Postprint on Flood Variation Characteristics of Alpine Watersheds on the Northern Slope of the Kunlun Mountains

Authors: Qiu Zewei, Fang Gonghuan, Chen Yaning, Zhu Chenggang, Liang Wenting, Di Yanfeng, Lü Haodong, Fang Gonghuan

Date: 2024-12-03T00:00:00+00:00

Abstract

Floods, as one of the most destructive natural disasters, have exhibited significant changes in intensity and timing in high-altitude mountainous regions under global warming, profoundly impacting human society and ecosystems. Therefore, this study employs the MissForest method to impute daily discharge series at the outlets of six major watersheds on the northern slope of the Kunlun Mountains, analyzing trends in flood intensity, occurrence timing, rising and recession times, and annual maximum flood daily average discharge at six outlet stations from 1961 to 2022. The results indicate that: (1) 97% of annual maximum 1-day flow (AMF) events occurred in summer. AMF at Wulawati and Tongguziluoke stations showed increasing trends, while Pishan, Cele, Nunumaimaiti Langan, and Qiemo stations exhibited decreasing trends; changes at all stations except Pishan and Wulawati were significant. Spring maximum 1-day flow (AMFSp) at all stations displayed increasing trends, with significant increases at Wulawati, Tongguziluoke, and Nunumaimaiti Langan stations. Regarding flood occurrence timing, except for Pishan station where the date of annual maximum 1-day flow (AMFD) showed a significant delaying trend, the AMFD at the remaining five stations displayed non-significant advancing trends; for the date of spring maximum 1-day flow (AMFDSp), all six stations exhibited non-significant advancing trends. (2) In terms of flood rising time, Tongguziluoke and Qiemo stations showed prolonged durations, while the remaining four stations showed shortened durations; for flood recession time, Pishan and Cele stations showed prolonged durations, while the other stations showed shortened durations, with overall trends being non-significant. Regarding annual maximum flood daily average discharge, Pishan station showed a significant increase, Nunumaimaiti Langan and Qiemo stations showed significant decreases, and other stations showed non-significant decreasing trends. The research findings hold significant importance for enhancing hydrological ecological benefits in arid regions, flood

prevention and mitigation, and regional water management and disaster risk assessment.

Full Text

Characteristics of Flood Change in Alpine Watersheds on the Northern Slope of the Kunlun Mountains

QIU Zewei[1,2], FANG Gonghuan[1], CHEN Yaning[1], ZHU Chenggang[1], LIANG Wenting[1,2], DI Yanfeng[1,2], LYU Haodong[1,2]

[1]State Key Laboratory of Desert and Oasis Ecology, Key Laboratory of Ecological Safety and Sustainable Development in Arid Lands, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Urumqi 830011, Xinjiang, China
[2]University of Chinese Academy of Sciences, Beijing 100049, China

Abstract

Flooding is one of the most destructive natural disasters. Under global warming, the magnitude and timing of floods in high-altitude mountain regions have undergone significant changes, profoundly impacting human society and ecosystems. This study employs the MissForest algorithm to impute missing daily discharge data at six mountain-pass hydrological stations on the northern slope of the Kunlun Mountains, analyzing trends in flood magnitude, occurrence timing, rise and recession durations, and daily average annual maximum flood discharge from 1961 to 2022. The key findings are as follows: (1) 97% of annual maximum 1-day flow (AMF) events occurred in summer. The AMF at Wuluwati and Tongguziluoke stations exhibited increasing trends, while Pishan, Qira, Nunumaimaitilangan, and Qiemo stations showed decreasing trends. Changes in AMF were statistically significant at all stations except Pishan and Wuluwati. The spring maximum 1-day flow (AMFSp) at all stations displayed increasing trends, with particularly significant increases at Wuluwati, Tongguziluoke, and Nunumaimaitilangan stations. Regarding flood timing, the annual maximum 1-day flow date (AMFD) at five stations (excluding Pishan) exhibited non-significant trends toward earlier occurrence. For the spring maximum 1-day flow date (AMFDSp), all six stations showed non-significant trends toward earlier timing. (2) In terms of flood rise time, Tongguziluoke and Qiemo stations experienced extended durations, while the other four stations showed reduced durations. For flood recession time, Pishan and Qira stations displayed extended durations, whereas other stations showed shortened durations, with no significant overall trend. The daily average discharge during maximum floods significantly increased at Pishan Station, significantly decreased at Nunumaimaitilangan and Qiemo stations, and showed no significant changes at other stations. These findings are crucial for enhancing hydrological and ecological benefits,

flood prevention and mitigation, and regional water management and disaster risk assessment in arid regions.

