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New Methods for the Assessment of Flow Regime Alteration under Climate Change and Human Disturbance

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Abstract: Climate change and anthropogenic activities do collectively lead to an alteration of the flow regime, posing a great influence upon the structure and persistence of native biotic communities within river ecosystems. The range of variability approach (RVA) method is commonly used to evaluate the flow regime alteration. However, it was reported to underestimate the degree of flow regime potentially. In this study, two new assessment methods/metrics for evaluating the process behaviors of the flow regime are developed based on Euclidean distance and dynamic time warping (DTW) distance. They are then integrated with the metric of RVA, generating two composite metrics that represent both frequency and process changes of the flow regime. The new methods/metrics were applied to identify the flow regime alteration in a typical basin in the middle reaches of the Yellow River, China. The results show that the composite metrics consistently reveal a high alteration degree of flow regime in the basin. The decreased biological integrity of fish demonstrates the reasonability of the high-level overall alteration to some degree. The updated methods enable more scientific evaluation for the complex hydrologic alteration under a changing environment.

Keywords: alteration of flow regime; range of variability approach (RVA); indicators of hydrologic alteration (IHAs); updated assessment methods; the middle reaches of the Yellow River Basin; changing environment

1. Introduction

The integrity and biodiversity of riverine ecosystems are related to natural flow regime [1–3]. Alteration of the flow regime would arouse the emergence of some ecological problems, such as failed recruitment, local extinction and the success invasion of exotic species [4,5].

It is one of the global issues, especially under the changing environment, which has attracted increasing concern from scientists and governments [6,7]. Hydrological alteration and its impacts on ecosystems play a vital role for the sustainable development of water resources [8,9], and changes of different hydrological variables result in complex set impacts [10–13]. Assessment of flow regime alteration is therefore a basic step calling for appropriate indicators. Many types of flow metrics and statistical methods have been proposed to analyze the impact of changes in flow regimes [14–17]. Indicators of hydrologic alteration (IHAs) are among the most popular metrics being widely used. IHAs were developed based on 32 parameters in five groups (i.e., flow magnitude, timing, duration, frequency and change rate) [18]. The IHAs are reported to be representative enough to describe the statistical alteration in the complete set of hydrologic indices [19]. The range of variability approach (RVA) was proposed to measure hydrologic changes, suggesting that the 25th and 75th percentiles of the IHA metrics should be the targets for maintaining environmental flow [10,20,21].

Notwithstanding, shortcomings exist in the current method to some extent. In the RVA method, the difference between the proportions (frequencies) of pre-impact and post-impact values falling within the target range is considered to represent the degree of alteration [20]. If the frequency is the same for pre-impact and post-impact time series, the flow regime alteration is considered to be negligible [22]. Only frequency is considered, resulting in that the RVA may underestimate the alteration of the flow regime. It was reported that the RVA could not account for alterations of the order of hydrologic year types [22]. For instance, the wet, average and dry years occur once every three years under a natural flow regime during a 30-year period, if the occurrence order changes but the frequency does not (e.g., all of the wet years occur in the first 10 years, and the average and dry years happen in the second and the last 10 years, respectively), the flow regime alteration is 0 according to the RVA method. Obviously, it does not reveal the true alteration.

Yin et al. [22] therefore developed a new method to assess the flow regime alteration by considering the order of hydrologic year types (HYTs), providing beneficial insight to conduct a more reasonable assessment of flow regime alteration. Nevertheless, taking the HYTs into consideration could not reflect the temporal changing behaviors for each IHA, which are actually important for the ecosystem. For example, low flow occurring in a certain period will bring a more destructive effect on aquatic species compared with that it occurs evenly. Hence, an updated assessment method considering the process changes of indicators is called for to precisely evaluate flow regime alteration. Actually, an important feature representing the difference between two sequential data is the similarity/diversity. The concept of similarity and its dual concept of diversity play a fundamental role in several Quantitative Structure-Activity Relationship (QSAR) strategies, chemometrics and library searching methods, virtual screening, as well as in relatively new fields such as genomics and proteomics [23]. It can be employed as a measure to characterize the changing behaviors of these IHAs. However, less attention has been paid to understanding the flow regime alteration by using the similarity/diversity of time series. Hence, we try to evaluate the alteration of the flow regime by using this similarity/diversity measure.

As the second longest river in China, the Yellow River plays a crucial role in facilitating the social-economic development and maintaining ecosystem health in north China. The discharge of the Yellow River has significantly decreased due to climate change and intensifying human activities [24–26]. Li et al. [27] studied annual streamflow and sediment discharge at a tributary in the middle reaches of the Yellow River, and reported a significant downward trend. Yang et al. [28] revealed that the dam construction triggers a middle level of hydrologic alteration, and climate change makes the situation more complicated. Though numerous studies reported the changes of flow regime in the middle reaches of Yellow River [25,28–31], a systematic assessment on this flow regime alteration, considering both the frequency changes and process changes, is limited so far. Climate change together with human activities undoubtedly makes the flow regime more complicated in terms of both the statistical characteristics and the temporal changing behaviors [28,32,33]. Consequently, a comprehensive assessment on flow regime alteration is urgently needed for the middle reaches of the Yellow River.

Recognizing the above concerns, this study aims to: (1) Characterize the changes in flow regimes by using IHAs, (2) develop updated assessment methods for flow regime alteration by using the similarity/diversity measure, which is then incorporated with the RVA method to construct composite assessment metrics, (3) identify the flow regime alteration in a typical basin in the middle reaches of the Yellow River Basin, China, and compare the results by different methods, and (4) explore the possible implications of hydrological alteration on the ecosystem to develop knowledge for sustainable water resources and eco-environmental management.

2. Study Area, Data, and Methodology

2.1. Study Area

The Yellow River Basin has served as the "cradle of Chinese civilization" over the past millennia and continues to play a critical role in the development of China [30,34]. The middle reaches of the Yellow River (MRYR) flow through the Loess Plateau. The water from MRYR accounts for 44.3% of the Yellow River streamflow, and the sediment accounts for 88.2% of the Yellow River sediment. The MRYR, with an area of 344,000 km^2, is located between the longitudes 104° E–113° E and latitudes 32° N–42° N. The Wei River is the largest tributary of the Yellow River, which is located at the MRYR [35]. The Wei River Basin includes Wei River, Jinghe River, and Beiluo River. The Jinghe River Basin (45,421 km^2) is selected as the study area of this work. It is located between latitudes 34°46′ N–37°19′ N and longitudes 106°14′ E–108°42′ E, whose outlet is the Zhangjiashan Hydrological Station (Figure 1). The elevation of this Jinghe Basin ranges from 421 to 2922 m a.s.l. The area is characterized by a temperate, continental climate. Mean annual temperature is 8 °C and the mean annual precipitation is around 350–600 mm, which mainly concentrates in summer and autumn (fall) (July to September). A series of floods happen during the rainy season. The average annual streamflow is about 18.32 × 10^8 m^3, 70% of which concentrates from June to October.

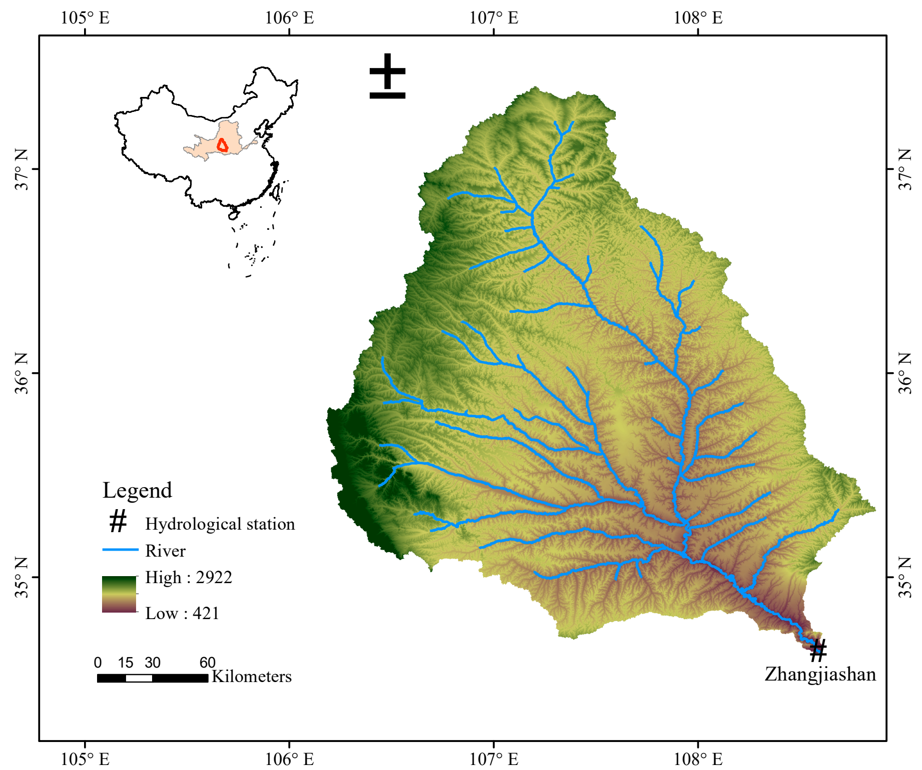


Figure 1. Map of China and the location of the Jinghe Basin in the middle reach of the Yellow River Basin.

2.2. Data

Daily discharge at the Zhangjiashan Station (1956–2010) is collected from the local hydrological bureau. The discharge data is measured by using the velocity-area method. The velocity is measured by a hydrometric propeller, and the area is calculated using the river width and the depth of river measured by sounding rod. The discharge is monitored twice every day in the normal season and several times (about once per hour) in the flood season. Daily discharge is the mean value of the monitoring data within one day. The homogeneity and reliability of the data were checked and firmly controlled by the hydrological bureau before the data were released. It is reported that the variation of annual runoff depth in the Jinghe Basin is −1.0–−0.5 mm/year [31], indicating an obvious downward trend of streamflow and water resources. In addition, poor biological integrity was reported over the basin in these years [36,37].

