levels of baseflow are higher. The impact of vegetation dynamics in WR4 and WR5 is stronger than in other sub-basins and significantly exceeds the impact of other factors in the two sub-basins. The finding aligns with the lower level of urbanization in WR4 and WR5. Furthermore, the impact of vegetation dynamics in WR5 is greater than in WR4, illustrating that the afforestation policy in WR5 has yielded positive results (Wu et al., 2023). Additionally, compared to WR2, WR3 has a higher proportion of irrigated areas, and the typical cropping pattern in these sub-basins includes winter wheat and summer maize. The vegetation dynamics within irrigation zones depend on changes in cropping patterns, thereby exerting complex effects on the PRR within the sub-basins. The impacts of ISR, NTL, and POP in WR3 are all in the top two levels, and their impacts in WR2 are slightly smaller than those in WR3. Conversely, the impact of vegetation dynamics in WR2 is greater than that in WR3. The rapid expansion of downstream urban clusters in WR3 is a significant factor contributing to this result. Simultaneously, in pursuit of higher economic income or a more convenient lifestyle, populations in WR4 and WR5 tend to migrate towards the central cities in WR3. This migration results in lower anthropogenic driving factors for PRR in WR4 and WR5. Additionally, as populations concentrate, local surface water resources become inadequate to meet regional water demands. Consequently, groundwater extraction and inter-basin water transfer are employed to alleviate water resource pressures, leading to complex artificial interventions that may impact the PRR. ET_0 has a smaller impact on the PRR in all five sub-basins. The ranking pattern of driving levels of ET_0 in the sub-basins is similar to that of vegetation dynamics. ISR and NTL have the strongest impact in WR1, likely due to its being the smallest basin area.

The maximum kernel density values of the absolute values of the DPRR (Figure R1a) are employed for comparing the results of DPRR and the mutual information approach. **The**

patterns exhibited by DPRR and the mutual information approach are generally consistent, which mutually validates the reliability of their assessment outcomes. Both DPRR and mutual information approach results illustrate that baseflow is the primary factor influencing PRR. Excluding WR5, the DPRR values of baseflow are the highest among the six factors. In WR5, the DPRR value of baseflow ranks second only to ET_0. The mutual information approach values of baseflow are significantly higher than those of other factors in all five sub-basins. Furthermore, the DPRR and mutual information approach results for ISR, NTL, and POP demonstrate the differences between WR2 and WR3. WR2 is located upstream of WR3 and there is a large urban cluster downstream of WR3. Therefore, ISR, NTL, and POP have a greater impact on PRR in WR3 compared to WR2. In contrast, WR4 and WR5 have smaller urban areas, so vegetation dynamics exhibit positive impacts in DPRR results and high-level influence in mutual information approach results. However, due to the distinct foundations of DPRR and mutual information approach, which are based on nonstationary and nonlinear theories, respectively. Their results exhibit minor disparities. For instance, in WR5, the results from DPRR show that ET_0 has a much higher impact on PRR than other factors, whereas, in mutual information approach results, the driving level of ET_0 is extremely low, almost equal to other factors. This disparity might be attributed to the implementation of afforestation policies in WR5, which altered the local climate, thereby causing an increase in the driving level of ET_0 on PRR during specific periods. DPRR captures the influence of ET_0 on PRR, hence demonstrating a high driving level in the maximum kernel density results.

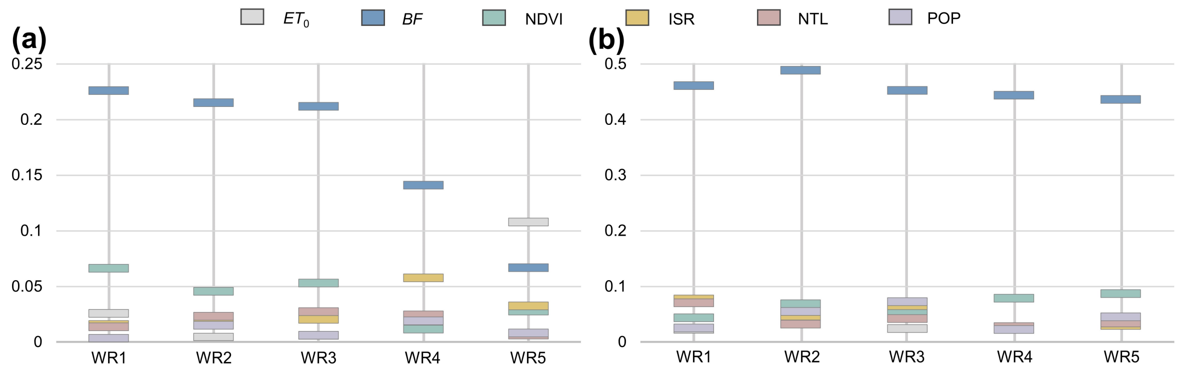

Figure R1 a, Maximum kernel density values of the absolute values of DPRR for possible influencing factors. **b,** Results of mutual information approach for possible influencing factors.

Various studies on the impact of various factors on runoff changes in the Wei River basin are further investigated and compared. Gao et al. (2013) found that human activities contributed as much as 82.80% to the reduction in streamflow in the Wei River basin. Zhan et al. (2014a) used the SIMHYD model to partition the effects of climate change and human activities on surface runoff in the Wei River basin and found that the contribution of human activities to streamflow change was more than 65%. Zhan et al. (2014b) proposed the improved climate elasticity method to investigate the contributions of climate change and human activities to runoff changes in the Wei River basin, with results showing a climatic contribution to runoff decrease of 22–29% and a human contribution of 71–78%. Chang et al. (2015), using the VIC model, found that the percentages of runoff change due to climate change were 36%, 28%, 53%, and 10% in the 1970s, 1980s, 1990s, and 2000s, respectively. The percentages of runoff change caused by human activity were 64%, 72%, 47%, and 90%, respectively. It can thus be concluded that human activity has a greater impact on basin runoff than climate change factors. He et al. (2019), based on the Budyko framework, found that for the upper reaches of the Beiluo River, the contribution of land-use change variations to runoff reduction was 95.3%. Gao et al. (2020), using the SWAT model, found that in the Jing River basin, the influence of climatic factors decreased from 85.70% to 42.43%, while that of anthropogenic factors increased from 14.3% to 57.57% between 1961 and 2015. **These studies indicate that human activities are the primary factor influencing PRR in the Wei River basin, which is consistent with the findings of this study. However, most existing research broadly categorizes influencing factors into climatic and anthropogenic factors, with some studies considering changes in potential evapotranspiration and land use as influencing factors. The quantitative assessment of human-induced impacts is often derived from the results of climatic factors without using specific data on human activities. In these regards, the method proposed in this study aims to the exploration of the impact of individual or specific driving factors on PRR.** The validation content based on the mutual information technique has been provided in the *Supporting Information*. Comparison with other studies has been supplemented in the *Discussion* section.

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