Keywords: MissForest; maximum 1-day flow; flood process; northern slope of the Kunlun Mountains

1 Introduction

Flooding represents one of the most destructive natural disasters globally. Against the backdrop of global warming, both the magnitude and timing of floods have undergone significant alterations. Since the 21st century, flood events have become more frequent and intense worldwide, causing direct economic losses estimated at $1100×10^{9} annually and nearly 10,000 deaths per year. In terms of flood frequency and duration, tropical, subtropical, and mid-latitude regions have shown increasing trends, with the duration of extreme floods exceeding 7 days, while in the 1950s, extreme floods typically lasted less than 4 days. Under higher warming scenarios, the impacts of flooding continue to intensify, directly affecting human well-being and the sustainable development of global socio-ecological systems.

Due to climate warming, atmospheric water-holding capacity increases by approximately 7% for every 1°C rise in temperature, leading to more intense extreme precipitation and potentially more frequent flood disasters. Globally, regions such as northeastern Brazil, southern Australia, and the Mediterranean show drying trends, while areas like northern Europe exhibit wetting trends, with corresponding changes in flood magnitude. Under RCP6.0 scenarios, Southeast Asia, East Africa, and Siberia will experience increased flood intensity, frequency, duration, and variability. In southern Africa, South America, and southern Australia, enhanced precipitation variability will exacerbate extreme hydrological events, with extreme floods showing increasing trends. In High Mountain Asia, floods triggered by heavy rainfall, snowmelt, and glacial lake outbursts will also undergo significant frequency changes.

In data-rich regions, patterns of flood timing changes are relatively consistent, with earlier flood occurrence primarily distributed across North America, Europe, and northeastern Australia, while delayed flood occurrence mainly observed in the Amazon, Cerrado, South Africa, India, and Japan. In watersheds with high snowmelt contributions, reduced winter snowfall leads to earlier runoff, whereas in watersheds with low snowmelt contributions, reduced winter snowfall delays runoff.

The northern slope of the Kunlun Mountains in Xinjiang represents a key area for national security strategic layout and the construction of the "Silk Road Economic Belt" core zone in Xinjiang, as well as a region sensitive to climate change. Previous research has made progress in flood typology and magnitude. For example, Zhang et al. analyzed flood intensity, frequency, and timing for four source streams of the Tarim River, finding increased flood intensity in summer and winter since the late 1990s. Fang et al. investigated climate factor impacts on flood intensity and timing using numerical experiments combined with random forest methods, revealing that flood intensity on the northern slope of the Kunlun Mountains correlates with the zero-degree level height. Luo et al. demonstrated through multi-model ensemble assessment that temperature is a key driver of streamflow changes in the upper Hotan River Basin, causing sharp increases in Hotan River flow during spring (March-May), with earlier and prolonged snowmelt periods.

However, due to scarce long-term observation data in the Kunlun Mountains region, particularly for small rivers, most previous studies have focused on large catchments with observation data, such as the Hotan River (Yurungkax River catchment area: 20,096 km^{2}), while long-term flood research on small watersheds with different geographical locations and runoff compositions remains extremely limited. This study addresses this gap by applying missing value imputation methods to daily streamflow data from 1961 to 2022 for large watersheds on the northern slope of the Kunlun Mountains, analyzing flood event characteristics and trends using maximum value sampling methods, and employing trend detection methods.