2.3. Methodology

The framework of this study is presented in Figure 2. The Mann-Kendall statistical test is employed to detect the change point of streamflow series. The streamflow series (1956–2010) is therefore divided into the pre-impact period and post-impact period by the abrupt point. The flow regimes are characterized by indicators of hydrologic alteration (IHAs) that are calculated based on the pre-impact and post-impact streamflow data. The commonly used range of variability approach (RVA) method is used to detect the alteration of flow regimes (denoted by D_m value). Then two new assessment methods are developed based on the concept of similarity/diversity. One is developed based on dynamic time warping (DTW) distance (denoted by SD_m value) and the other one is based on Euclidean distance (denoted by S_m value). These three methods describe the alteration degree in terms of the prospective of frequency changes as well as process changes. In addition, the individual metrics are integrated pairwise to obtain two composite metrics (OD_SD_m, OD_S_m) for comprehensive description of the alteration degree of flow regimes. The overall alteration degree for 32 IHAs by the five metrics (D_m, SD_m, S_m, OD_SD_m, OD_S_m) are denoted as D, SD, S, OD_SD and OD_S, respectively. In addition, the alteration degrees calculated by these five metrics are compared. Some terminology and the description in this work are shown in Table A1.

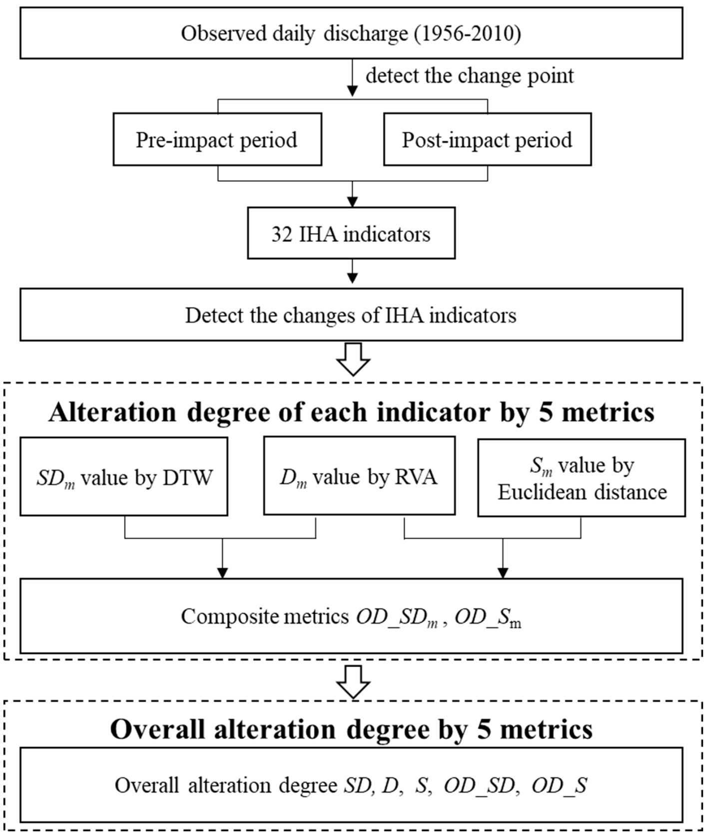


Figure 2. Overall procedures for assessing flow regime alteration.

2.3.1. Mann-Kendall Statistical Test

Mann–Kendall [38] and Pettitt's change point [39] are commonly used to detect the change point of the streamflow series.In this work, the Mann-Kendall (M–K) test [40,41] is employed to analyze trends and to detect abrupt changes in the time series of the streamflow. The M–K method defines a test statistic, d_k, that is calculated based on the rank series, r_i as in the following Equation:

$$d_k = \sum_{i=1}^{k} r_i (2 \le k \le n) \tag{1}$$

where, r_i is defined as:

$$r_i = \begin{cases} +1 & \text{if } x_i > x_j \\ 0 & \text{others} \end{cases} \quad (j = 1, 2, \ldots, i) \tag{2}$$

where, x_i refers to the time series, d_k refers to the sum of r_i related to x_i. The definition of the statistic index, UF_k, is then calculated as

$$UF_k = \frac{d_k - E[d_k]}{\sqrt{Var[d_k]}} \tag{3}$$

where $E[d_k] = n(n-1)/4$ is the expected value of d_k, and $Var[d_k] = n(n-1)(2n+5)/72$ is the variance of d_k, n is the number of time series data, and UF follows the standard normal distribution. In a two-sided test for trend, if $|UF| > U_{1-\alpha/2}$, then the null hypothesis is rejected at the significance level of α, where $U_{1-\alpha/2}$ is the critical value of the standard normal distribution. A corresponding rank series is then obtained by arranging the time series in reverse order, and the same processes are conducted to obtain the other statistical index, UB. A positive value of UF indicates an upward trend, and a negative value denotes a downward trend [42,43]. In this study, α equals to 0.05 and the corresponding $U_{1-\alpha/2}$ equals to 1.96. If $UF > 1.96$ or $UF < -1.96$ in a time series, then it shows a significant increasing or decreasing trend at the level of 0.05. Additionally, if the two lines, UF and UB, have an intersection point within the significance level, the intersection point is regarded as an abrupt point in the time series with a significance value of α.

2.3.2. The IHA Method for Hydrologic Alteration Assessment

The IHA method [18] is based on a set of 32 indicators classified into five groups, including magnitude, duration, timing, frequency and change rate (Table 1). The magnitude of the water condition at any given time is a measure of the availability or suitability of the habitat. The timing of the occurrence of particular water conditions can determine whether certain life-cycle requirements are met, or can influence the degree of stress or mortality associated with extreme water conditions, such as floods or droughts. The frequency of occurrence of specific water conditions such as droughts or floods may be tied to reproduction or mortality events for various species, thereby influencing population dynamics. The duration of time over which a specific water condition exists may determine whether a particular life-cycle phase can be completed, or the degree to which stressful effects such as inundation or desiccation can accumulate. The rate of change in water conditions may be tied to the stranding of certain organisms along the water's edge or in ponded depressions, or the ability of plant roots to maintain contact with phreatic water supplies. For more details, refer to Richter et al. [18]. The indicators are calculated based on daily discharge data. The IHA is generally calculated following the steps below:

(1) Divide the daily discharge data into two parts, i.e., a baseline pre-impact period (here from 1959–1996) and a perturbed post-impact period (here from 1997–2010).
(2) Calculate the median and interquartile range of the magnitude and variability of each IHA, respectively.
(3) Count the number of indicators falling within its target range and identify the alteration degrees of the flow regime.

Table 1. The 32 indicators of hydrologic alteration (IHAs) [10,18,44].

IHA Parameters Group	Hydrologic Parameters	Examples of Ecosystem Influences
1. Magnitude of monthly water conditions	Mean discharge for each calendar month (12 parameters) (m^3/s)	Provide availability of habitat, soil moisture, water and food; access by predators to nesting sites; functional link to water temperature, oxygen levels, photosynthesis
2. Magnitude of annual extreme discharge events with different durations	Annual 1-,3-,7-,30-,90-day minimum flow (m^3/s)	Creation of sites for plant colonization; structuring of river channel morphology and physical habitat conditions; nutrient exchanges between rivers and floodplains; distribution of plant communities in lakes, ponds and floodplains
	Annual 1-,3-,7-,30-,90-day maximum flow (m^3/s)	
	Base-flow index (m^3/s)	
3. Timing of annual extreme water conditions	Julian data of annual 1-day minimum	Provide special habitats during reproduction or to avoid predation; influences spawning for migratory fish, evolution of life history strategies
	Julian data of annual 1-day maximum	
4. Frequency and duration of high/low pulses	Number of low pulses each year	Connection to soil moisture and anaerobic stress for plants; Provide floodplain habitats; ensure nutrient and organic matter exchanges between river and floodplain, soil mineral availability Influences bedload transport, channel sediment textures and duration of substrate disturbance (high pulses)
	Mean duration of low pulses (d)	
	Number of high pulses each year	
	Mean duration of high pulses (d)	
5. Rate/frequency of flow condition changes	Rise rate Fall rate Number of reversals	Drought stress on plants (falling levels) Entrapment of organisms on islands, floodplains (rising levels) Desiccation stress on low-mobility stream edge (varial zone) organisms

In this study, the conventional RVA method and the updated methods considering the process changing behaviors of each of the indicators are shown in Sections 2.3.3–2.3.5.

2.3.3. Accounting for Alteration of Indicators in the RVA

In the RVA method [1], the degree of alteration for hydrologic indicator m, D_m, is used to measure the deviation of the post-impact flow regime from the natural regime, which is defined as follows:

$$D_m = \left| \frac{N_{om} - N_{em}}{N_{em}} \right| \times 100\% \tag{4}$$

where, N_{om} is the observed number of post-impact years in which the value of indicator m falls within its RVA target range and N_{em} is the expected number of post-impact years in which the indicator value falls within the RVA target range (i.e., between the 75th and 25th percentiles for the natural daily flows). Then the average degree of alteration for these hydrologic indicators is applied to quantify the overall impact on the riverine system, which is expressed as follows:

$$D = \frac{1}{H} \sum_{m=1}^{H} D_m \tag{5}$$

where, D is the overall alteration degree of the flow regime and H is the number of the hydrologic parameters. The higher the value of D, the greater the degree of alteration. 33% and 66% are defined as the thresholds to distinguish low (0–33%), medium (33–66%) and high alteration (>66%).

2.3.4. Accounting for the Alteration of Indicators Based on the Concept of Similarity/Diversity

- A Method Based on Euclidean Distance

It is known that the RVA method concentrates on considering the frequency of indicators falling within the target range, whereas neglecting the process of indicators deviating from the target range. In this work, the method by Yin et al. [22] is employed and updated to measure the alteration induced by the process deviation.