2 Materials and Methods

2.1 Study Area

This study selected six source streams on the northern slope of the Kunlun Mountains: the Pishan River, the Karakax and Yurungkax Rivers (Hotan River), the Qira River, the Keriya River, and the Qarqan River (Figure 1). All rivers originate from the southern mountainous region, primarily fed by seasonal mountain precipitation and high-altitude snow and ice melt. These rivers traverse oases before terminating in the northern desert. The towering southern mountain system blocks warm-moist airflows from the Pacific and Indian Oceans, decisively influencing the regional climate pattern. The southern mountainous area belongs to temperate or cold-temperate climate zones; the central oasis plain features a desert climate and represents the primary area of human economic activity; and the northern Taklamakan Desert exhibits an extremely typical continental desert climate.

Against the backdrop of global change, glacial and snow hydrological processes and extreme hydrological events in this region have become increasingly complex. First, against the context of global glacier retreat, temperature increases are more pronounced, and hydrological processes are more sensitive to climate change. The Kunlun and Karakoram Mountains have experienced glacier stagnation or even advancement. Second, extreme hydrological events have increased in frequency and intensity. In recent years, daily maximum precipitation at multiple stations has set new historical records. For instance, a rainstorm event in Pishan, Hotan, recorded 53.8 mm, exceeding the multi-year average precipitation of 106 mm. Increased precipitation variability, combined with more frequent heavy rainstorms in low and mid-mountain zones, has expanded flood scales and increased the risk of sudden rainstorm-induced flash floods, causing substantial impacts on local agriculture and animal husbandry.

shows the six source streams on the northern slope of the Kunlun Mountains and their corresponding mountain-pass hydrological stations.

2.2 Data Sources

This study utilized geographic information base data, meteorological data, glacier data, land use data, and hydrological observation data. The Digital Elevation Model (DEM) employed SRTM V3 data (resolution: 0.25° ×0.25°) from NASA JPL. Climate data used the CN05.1 gridded dataset (latitude-longitude resolution: 0.25°), interpolated from observations at over 2,400 Chinese surface meteorological stations, including daily precipitation, mean temperature, maximum temperature, and minimum temperature, provided by the China Meteorological Administration' s Meteorological Data Service Center.

The First Chinese Glacier Inventory dataset was obtained from the "Heihe Plan Data Management Center" and the Second Chinese Glacier Inventory dataset (version 1.0) from the National Cryosphere Desert Data Center. Land use data were derived from the Chinese Academy of Sciences' Resource and Environmental Science and Data Center' s land use remote sensing monitoring dataset. Hydrological observation data comprised daily streamflow data from six hydrological stations within the study area, collected from the "Inland River and Lake Hydrological Data" volumes of the "People' s Republic of China Hydrological Yearbook." All hydrological stations had incomplete daily flow data, with missing rates ranging from 0.20 to 0.43 (Table 2).

2.3 Methods

2.3.1 MissForest Missing Value Imputation Method Due to scarce hydrological data in high mountain regions with numerous daily flow missing values, this study employed MissForest, an iterative imputation method based on Random Forest that constructs a multiple imputation scheme by averaging many unpruned classification or regression trees. Using built-in out-of-bag error estimation, MissForest can estimate imputation error without requiring a test set. The method involves three main steps: first, replacing missing values with means (for continuous variables) or most frequent categories (for categorical variables); second, using observed values as training sets and missing values as prediction sets in the MissForest model, then replacing predictions to create transformed datasets; and third, completing an imputation cycle once all missing values are imputed. This study repeated the imputation process 10 times per station.

MissForest offers several advantages: it effectively imputes missing values for different data types (continuous, categorical, or mixed) without performance limitations due to data length, requires minimal data assumptions or transformations, and demonstrates superior performance in accuracy and computational efficiency compared to other imputation algorithms across various fields including ecology, medicine, meteorology, and hydrology. In hydrology, MissForest has proven effective for imputing daily streamflow data gaps.

During imputation, this study selected daily precipitation, mean temperature, maximum temperature, and minimum temperature as input variables. To quantify imputation accuracy, we used the Kling-Gupta Efficiency coefficient (KGE), Nash-Sutcliffe Efficiency coefficient (NSE), coefficient of determination (R^{2}), and Root Mean Square Error (RMSE) as evaluation metrics. Values closer to 1 for the first three metrics indicate better performance, while smaller RMSE values indicate estimates closer to true values. KGE > 0.3 indicates acceptable simulation results, KGE > 0.5 indicates high credibility, and NSE > 0.5 indicates good performance. The calculation formulas are:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{sim}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{sim}}{\mu_{obs}} - 1\right)^2}$$

$$NSE = 1 - \frac{\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}{\sum_{i=1}^{n}(Q_{obs,i} - \bar{Q}_{obs})^2}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Q_{obs,i} - Q_{sim,i})^2}$$

where r is the Pearson correlation coefficient; σ_{sim} and σ_{obs} are standard deviations of simulated and observed values; μ_{sim} and μ_{obs} are means of simulated and observed flows; n is the number of observations; $Q_{obs,i}$ is the observed flow on day i; and $Q_{sim,i}$ is the simulated flow on day i.

2.3.2 Flood Indicators and Trend Analysis This study employed the block maximum method to obtain flood samples, with floods represented by annual maximum daily flow. The block maximum method selects the maximum daily flow within a time step (e.g., year, season, month) as the unique flood peak for that period. We used four flood indicators to quantify flood intensity and timing: annual maximum 1-day flow (AMF), spring maximum 1-day flow (AMFSp), annual maximum 1-day flow date (AMFD), and spring maximum 1-day flow date (AMFDSp). The Mann-Kendall trend test detected changes in flood intensity, timing, and process.

Additionally, based on the USGS criteria, we identified the rise and recession times and daily average discharge for annual maximum floods. The US Water Resources Association' s criteria for flood peak independence were applied:

$$D > 5 + \ln(A)$$

$$Q_{min} < \frac{3}{4} \times \min(Q_{p1}, Q_{p2})$$

where D is the interval between consecutive flood peaks; A is the catchment area (in square miles, 1 mi^{2} = 2.59 km^{2}); Q_{p1} and Q_{p2} are the magnitudes of consecutive flood peaks; and Q_{min} is the minimum flow between them.

3 Results

3.1 Daily Flow Reconstruction Results

Daily flow data from the six hydrological stations were incomplete, with missing rates ranging from 0.20 to 0.43. The MissForest algorithm was applied to impute daily flow data from 1961 to 2022, yielding complete daily flow sequences. To ensure imputation quality, we artificially created 365-day data gaps in continuous sequences for each station, randomly repeating the experiment 10 times.

The results (Table 3) demonstrate that MissForest performed well in daily streamflow reconstruction. Through ten-fold cross-validation, KGE, NSE, and R^{2} for all six stations on the northern slope of the Kunlun Mountains exceeded 0.9, with R^{2} values above 0.95 at four stations. We found a negative correlation between imputation effectiveness and daily flow data missing rate —lower missing rates corresponded to higher KGE values and better simulation performance. Although missing data rates and imputation effects varied across stations, the algorithm overall demonstrated satisfactory performance in improving data completeness and usability.

3.2 Changes in Flood Intensity and Timing

From 1961 to 2022, 97% of AMF events occurred in summer across the six hydrological stations on the northern slope of the Kunlun Mountains. Consequently, subsequent analyses focused on annual and spring flood changes. During this period, AMF at Wuluwati and Tongguziluoke stations showed increasing trends, with only Tongguziluoke displaying a statistically significant increase at a rate of 21.09 $m^{\{3\} \cdot s}${-1} · a^{-1} (P < 0.01). Wuluwati station' s AMF showed an increasing trend but was not statistically significant (Figure 2). Meanwhile, Pishan, Qira, Nunumaimaitilangan, and Qiemo stations showed decreasing trends, with Qira, Nunumaimaitilangan, and Qiemo stations demonstrating statistically significant decreases at rates of 6.23 $m^{\{3\} \cdot s}${-1} · a^{-1}, 13.20 $m^{\{3\} \cdot s}${-1} · a^{-1}, and 2.37 $m^{\{3\} \cdot s}${-1} · a^{-1}, respectively (P < 0.01).

All stations exhibited increasing trends in AMFSp, with Wuluwati and Tongguziluoke showing statistically significant increases at rates of 15.35 $m^{\{3\} \cdot s}${-1} ·

a^{-1} and 0.98 m$^{\{3\}\cdot\mathrm{s}}${-1} · a^{-1}, respectively (P < 0.05). Nunumaimaitilangan station also showed a significant increase in AMFSp at a rate of 0.98 m$^{\{3\}\cdot\mathrm{s}}${-1} · a^{-1} (P < 0.05), while other stations showed non-significant increasing trends.