DF measures the difference between the pre-impact (denoted as $A(a_1, a_2, \ldots a_n)$) and post-impact time series (denoted as $B(b_1, b_2, \ldots b_l)$), where q and l represent the number of years within the pre-impact time series and duration of the post-impact period, respectively. T is the maximum distance among the hydrologic year types (HYTs), which equals 2 when there are only three hydrologic year types (HYTs) categories.

$$\text{If } q = l,\ DF = \sqrt{\sum_{i=1}^{l} (a_i - b_i)^2} \tag{6}$$

$$\text{If } q > l,\ DF = \min \sqrt{\sum_{i=1}^{l} (a_{k+i} - b_i)^2},\ k = 0, 1, \ldots, n - l \tag{7}$$

$$\text{If } q < l,\ DF = \min \sqrt{\sum_{i=1}^{n} (a_i - b_{k+1})^2},\ k = 0, 1, \ldots, l - n \tag{8}$$

where *min* represents the minimum value of distance.

S is the alteration degree of the HYT (hydrologic year types) order, which is the normalized value of the difference between two time series (*DF*):

$$S = DF/[T \times \min(n^{1/2}, l^{1/2})] \tag{9}$$

for more details about the method, refer to Yin et al. [22].

In the study by Yin et al. [22], S represents the alteration degree of the HYT order, which is integrated with the alteration degree evaluated by RVA. In this work, we made a modification on the method. We treat S as the degree of alteration for time series of each indicator, instead of that for hydrologic year types (HYT). We can get two time series $A(a_1, a_2, \ldots a_q)$ and $B(b_1, b_2, \ldots b_l)$ to represent pre-impact and post-impact periods for each indicator. The time series of each indicator are normalized: values lower than the 25th percentile, between the 25th percentile and 75th percentile and larger than the 75th percentile, are assigned 0, 1 and 2, respectively. Note that the thresholds (25th percentile and 75th percentile) used here are calculated using the pre-impact series data. We can then obtain that $|a_i - b_i| = 0$, or $|a_i - b_i| = 1$, or $|a_i - b_i| = 2$. S for each IHA (S_m) thereafter can be calculated. The overall alteration degree (S) of the flow regime can be calculated by averaging S_m, which can be referred to Equation (5). Same to that used in RVA, 33% and 66% are defined as the thresholds to distinguish low (0–33%), medium (33–66%) and high alteration (>66%).

- A method Based on Dynamic Time Warping (DTW) Distance

The dynamic time warping (DTW) distance is a technique that finds the optimal alignment between two time series if one time series may be "warped" non-linearly by stretching or shrinking it along its time axis [45]. DTW is often used to determine time series similarity, classification and to find corresponding regions between two time series [46]. It is often used in speech recognition to determine if two waveforms represent the same spoken phrase. In a speech waveform, the duration of each spoken sound and the interval between sounds are permitted to vary, but the overall speech waveforms must be similar. In addition to speech recognition, dynamic time warping has also been found useful in many other disciplines [47], including data mining, gesture recognition, robotics, manufacturing and medicine. It is commonly used in data mining as a distance measure between time series [48].

The dynamic time warping problem is stated as follows [49]: Given two time series X and Y,

$$X = x_1, x_2, \ldots, x_n \tag{10}$$

$$Y = y_1, y_2, \ldots, y_m \tag{11}$$

construct a warp path W:

$$W = w_1, w_2, \ldots, w_K \max(m, n) \le K < m + n \tag{12}$$

where K is the length of the warp path and the kth element of the warp path is

$$w_k = (i, j) \tag{13}$$

where i is an index of time series X, and j is an index of time series Y. The warp path must start at the beginning of each time series at $w_1 = (1, 1)$ and finish at the end of both time series at $w_k = (m, n)$. Every index of each time series must be used, which is stated as follows:

$$w_k = (i, j),\ w_{k+1} = (i', j')\ i \le i' \le i + 1,\ j \le j' \le j + 1 \tag{14}$$

Since a single point may map to multiple points in the other time series, the time series do not need to be of equal length, which is more advanced than Euclidean distance. If X and Y were identical time series, the warp path through the matrix would be a straight diagonal line. The optimal warp path is the warp path with the minimum distance, where the distance of a warp path W is:

$$Dist(W) = \sum_{k=1}^{k=K} Dist(w_{ki}, w_{kj}) \tag{15}$$

$Dist(W)$ is the distance (typically a Euclidean distance) of the warp path W, and $Dist(w_{ki}, w_{kj})$ is the distance between the two data point indices (one from X and one from Y) in the kth element of the warp path.

The rationale of the DTW algorithm to find the minimum-distance warp path is a dynamic programming approach. For more details about the algorithm, please refer to Salvador and Chan. [49].

In this work, the state-of-the-art FastDTW method is employed to identify the similarity of pre-impact and post-impact series. It can be used on much larger data sets than DTW. Standard dynamic time warping (DTW) is an O(N^2) algorithm because every cell in the cost matrix must be filled to ensure an optimal answer is found, and the size of the matrix grows quadratically with the size of the time series. In FastDTW, the cost matrix is only filled in the neighborhood of the path projected from the previous resolution. The length of the warp path grows linearly with the size of the input time series, the multilevel approach is thus an O(N) algorithm. FastDTW is an order of magnitude faster than DTW, and it also compliments existing indexing methods that speed up time series similarity search and classification. For more details about FastDTW, please refer to Salvador and Chan. [49].

The inputs here are pre-impact and post-impact series of each indicator, and they are normalized through the method shown above. That is to say, the values of each indicator are normalized to 0, 1 and 2. The outputs are a warp path (W) and a distance between two time series along that warp path ($Dist$). $Dist$ is the accumulated distance of the warp path, indicating similarity/diversity of the two sequential data (pre-impact and post-impact series). In this work, we normalize it using the following Equation:

$$SD_m = Dist/[T \times K] \tag{16}$$

where T is the maximum distance between the two data point indices (one from X and one from Y), which equals to 2 in this case. K is length (number) of the warp path. SD_m is the alteration degree induced by the process differences of the pre- and post-impact time series for each indicator. The overall alteration degree (SD) of the flow regime can be calculated by averaging SD_m, which can be referred to from Equation (5). It describes the features of post-impact indicators deviating from the natural flow regimes. It ranges between 0 and 1. The larger the value of SD, the greater the degree of alteration and more serious the degradation of the riverine ecosystem. Same to that used in RVA, 33% and 66% are defined as the thresholds to distinguish low (0–33%), medium (33–66%) and high alteration (>66%).

2.3.5. Integrated Measure for Alteration Degree of Flow Regime

The RVA will underestimate the degree of flow regime alteration in terms of that only frequency is considered to represent the degree [22], i.e., the difference between the proportion of pre-impact and post-impact values falling within the target range is considered to represent the degree of alteration. In this work, we develop two integrated metrics based on the equation proposed by Yin et al. [22]:

$$OD = 1 - [(1 - D) \times (1 - M)] \tag{17}$$

where OD varies between 0 and 1. The greater the value of OD, the more serious the degradation of the riverine ecosystem. In the study by Yin et al. [22], D is the alteration degree by RVA, and M is the alteration degree of the HYT (hydrologic year types) order.

In this work, we deem D as the alteration degree representing frequency features, and M is the degree representing process features. OD is the degree of alteration considering both changes in frequency and process. Therefore, two integrated metrics are developed as follows:

$$OD\_S = 1 - [(1 - D) \times (1 - S)] \tag{18}$$

$$OD\_SD = 1 - [(1 - D) \times (1 - SD)] \tag{19}$$

where D is the alteration degree calculated by RVA, S is the degree calculated by the method based on Euclidean distance (Equation (9)), and SD is the degree calculated by the method based on FastDTW (Equation (16)). These two Equations can be used both in estimating the overall alteration degree for all indicators and in estimating the degree for each indicator. When it is used to estimate the degree for each indicator, $|D_m|$, S_m and SD_m should be used instead of D, S and SD. Same to that used in RVA, 33% and 66% are defined as the thresholds to distinguish low (0–33%), medium (33–66%) and high alteration (>66%).

3. Results

3.1. Changes in Annual Mean Streamflow

The Mann–Kendall test method (M–K) is employed to examine abrupt changes in annual mean streamflow at the Zhangjiashan Station. Figure 3 shows the test for abrupt changes in annual streamflow. It suggests that a significant abrupt change point occurs after 1996. The annual mean streamflow before and after 1996 is 57.84 m^3/s and 31.35 m^3/s, respectively. The variation amplitude is −45.80%. Additionally, the results by M–K suggest that the annual mean streamflow tends to slightly increase during the period 1960–1970 and decrease after 1970. There is an intersection of UF_k and UB_k between the value of 1996 and 1997, indicating that a sharp decrease appears after 1996 and the decreasing trend is significant after 1997 (Sig. = 0.05).

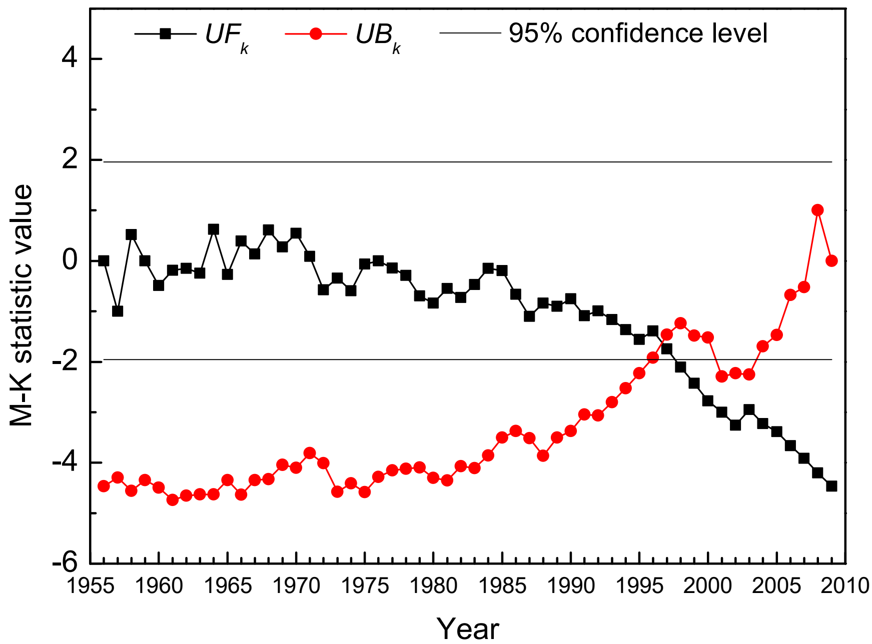


Figure 3. Statistical test for abrupt changes in annual streamflow (There is an intersection point of the *UF* and *UB* lines after year 1996, suggesting an abrupt point).