Regarding flood timing, AMFD at Wuluwati, Tongguziluoke, Qira, Nunumaimaitilangan, and Qiemo stations showed non-significant trends toward earlier occurrence, averaging 0.78 days earlier per decade. Pishan station' s AMFD showed a delayed trend, averaging 0.62 days later per decade, reaching statistical significance (P < 0.05). For AMFDSp, all six stations showed non-significant trends toward earlier timing, averaging 1.90 days earlier per decade (Figure 3; Table 4).

3.3 Flood Process Characteristics

In terms of flood rise time, Tongguziluoke and Qiemo stations showed extended durations, increasing from 10.03 days to 10.51 days and from 8.17 days to 8.76 days, respectively. Pishan, Wuluwati, Qira, and Nunumaimaitilangan stations showed gradually shortening rise times, decreasing from 9.11 days to 7.92 days, 7.47 days to 6.53 days, 10.80 days to 9.43 days, and 7.93 days to 7.13 days, respectively. For flood recession time, Pishan and Qira stations showed extended durations, increasing from 7.11 days to 8.47 days and from 8.60 days to 7.50 days, respectively, while other stations showed shortened recession times. All changes in flood rise and recession times were non-significant (Figure 4; Table 5).

Regarding daily average discharge during annual maximum floods (Table 5), Pishan station showed a significant increasing trend (P < 0.05), rising from 29.84 m$^{\{3\}\cdot\mathrm{s}}${-1} to 38.37 m$^{\{3\}\cdot\mathrm{s}}${-1}. The remaining five stations showed varying degrees of decrease, with Wuluwati, Tongguziluoke, and Qira showing non-significant decreasing trends. Nunumaimaitilangan station showed a significant decreasing trend (P < 0.05), dropping from 74.36 m$^{\{3\}\cdot\mathrm{s}}${-1} to 43.22 m$^{\{3\}\cdot\mathrm{s}}${-1}, while Qiemo station also showed a significant decreasing trend (P < 0.05), falling from 88.31 m$^{\{3\}\cdot\mathrm{s}}${-1} to 40.31 m$^{\{3\}\cdot\mathrm{s}}${-1}.

4 Discussion

MissForest serves as a stable imputation method that outperforms other algorithms in handling high missing rates and long-duration continuous gaps. This study successfully applied MissForest to impute daily streamflow data for hydrological stations on the northern slope of the Kunlun Mountains, significantly improving data completeness and accuracy. This successful application not only solved the challenge of missing hydrological data in alpine watersheds but also provided a reliable data foundation for subsequent flood characteristic analysis. However, this method has notable limitations: imputation effectiveness negatively correlates with daily flow data missing rates, and MissForest cannot accurately simulate significant fluctuations in daily flow. During extreme events, MissForest tends to underestimate peaks and overestimate low values. For instance, during an extreme flood event on July 29, 1999, MissForest failed to accurately simulate the flood peak at Pishan station. Ultimately, the most fundamental way to improve peak simulation accuracy lies in the accuracy of observational data itself.

The diverse trends in flood indicators across stations reflect the complex runoff composition in the Kunlun Mountains region, influenced by high-altitude glacial snowmelt, low-mountain heavy rainfall, and glacial lake outburst floods. Although all stations are located on the northern slope of the Kunlun Mountains, different stations show varying trends. Wuluwati and Tongguziluoke stations showed increasing AMF trends, while Pishan, Qira, Nunumaimaitilangan, and Qiemo stations showed decreasing trends. Analysis using CN05.1 gridded data revealed that the catchments of Wuluwati and Tongguziluoke stations experienced overall precipitation increases at rates of 0.465 mm · a^{-1} and 0.358 mm · a^{-1}, respectively, with temperature increases of 0.032 ℃ · a^{-1} and 0.035 ℃ · a^{-1}. Considering these two watersheds are extensively glaciated (glacier meltwater accounts for 45%-60% of total runoff), and glacier areas increased from 1,849.1 km^{2} to 2,216.8 km^{2} and from 2,805.0 km^{2} to 3,047.0 km^{2}, respectively, the increases in both temperature and precipitation led to higher overall meltwater and rainfall runoff, resulting in increasing AMF trends at Wuluwati and Tongguziluoke stations.