3.2. Changes in the Hydrologic Parameters

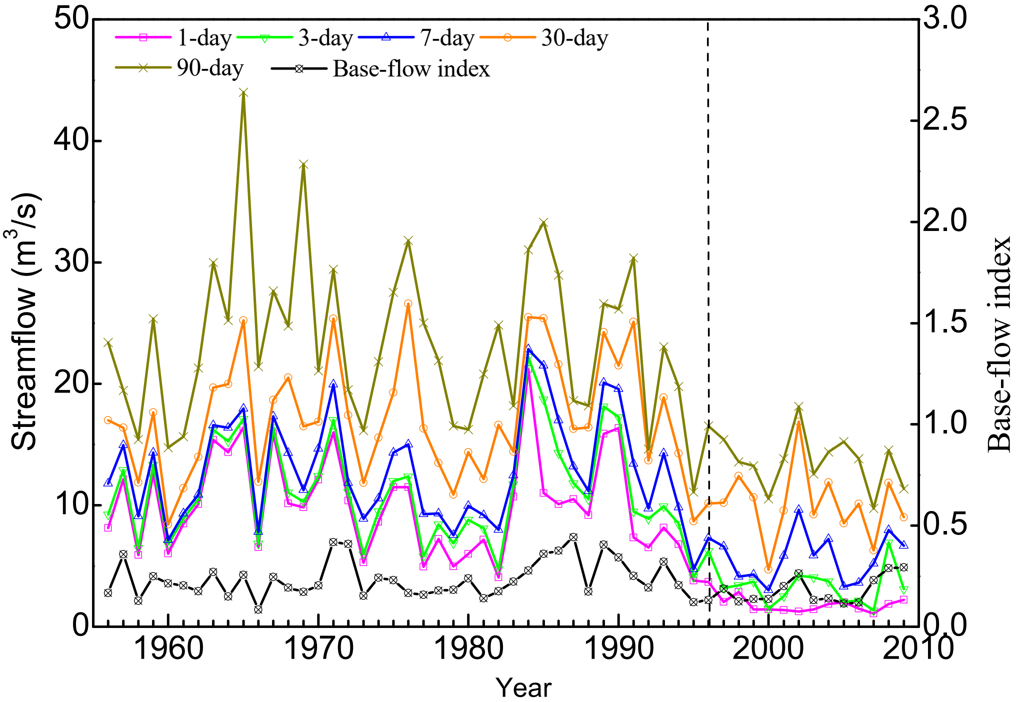
As shown in Table 2, the streamflow of each month obviously decreases, especially during the wet season. There is an average of 51.36% reduction for the median values of streamflow in June, July, August and September, while the reduction is 38.63% in the dry season. The large amount of reduction of monthly flow indicates an obvious decrease of water resources in the basin.

Table 2. Variation and degree of alteration for hydrologic parameters.

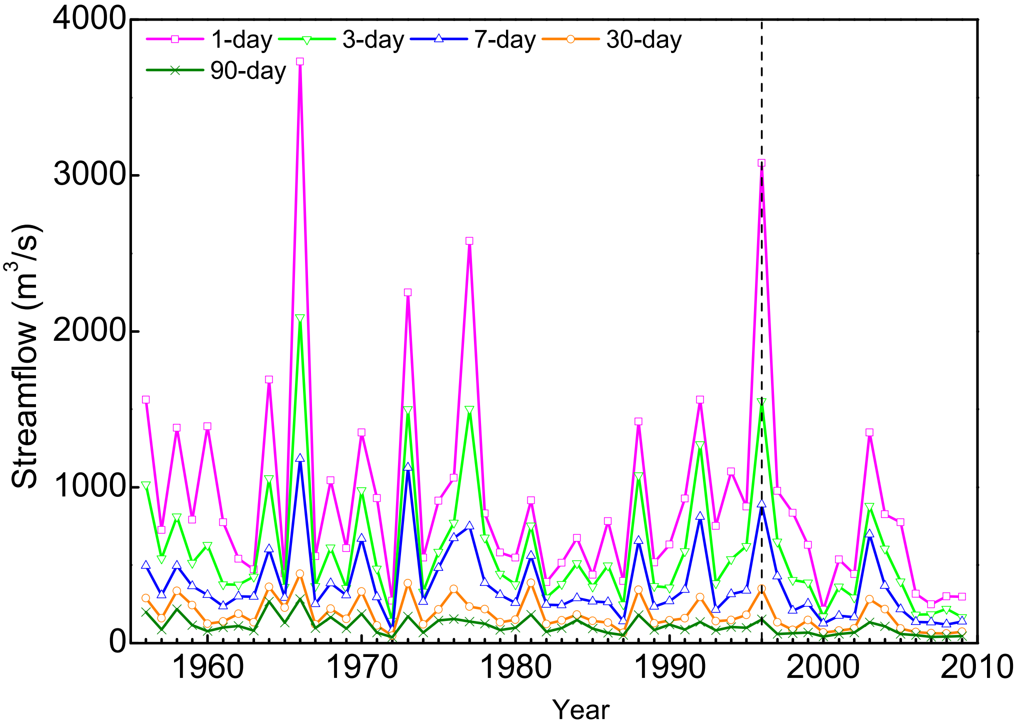
Group	Hydrologic Parameters	Median		Variation
		Pre-Impact	Post-Impact	
1	Mean discharge for January	18.6	14.13	−24.03%
	Mean discharge for February	28.6	18.7	−34.62%
	Mean discharge for March	39.7	21.7	−45.34%
	Mean discharge for April	31.85	13.85	−56.51%
	Mean discharge for May	25.1	15.4	−38.65%
	Mean discharge for June	25.75	14	−45.63%
	Mean discharge for July	50	25.6	−48.80%
	Mean discharge for August	67.8	30.9	−54.42%
	Mean discharge for September	53.3	23.15	−56.57%
	Mean discharge for October	44.7	29.9	−33.11%
	Mean discharge for November	36.9	21.55	−41.60%
	Mean discharge for December	23.9	15.5	−35.15%
2	Minimum 1-day	9.84	1.48	−84.96%
	Minimum 3-day	10.5	3.183	−69.69%
	Minimum 7-day	11.84	5.863	−50.48%
	Minimum 30-day	16.51	10.13	−38.64%
	Minimum 90-day	21.92	13.83	−36.91%
	Maximum 1-day	792	535	−32.45%
	Maximum 3-day	515.3	363	−29.56%
	Maximum 7-day	307.9	174.9	−43.20%
	Maximum 30-day	158.8	83.77	−47.25%
	Maximum 90-day	102.1	58.06	−43.13%
	Base-flow index	0.204	0.140	−31.37%
3	Julian data of annual 1-day minimum	168	178	10 day
	Julian data of annual 1-day maximum	217	214	−3 day
4	Number of low pulses each year	10	19	90%
	Mean duration of low pulses (day)	4	3.5	−0.5 day
	Number of high pulses each year	12	10	−16.67%
	Mean duration of high pulses (day)	3	2	−1 day
5	Rise rate	2.6	2.6	0%
	Fall rate	−2.7	−3	−11.11%
	Number of reversals	136	168	23.53%

Figure 4 shows the changes in magnitude of annual extreme discharge events with different durations. All the minimum indicators have a decreasing trend (Figure 4a). Compared with the mean values in the pre-impact period, the annual 1-day, 3-day, 7-day, 30-day and 90-day minimum flows in the post-impact period decrease by 84.96%, 69.69%, 50.48%, 38.64%, and 36.91%, respectively (Table 2). As to the maximum metrics, a decrease occurs as well (Figure 4b).

The variations of 1-day and 3-day maximum flows are lower than that of 7-day, 30-day and 90-day maximum flows. Decrease is also found for the base-flow index (Figure 4a and Table 2).



(a)



(b)

Figure 4. Changes in the magnitude of (**a**) annual minimum flow and (**b**) annual maximum flow with different durations at Zhangjiashan Station (the outlet of the Jinghe Basin).

Figure 5 shows the timing of annual extreme water conditions. As to the annual 1-day minimum flow, it occurs in almost every month during the pre-impact period except November and March (Figure 5a). It frequently occurs in May, June and July, and the median of the occurrence happens in June (Figure 5a). In comparison, the median occurrence of 1-day minimum flow in post-impact period delays 10 days (Figure 5b). For the annual 1-day maximum flow, it occurs from May to October in the pre-impact period, which mainly concentrates in July and August (Figure 5c). The median locates in August. In comparison, the median occurrence in the post-impact period advances three days (Figure 5d).

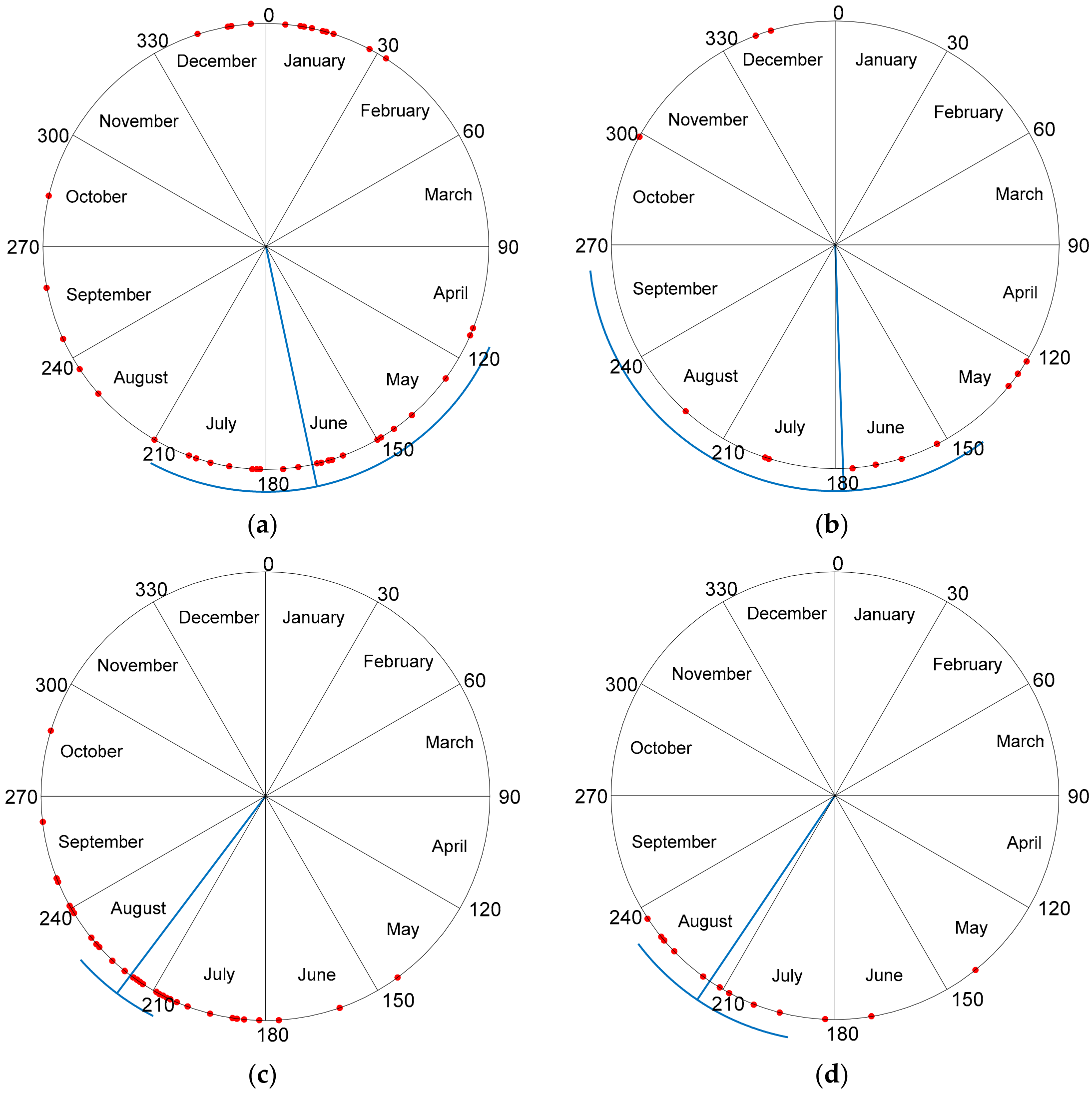
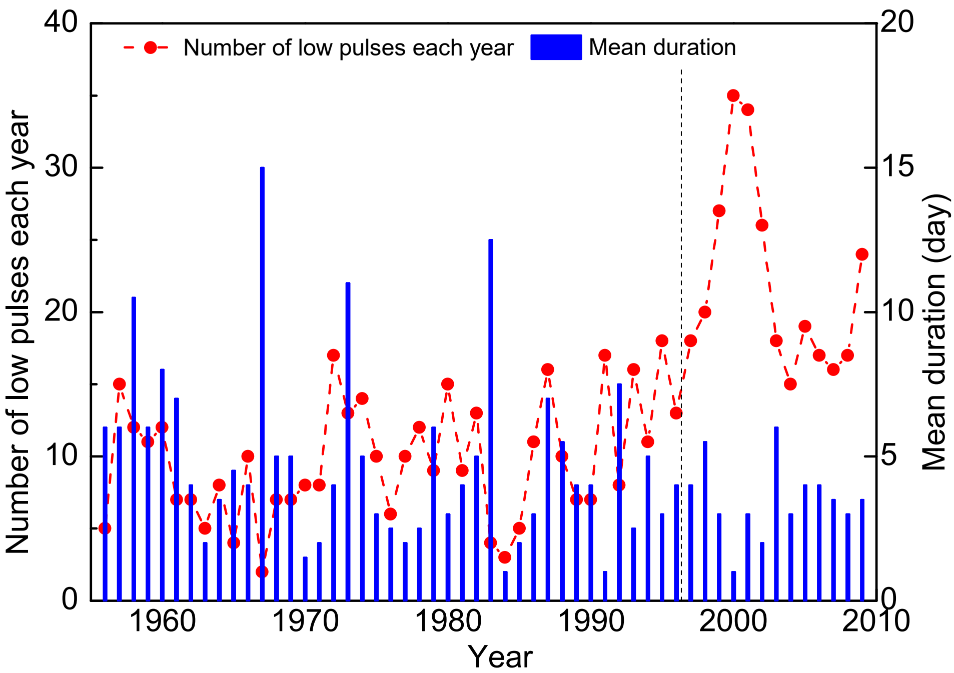
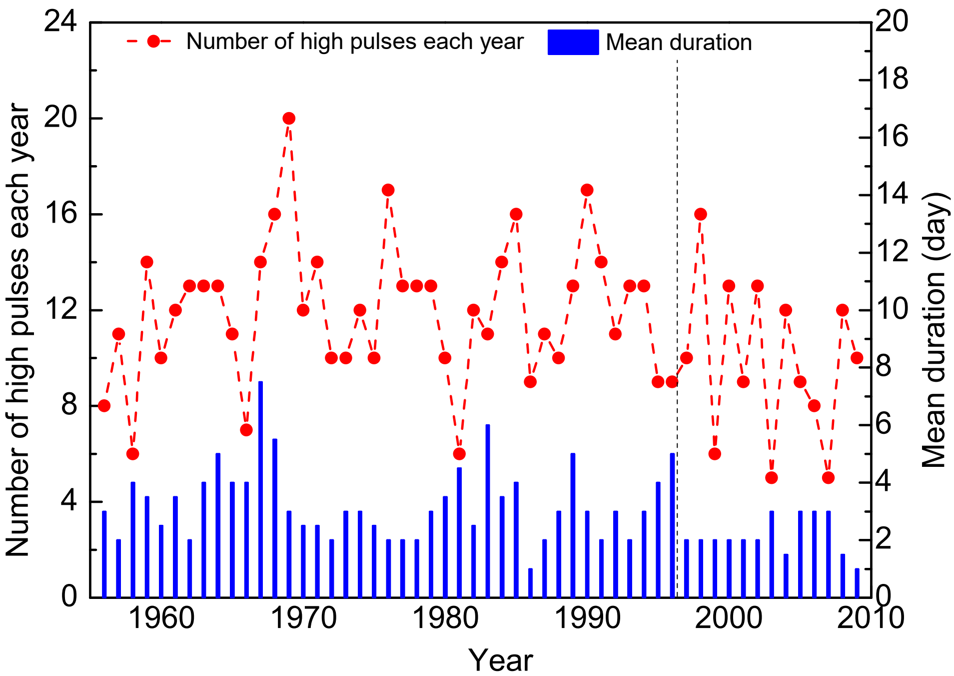


Figure 5. Timing of annual 1-day minimum in (**a**) the pre-impact period and (**b**) the post-impact period, and the timing of annual 1-day maximum in (**c**) the pre-impact period and (**d**) the post-impact period.

Figure 6 shows the number and duration of low and high pulses within each year. The number of low pulses within each year has an obvious growing trend (Figure 6a). The median in the post-impact period increases by 90% compared with that in the pre-impact period (Table 2). Mean duration of low pulses in the post-impact period decreases by 0.5 day compared with that in the pre-impact period (Table 2). As to the high pulses, the median number in this post-impact period reduces 16.67% compared with that in our pre-impact period (Table 2). Mean duration of high pulses reduces by 1 day (Table 2).



(**a**)



(**b**)

Figure 6. Number and mean duration of (**a**) low and (**b**) high pulses each year at Zhangjiashan Station (the outlet of Jinghe Basin).

Figure 7 shows the rise rate, fall rate and number of reversals. The median rise rate in the post-impact period is consistent with that in the pre-impact period, and no change (0%) is found for the median values (Table 2). The median fall rate in the post-impact period has 11.11% reduction compared with that in the pre-impact period (Table 2). As to the number of reversals, the median in this post-impact period increases by 23.53% compared to that in our pre-impact period (Table 2).