For the Pishan River Basin, although precipitation showed a clear increasing trend (0.555 mm · a^{-1}) and temperature increased significantly (0.029 ℃ · a^{-1}), the small glacier area (only 70.5 km^{2}, accounting for 7.94% of the total watershed area) meant that the meltwater increase effect from rising temperatures was weak. Simultaneously, temperature increases enhanced evapotranspiration in the watershed dominated by high-coverage grassland. Under this combined effect, the watershed's AMF showed a non-significant decreasing trend. For the remaining three watersheds (Qira, Nunumaimaitilangan, and Qiemo), precipitation increased slightly, glacier meltwater proportion was relatively low, and temperature increases were significant (0.030-0.037 ℃ · a^{-1}). Since the mid-20th century, global water cycling processes have been significantly affected by climate change, with the frequency of extreme hydrological events like floods increasing. As global temperatures rise, glaciers are accelerating melt and retreat. Since the late 1980s, northwestern arid regions including the northern slope of the Kunlun Mountains have shown characteristics of increased extreme precipitation and climatic warming-humidification. Climate warming has enhanced spring snowmelt in snowmelt-dominated rivers, leading to increased and earlier spring meltwater floods, consistent with global observations of enhanced spring floods in snowmelt-dominated watersheds. The increased spring meltwater provides opportunities for the development of irrigated agriculture and ecological restoration on the northern slope of the Kunlun Mountains.

Regarding the large fluctuations in various flood indicators and flood processes at Qiemo station, we analyzed the area distribution across elevation zones for each watershed (Figure 6). The Qarqan River Basin where Qiemo station is located has the largest area, but due to concentrated elevation distribution (48.95% of area between 4,600-5,200 m), the dominant hydrological process mechanism is relatively singular, leading to larger runoff fluctuations in this watershed.

Flood occurrence timing is jointly influenced by precipitation and snowmelt factors. The AMFDSp on the northern slope of the Kunlun Mountains showed a non-significant earlier trend, consistent with global observations of earlier flood timing in snowmelt-dominated rivers under climate warming. Flood rise and recession speeds are closely related to precipitation patterns, particularly maximum precipitation rates and the centroid timing of rainfall events. Additionally, flood rise and recession speeds are affected by watershed underlying surface characteristics, such as increased vegetation in alpine bare soil areas, permafrost degradation, glacial lake formation at glacier termini, and forest coverage under climate change. In this study, none of the six watersheds showed significant changes in flood rise speed, indicating that changes in soil infiltration capacity, permafrost, and grassland/forest cover area in this region have not yet caused changes in flood processes.

5 Conclusions

This study reached the following conclusions:

(1) Regarding flood intensity changes on the northern slope of the Kunlun Mountains, 97% of AMF events occurred in summer. From 1961 to 2022, AMF at Wuluwati and Tongguziluoke stations showed increasing trends, while Pishan, Qira, Nunumaimaitilangan, and Qiemo stations showed decreasing trends. All stations exhibited increasing trends in AMFSp, with particularly significant increases at Wuluwati, Tongguziluoke, and Nunumaimaitilangan stations. Concerning flood timing, AMFD showed non-significant earlier trends at five stations, while Pishan station showed a significant delayed trend. AMFDSp exhibited non-significant earlier trends at all six stations.

(2) In terms of flood rise time, Tongguziluoke and Qiemo stations experienced extended durations, while Pishan and three other stations showed shortened durations. Regarding flood recession time, Pishan and Qira stations showed extended trends, while four stations showed shortened trends, with no significant changes overall. For daily average annual maximum flood discharge, Pishan station showed a significant increase, Nunumaimaitilangan and Qiemo stations showed significant decreases, and other stations showed non-significant decreasing trends.

These research findings are significant for improving water ecological benefits, flood prevention and disaster reduction in arid regions, and provide scientific basis for regional water management and disaster risk assessment.

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Note: Figure translations are in progress. See original paper for figures.