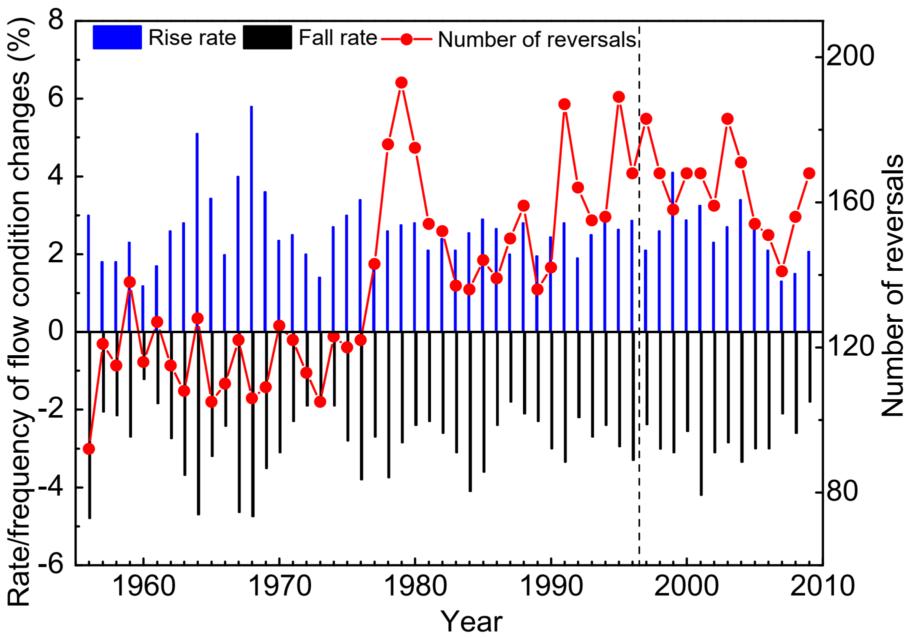
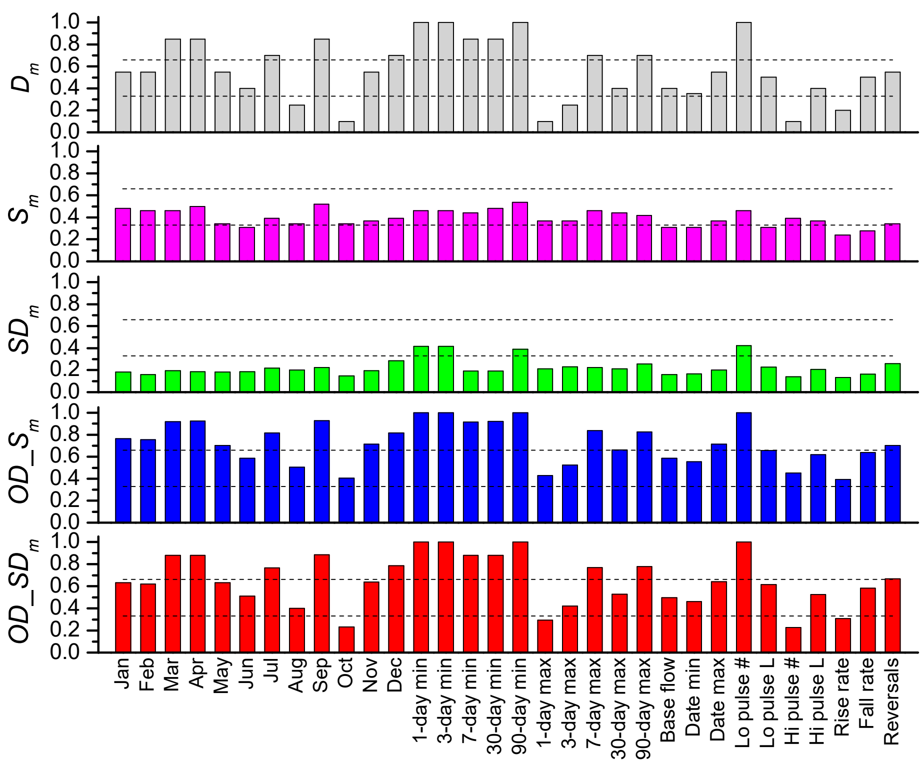


Figure 7. Rise rate, fall rate and number of reversals at Zhangjiashan Station (the outlet of the Jinghe Basin).

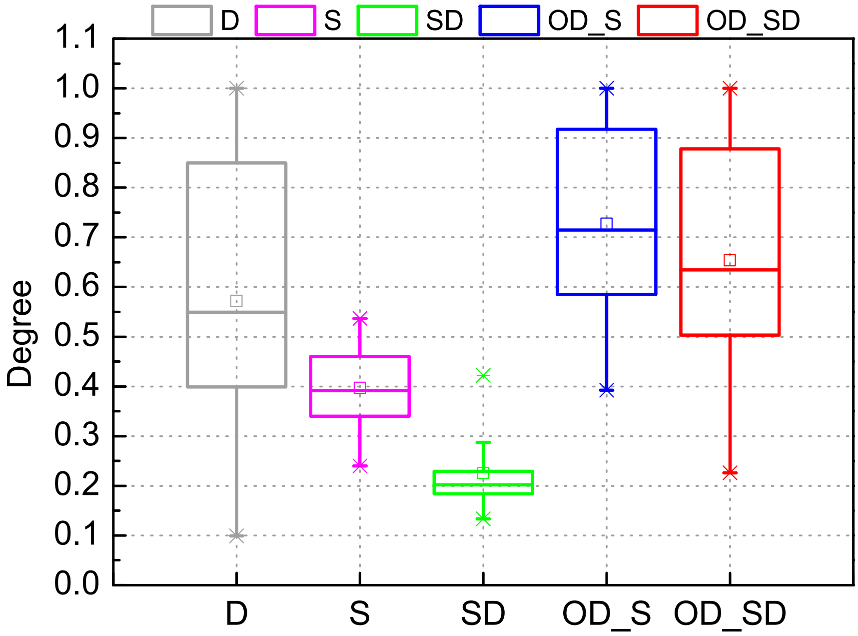
3.3. Alteration Degree of the Hydrologic Parameters

The alteration degrees by five metrics (i.e., *D*, *S*, *SD*, *OD_S*, and *OD_SD*, including three single metrics and two composite metrics) for each hydrologic parameter are shown in Figure 8a and Table 3. The alteration degrees for 32 hydrologic parameters by each assessment method are aggregated as box-plots and are shown in Figure 8b.



(a)

Figure 8. *Cont.*



(**b**)

Figure 8. (**a**) Alteration degrees by five measures (i.e., *D*, *S*, *SD*, *OD_S*, and *OD_SD*, including three single measures and two composite measures) for each hydrologic parameter, (**b**) Alteration degree of the 32 hydrologic parameters by five assessment methods.

Table 3. Alteration degree of the 32 hydrologic parameters.

Group	Hydrologic Parameters	D_m	S_m	SD_m	OD_S_m	OD_SD_m
1	Mean discharge for January	−0.55	0.48	0.18	0.77	0.63
	Mean discharge for February	−0.55	0.46	0.16	0.76	0.62
	Mean discharge for March	−0.85	0.46	0.20	0.92	0.88
	Mean discharge for April	−0.85	0.50	0.19	0.93	0.88
	Mean discharge for May	−0.55	0.34	0.18	0.70	0.63
	Mean discharge for June	−0.40	0.31	0.19	0.59	0.51
	Mean discharge for July	−0.70	0.39	0.22	0.82	0.77
	Mean discharge for August	−0.25	0.34	0.20	0.50	0.40
	Mean discharge for September	−0.85	0.52	0.22	0.93	0.88
	Mean discharge for October	−0.10	0.34	0.15	0.41	0.23
	Mean discharge for November	−0.55	0.37	0.20	0.71	0.64
	Mean discharge for December	−0.70	0.39	0.29	0.82	0.79
2	Minimum 1-day	−1.00	0.46	0.42	1.00	1.00
	Minimum 3-day	−1.00	0.46	0.42	1.00	1.00
	Minimum 7-day	−0.85	0.44	0.19	0.92	0.88
	Minimum 30-day	−0.85	0.48	0.19	0.92	0.88
	Minimum 90-day	−1.00	0.54	0.39	1.00	1.00
	Maximum 1-day	−0.10	0.37	0.21	0.43	0.29
	Maximum 3-day	−0.25	0.37	0.23	0.52	0.42
	Maximum 7-day	−0.70	0.46	0.22	0.84	0.77
	Maximum 30-day	−0.40	0.44	0.21	0.66	0.53
	Maximum 90-day	−0.70	0.42	0.26	0.82	0.78
	Base-flow index	−0.40	0.31	0.16	0.59	0.49

Table 3. *Cont.*

Group	Hydrologic Parameters	D_m	S_m	SD_m	OD_S_m	OD_SD_m
3	Julian data of annual 1-day minimum	0.35	0.31	0.17	0.55	0.46
	Julian data of annual 1-day maximum	−0.55	0.37	0.20	0.71	0.64
4	Number of low pulses each year	−1.00	0.46	0.42	1.00	1.00
	Mean duration of low pulses (d)	0.50	0.31	0.23	0.66	0.62
	Number of high pulses each year	−0.10	0.39	0.14	0.45	0.23
	Mean duration of high pulses (d)	−0.40	0.37	0.21	0.62	0.52
5	Rise rate	0.20	0.24	0.13	0.39	0.31
	Fall rate	0.50	0.28	0.16	0.64	0.58
	Number of reversals	−0.55	0.34	0.26	0.70	0.67
Overall		D	S	SD	OD_S	OD_SD
		0.57	0.40	0.23	0.74	0.67

3.3.1. Alteration of Monthly Streamflow

It is seen in Figure 8a that D_m values for the monthly streamflow suggest almost all of them show moderate and high levels of their degree of alteration, except the streamflow of August and October (low level degree).

The S_m values indicate that 11 parameters present a moderate level degree and 1 parameter (June) shows a low level degree. SD_m values show a low level degree of alteration for all the 12 parameters, which are lower than those by S_m. As to the composite metrics, they show a larger degree than that by the individual ones. OD_S_m indicate all the 12 parameters have moderate or high degree of alteration. Monthly flow of June, August and October are altered with a moderate degree and the others with a high degree. OD_SD_m show a similar trend with OD_S_m, but there are differences in the degree for five months. January, February, May and November show a moderate alteration degree by OD_SD_m while a high degree by OD_S_m. October shows a low alteration degree by OD_SD_m while a moderate one by OD_S_m.

3.3.2. Alteration of Magnitude of Annual Extreme Streamflow

It is seen in Figure 8a that the D_m values for 1-day, 3-day, 7-day, 30-day and 90-day minimum flows indicate a high degree of alteration, S_m values suggest a middle degree of alteration, and SD_m values show moderate and low degrees of alteration. OD_S_m and OD_SD_m values show a high degree of alteration, which are consistent with the degree by D_m.

As to the maximum metrics, the D_m values suggest that 1-day and 3-day maximum flows have low levels of alteration and 7-day, 30-day and 90-day maximum flows have both the high and moderate levels. The S_m values suggest a moderate level of alteration for all the five parameters, while the SD_m values show a consistent low level of alteration. OD_S_m and OD_SD_m show a consistent moderate degree for 3-day maximum flow and a high degree for 7-day and 90-day maximum flows, while different degrees for the 1-day maximum and 30-day maximum. In addition, for the base-flow index, D_m indicates a moderate level of alteration, while S_m and SD_m suggest a consistent low level degree. OD_S_m and OD_SD_m consistently show a moderate degree.

3.3.3. Alteration of Timing of Annual Extreme Water Conditions

For the annual 1-day minimum flow, D_m suggests a moderate level of alteration, and S_m as well as SD_m suggest low levels of alteration. Similar to that by D_m, OD_S_m and OD_SD_m show moderate degrees as well. For the annual 1-day maximum flow, D_m and S_m both suggest moderate levels of alteration, and SD_m shows a low level of alteration. OD_S_m and OD_SD_m suggest high and middle degree, respectively.

3.3.4. Alteration of Frequency and Duration of High and Low Pulses

As to the number of low pulses each year (denoted as Lo pulse # in Figure 8a), D_m suggests the high degree of alteration, while S_m and SD_m suggest a moderate degree. Both OD_S_m and OD_SD_m show a high alteration degree, which is same to that by D_m. For the mean duration of low pulses (denoted as Lo pulse L in Figure 8a), D_m suggests a moderate degree, and S_m and SD_m suggest low degree of alteration. OD_S_m and OD_SD_m show high degree and moderate degree, respectively. As to the high pulses, low degree is detected for the median of number (denoted as Hi pulse # in Figure 8a) by D_m and SD_m, while a moderate degree by S_m.

The moderate degree is detected for a mean duration of high pulses (denoted as Hi pulse L in Figure 8a) by D_m and S_m, while a low degree by SD_m. OD_S_m and OD_SD_m suggest moderate degrees for the mean duration of high pulses.

3.3.5. Alteration of Streamflow Variability

It is seen in Figure 8a that the median rise rate has low degrees of alteration detected by D_m, S_m, SD_m and OD_SD_m, and moderate degrees by OD_S_m. The median fall rate has moderate degrees of alteration detected by D_m, OD_S_m and OD_SD_m, and low degrees by S_m and SD_m. As to the number of reversals, D_m and S_m suggest a moderate degree of alteration, SD_m suggests a low degree of alteration, then OD_S_m and OD_SD_m suggest high degrees of alteration.

3.3.6. Overall Alteration of Flow Regime

According to Equation (5), the overall alteration of the flow regime was calculated (Table 3). The overall alteration degree of the basin is moderate level denoted by D (0.57) and S (0.40), and low level by SD (0.23). OD_S (0.74) is the combination of D and S, indicating a high degree of alteration. OD_SD (0.67) is the combination of D and SD, suggesting a high degree of alteration as well. These composite metrics consistently show that the basin suffered a high degree of alteration.

3.4. Comparison of Alteration Degree by Different Methods

It is seen in Figure 8a that there are differences in alteration degree measured by diverse methods. D_m detected low degree for six parameters, moderate degree for 13 parameters and high degree for 13 parameters. S_m detected low degree for six parameters and moderate degree for 26 parameters. SD_m found low degree for 28 parameters and moderate degree for four parameters. To further show the difference of the alteration degree by different measures, we draw a box-plot to make a brief comparison (Figure 8b). It is seen that D values range from 0.1 to 1.0, indicating low, moderate and high alteration degrees for the 32 hydrologic parameters. S values range from 0.24 to 0.54, suggesting low and moderate alteration degrees. SD values vary from 0.13 to 0.42, most of which denote a low degree. OD_S ranges from 0.39 to 1.0 and OD_SD from 0.23 to 1.0, most of which suggest moderate and high levels of alteration.

Through a comparison between D_m and OD_SD_m, we can find a large similarity between them (Figure 8a). Almost all the hydrologic parameters show same alteration degree, except two parameters (monthly flow of August and 3-day maximum flow). D_m shows a low degree for the monthly flow of August and a 3-day maximum flow, while OD_SD_m suggests a moderate level. It could be deemed that the increases of the level for these two parameters are induced by process changes of the time series. The overall alteration degree increases from middle level (D = 0.57) to high level (OD_SD = 0.67).

Comparison between D_m and OD_S_m reveals that the alteration degree of eight hydrologic parameters (that is, Jan, Feb, May, Nov, 30-day max, date max, Lo pulse L and reversals) increases from middle level to high level. Additionally, six hydrological parameters with low alteration degree by RVA (being August, October, 1-day max, 3-day max, high pulse # and rise rate) tend to have moderate level alteration by OD_S_m. The overall alteration degree increases from middle level (D= 0.57) to high level (OD_S = 0.74).

4. Discussion

Although there are differences amongst the values by individual metrics and the composite metrics, they are not contradictory. These metrics were constructed based on different concepts, describing different features of flow regime alteration. The objective of *D* by the RVA method is to attain the targeted range at the same frequency as occurred in the natural or pre-impact flow regime. The RVA is useful for setting preliminary or interim flow targets for river reaches with highly altered hydrological regimes, i.e., where one or more annual streamflow characteristics frequently fall outside their historic ranges of variability [20].

As to the *S* and *SD*, they are aimed to measure the deviation of the post-impact flow regime from the natural regime as well, which concentrates on describing the deviation of magnitude from the prospective of the process changes of IHAs. *S* is calculated based on similarity/diversity concept by using Euclidean distance that measures the difference between pre-impact and post-impact hydrologic parameters. *SD* is constructed based on this same similarity/diversity concept as well, which measures the difference by using the dynamic time warping distance. The advantage of *SD* is that it does not require the same length of data for pre-impact and post-impact time series. Those two composite metrics (*OD_S* and *OD_SD*) capture the alteration induced both by frequency changes and process changes. That is to say, the difference between the proportions of pre-impact and post-impact values falling within the target range is considered, and the difference between the process behaviors of pre-impact and post-impact sequential data is considered as well.

The parameters for annual extreme flow (including 1-day min, 3-day min, 7-day min, 30-day min, 90-day min, 7-day max, 90-day max and Lo pulses #) and some monthly flow (March, April, July, September and December) are characterized by a high alteration degree (denoted by the conventional RVA method). It indicates that these parameters are highly altered in terms of falling outside their historic ranges of variability. In addition, the parameters with moderate alteration (including January, February, May, November, 30-day max, date max, Lo pulse L and reversals) tend to have high level alteration when considering the process behaviors of their time series (denoted by S_m), indicating that these parameters alter, not only in appearance frequency of falling within historic ranges, but also in process behaviors, including magnitude and shape of time series.

On the other hand, two parameters (monthly flow of August and 3-day maximum flow) with low alteration degree (denoted by the conventional RVA method) tend to have a moderate alteration degree when considering the process behaviors of their time series (denoted by SD_m). Different to the effect by SD_m, the S_m makes 14 hydrologic parameters increase by an alteration level (8 from moderate to high, 6 from low to moderate). It seems that the effect from S_m is larger than that from SD_m, which is mainly because the values by S_m are generally larger than that by SD_m. The difference between S_m and SD_m originates from the disparity of calculated distance between pre-impact and post-impact data series. However, what is similar, is that S_m and SD_m lead to a same level effect for the overall alteration degree. In other words, the overall alteration of the flow regime for the basin is at a moderate level measured by *D*, whereas at the high level when incorporated with S_m or SD_m. The two aggregated metrics (*OD_S* and *OD_SD*) consistently suggest a high degree of alteration in the basin.

It was reported that the RVA underestimates the degree of flow regime alteration in terms of the fact that only frequency is considered to represent the degree [22]. Hence, the composite metrics are recommended to assess flow regime alteration, especially in the basin influenced both by climate change and human activities. Climate change and anthropogenic disturbance (including water withdraw, reservoir and check-dams construction, soil and water conservation practices) deeply influence flow regimes. A series of soil and water conservation practices have been carried out in the MRYR since the late 1950s, including engineering structures, such as terraces and dams, and biological measures such as afforestation and planting grass [31].

Afforestation and planting grass projects were implemented since the 1990s and intensified since the 2000s in the Jinghe Basin, leading to great changes in the riverine system. Consequently, both the changes in statistical features and in process features should be taken into account when assessing the alteration of flow regimes.

The two metrics (*S* and *SD*) describing the process changes of IHAs suggest a different overall alteration level. The former one indicates a moderate level (0.40) and the latter one the low level (0.23). The disparity originates from the calculation for the distance between pre-impact and post-impact time series. A same length of data is necessary by measure *S*, thus the distance is calculated using the short one. It means that only a part of the data of the long one is used to make a comparison with the short one, which may overestimate the distance between two sequential data. As to the *SD*, it is constructed based on the dynamic time warping (DTW) distance. The time series inputs of pre-impact and post-impact do not need to be of equal length. Hence, *SD* is more reasonable than *S*, and should be recommended when incorporated with *D* generated by RVA.

The alteration of the flow regime has important effect on the ecological process and threatens the biodiversity and rivers ecosystem functions [10,50]. In this work, we mainly examine the implication of hydrological changes for the fish species. The community structure and index of biotic integrity (IBI) of the fish assemblage are good indicators of flow regime alteration under human disturbance and climate change [36]. Compared with the periphytic algae, zooplankter and aquatic higher plants, fish are at the top of the food chain. The fish are sensitive to environmental changes, which can comprehensively indicate the health level of the riverine water ecosystem.

Chinese scientists conducted investigations on the fish community structure and biological integrity in the Wei River Basin (134,800km^2, the largest tributary of the Yellow River) during 2011–2012 based on 55 sampling sites [36]. The ecosystem health was evaluated based on fish assemblages. The index of biotic integrity (IBI) for fish was used to assess the ecosystem health in the whole Wei River Basin (including the Wei River, Jinghe River, and Beiluo River). The integrity classes were classified into four groups: good, fair, poor and very poor. The results show that 7 of 13 sites (total 13 sites sampled in the Jinghe Basin) in the Jinghe Basin were in poor or very poor condition. In their field investigation in the Wei River Basin, 51 kinds of fish species were detected [36,37], and *Cyprinidae* and *Cobitidae* are the dominant fish species. Compared to the 58 kinds of fish in the last investigation during the 1980s, seven kinds of fish were extinct. As the largest tributary of the Wei River Basin, the Jinghe Basin has the lowest number of fish species and individuals. There are only 23 kinds of fish species in the Jinghe Basin, and the dominant species are *Cobitidae* (11 kinds) and *Cyprinidae* (9 kinds). Additionally, the Shannon-Weiner diversity index showed the least value in the Jinghe Basin.

The degradation of fish integrity can be explained from the prospective of an alteration of the flow regime. It is seen in Tables 2 and 4, all the indicators describing magnitude of flow (monthly flow and extreme flow) decrease obviously and the number of low pulses each year increases by 90%, indicating the dry condition of the basin. It was reported that the index of biotic integrity (IBI) for fish was positively related to river depth [35,36]. Dissolved oxygen availability and water chemistry may be highly stressful to many organisms for low flow duration, leading to the increase of biotic interactions, such as competition and predation [51]. Some aquatic plants will be significantly reduced during continuous low flow [21], meanwhile leading to reduced periphytic algae. As a consequence, the biotic capacity of fish species decreases due to the reduction of abundant and varied food for fish. High flow pulses are vital for reducing any negative effects caused by low flows. Unfortunately, both the number and duration of high pulses reduce in the Jinghe Basin (Table 2), leading to failure in delivering a sufficient nourishing subsidy. The changes of IHAs (decreased magnitude of flow, increased number of low pulses, decreased number and duration of high pulses) described above explain the decrease in the biological integrity of fish to some degree. As suggested by OD_SD_m, most of the indicators related to the health of the fish community suggest a moderate and high alteration level (Tables 3 and 4), which is an important reason for the poor biological integrity of fish.

On the other hand, the index of water and habitat quality (IWHQ) was used to evaluate the environmental quality in the Wei River Basin, and results show that 7 of 13 sites in the Jinghe Basin were in highly degraded condition (IWHQ > 4) [36]. As the largest tributary of the Wei River Basin, this Jinghe Basin suffers poor water and habitat quality. The Jinghe Basin is characterized by high Cond, suspended solids (SS), total phosphorus (TP) and total dissolved solids (TDS).

Table 4. The hydrologic parameters and corresponding changes related to fish integrity.

Hydrologic Parameters	Variation	Alteration Degree					Ecological Implication
		D_m	S_m	SD_m	OD_S_m	OD_SD_m	
Mean discharge for each calendar month (m^3/s)	−42.87%	−0.58 (M)	0.41 (M)	0.20 (L)	0.74 (H)	0.66 (H)	Aridification; River depth decreases; Index of biotic integrity decreases
Magnitude of annual extreme discharge events with different durations (m^3/s)	−47.63%	−0.69 (H)	0.44 (M)	0.27 (L)	0.81 (H)	0.76 (H)	Nutrient exchanges between rivers and floodplains decrease
Number of low pulses each year	90%	−1.00 (H)	0.46 (M)	0.42 (L)	1.00 (H)	1.00 (H)	Increase of biotic interactions, such as competition and predation; Aquatic plants reduce; Periphytic algae reduce
Number of high pulses each year	−16.67%	−0.10 (L)	0.39 (M)	0.14 (L)	0.45 (M)	0.23 (L)	Delivery of nourishing subsidy decreases
Mean duration of high pulses (d)	−1day	−0.40 (M)	0.37 (M)	0.21 (L)	0.62 (M)	0.52 (M)	Delivery of nourishing subsidy decreases
Overall		0.57 (M)	0.40 (M)	0.23 (L)	0.74 (H)	0.67 (H)	7 kinds of fish were extinct in Wei river basin; Endangered species: *Brachymystax* (i.e., lenok); The least kinds of fish in Jinghe basin (23 in Jinghe, 51 in Wei river, 31 in Beiluo river)

It was mainly caused by three factors [36]: (1) flowing through the Loess Plateau, which exhibits serious soil erosion and high suspended solid, (2) poor water quality in the natural state and characteristics of high total dissolved solids, saline and hardness and (3) a massive development of the petroleum industry in the Malian River that is a tributary of the Jinghe River. The results show that the IBI scores were correlated with IWHQ.

According to the analysis above, it can be concluded that both the alteration of flow regime and the water and habitat quality influence the biotic integrity for fish. It should be noted that the alteration of flow regime is also one of the important factors influencing the water and habitat quality [52]. The soil and water conservation practices, including engineering structures such as terraces and check dams, and biological measures such as afforestation and planting grass, directly alter the flow regime of Jinghe Basin, leading to changes in water and habitat quality. On the other hand, the poor biological integrity of fish also demonstrates the reasonability of the high-level overall alteration suggested by the composite metrics to some degree.

5. Conclusions

The natural flow regime is the dominant factor that affects the health of a riverine ecosystem. Climate change and anthropogenic disturbance lead to alteration of the flow regime, commonly causing a series of ecological degradations of rivers. Measuring the extent of the alteration of the flow regime is significant for river protection and restoration. In this study, two new methods were developed for an assessment on flow regime alteration under climate change and human disturbance. The updated methods were employed to detect the flow regime alteration in a typical basin (Jinghe Basin) in the middle reaches of the Yellow River Basin, China. In addition, the alteration levels by three individual metrics and two composite metrics were compared, which were interpreted in terms of the concepts of these metrics. The main points can be summarized as follows:

(1) The concept of similarity/diversity was introduced to formulate the assessment method for flow regime alteration. Two metrics, *SD* and *S*, were constructed based on the dynamic time warping (DTW) distance and Euclidean distance, respectively. The metrics concentrate on describing the deviation from the prospective of process behaviors in the time series for IHAs, which are supplements of the RVA method that describes the frequency changes of these IHAs.

(2) The metrics, *SD* and *S*, were incorporated with the *D* metric of RVA, respectively. Thereafter, two composite metrics (*OD_SD* and *OD_S*) were constructed to comprehensively evaluate the alteration of the flow regime. The composite metrics represent not only the changes in the frequency deviated from the target range, but also the process changes deviated from the pre-impact process. Those composite metrics consistently reveal that the Jinghe Basin suffers a high-level alteration of flow regime, while the conventional RVA method evaluate it as moderate-level. The mean value of all the 12 monthly discharge decreases by 42.87%, the mean value of all the 10 annual extreme discharge decreases by 47.63% and the number of low pulses each year increase by 90% (Figure 4), which may be strong evidence for the high-level alteration of flow regime. The composite metrics are recommended rather than RVA for assessment on flow regime alteration due to the complex changes of flow regime under climate change and human activities.

(3) *SD* suggests a low degree of overall alteration, while *S* suggests a moderate degree. *SD* is theoretically more advanced as the time series inputs of the pre-impact and post-impact do not need to be of equal length. Hence, the *SD* metric based on dynamic time warping (DTW) distance is recommended for assessment on process changes in the time series of IHAs. The *OD_SD* is more recommended than *OD_S*.

(4) The high-level changes of IHAs (Table 4) (decreased magnitude of flow, increased number of low pulses) explain the decrease in the biological integrity of fish to some degree. The magnitude of monthly flow and extreme flow decreases (42.87% and 47.63%, respectively), leading to lower river depth and decreased nutrient exchanges between rivers and floodplains. The number of low pulses each year increases obviously (90%), leading to increased biotic interaction, such as competition and predation.

In a word, high-level alteration of flow regimes leads to decreased biological integrity of fish in the Jinghe Basin, and meanwhile the poor biological integrity of fish to some degree demonstrates the reasonability of the high-level overall alteration suggested by composite measures.

The methods developed in this work can be widely used in other basins with diverse scales worldwide, which enable more scientific evaluation for the complex hydrologic alteration under climate change and anthropogenic disturbance. The achievement of this study facilitates sustainable water resources management and eco-environmental management.

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Appendix A

Table A1. Some terminology and the description.

Terminology	Description
Discharge	In hydrology, discharge is the volumetric flow rate of water that is transported through a given cross-sectional area.
Streamflow	Streamflow, or channel runoff, is the flow of water in streams, rivers, and other channels, and is a major element of the water cycle.
Biological integrity	Biological integrity is associated with how "pristine" an environment is, and its function relative to the potential or original state of an ecosystem before human alterations were imposed. Biological integrity is built on the assumption that a decline in the values of an ecosystem's functions are primarily caused by human activity or alterations. The more an environment and its original processes are altered, the less biological integrity it holds for the community as a whole.
Base-flow	Base-flow is the portion of the streamflow that is sustained between precipitation events, fed to streams by delayed pathways.
Extreme flow	It is usually descripted as annual extreme discharge events with different durations, such as annual 1-,3-,7-,30-,90-day minimum flow, annual 1-,3-,7-,30-,90-day maximum flow.
Julian data of annual 1-day minimum/maximum	It is a terminology used in indicators of hydrologic alteration (IHAs). If there are multiple days in the water year with the same flow value, the earliest date is reported.
Low pulse	It is a terminology used in indicators of hydrologic alteration (IHAs). A day is classified as a low pulse if it is less than a specified threshold, which can be set by the user.
High pulse	It is a terminology used in indicators of hydrologic alteration (IHAs). A day is classified as a high pulse if it is greater than a specified threshold, which can be set by the user.

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