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Observed Changes in Extreme Precipitation over the Tienshan Mountains
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ABSTRACT

Under global warming, extreme hydrological events are experiencing increasingly violent fluctuations. Investigating changes in the intensity and frequency of extreme precipitation (EP) events is particularly critical for understanding the hydrological response to climate change. Based on high-precision and long-term daily grid precipitation data obtained from Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), 25 EP indices were examined for the Tienshan Mountains region of Central Asia (TMCA). Here, the relationship between EP and associated large-scale climate teleconnections is revealed by using a series of approaches such as trend analysis and the geographical detector method (GMD), a statistical tool to measure and attribute spatial stratified heterogeneity. The results show an overall increase in EP during 1951-2014, as reflected in the 25 indices. Furthermore, the number of consecutive dry days (CDD) decreased from 87.02 to 69.35 while the number of consecutive wet days (CWD) increased from 3.89 to 4.61. Meanwhile, the increasing trend of total precipitation (PRCPTOT) was 18.43 mm/10a, and changes in EP frequency were shown to increase with event rareness. For R95p, the observed changes in frequency are 34.46%, but these jump to 96.58% for R99p. Moreover, the study also notes that changes in EP are elevation-dependent, with middle altitude areas (1,500–3,500 m) being most sensitive to change rates. As well, the study reveals that the occurrence of EP responds non-linearly to climatic teleconnections, and that the combined effect of two factors generally make much larger contributions to EP than the summation of individual factors. Further analyses indicate strong zonal circulation at 500hPa, 1,000hPa potential height increases airflow from west to east. And the weakening of the East Asian Summer Monsoon accompanied by the westward extension of the western Pacific subtropical high and the increase in Mongolian anticyclone activity all bring sufficient exogenous water vapor from the North Atlantic and Indian Ocean to the TMCA.
Keywords: global warming, extreme precipitation, large-scale climate teleconnections, 
Tienshan Mountains, Central Asia

1. Introduction

Extreme precipitation (EP) often causes natural disasters such as floods, landslides and 
mudslides, posing an enormous threat to human society (Donat et al., 2016; Gao et al., 2020; 
Fischer et al., 2015). With global warming, there is an increase in the water vapor content in 
the atmosphere as well as an acceleration of the water cycle (Alexandra, 2018; Allen et al., 
2002; Fischer et al., 2016; Irannezhad et al., 2020; Lenderink et al., 2017; Zhang et 
al., 2012c). More importantly, the changes and trends of EP events are more sensitive to 
climate change than average precipitation (Chen et al., 2016; Schär et al., 2016; Duan et al., 
2019; Fischer et al., 2014). From a global perspective, although the total amount of 
precipitation has not changed significantly (Trenberth et al., 2011), detectable increases in EP 
have been found (Westra et al., 2013). Still, the intensity, frequency, and duration of EP show 
an upward trajectory that is largely attributable to human activities (Gudmundsson et al., 
2021). Meanwhile, the spatial patterns of changes in EP are complex, with regionally distinct 
trend signs (Donat et al., 2013; Konapala et al., 2017; Lehmann et al., 2015; Min et al., 2011; 
Pfahl et al., 2017). Consequently, EP research has become an increasingly important topic 
(Fang et al., 2019; Myhre et al., 2019; Duan et al., 2019; Fischer et al., 2015).

Generally, human-induced climate change has affected many weather and climate 
trend in intensity over large parts of Eastern Europe, Asia, South America, the 
Mediterranean, Southeast Asia, and northwestern parts of North America (Donat et al., 2013). 
Specifically, Ma et al. (2020) found that total summer precipitation, precipitation extreme 
(maximum 1-day precipitation, heavy precipitation days [daily precipitation ≥ 10mm],
consecutive wet days (daily precipitation $\geq 1$mm) significantly increased in Central Asia. Besides, Myhre et al. (2019) indicated that the increase in the frequency and intensity of EP (i.e., the amount of daily precipitation above the 99th percentile [$R_{99p}$] and the amount of daily precipitation above the 99.97th percentile including all days [$R_{99.97pall}$]) was generally greater in Europe and Japan than that experienced in the United States or Australia. From 1981 to 2010, the number of global precipitation events exceeding the record increased substantially, with quite pronounced regional differences such as an increase of 80% in Southeast Asia (summer) and a decline of 24% in Australia (winter) (Lehmann et al., 2015). With every additional increment of global warming, changes in extremes will continue to become larger (IPCC, 2021). The high sensitivity of EP to the additional 0.5$^\circ$C warming (at 1.5$^\circ$C and 2.0$^\circ$C global warming levels) will be observed in Southeast Asia; for example, the magnitude of the increase in R20mm (very heavy precipitation days), will reach 29.28% from the original 20.66% (Ge et al., 2019). Furthermore, Duan et al. (2019) indicated that averaged maximum yearly precipitation will be likely to increase by approximately 18% under +4K compared to the past in China.

Meanwhile, EP variability is affected by multiple factors, including the climate system variability (Ali et al., 2018; Berg et al., 2009; Ding et al., 2019; Parisa et al., 2020), the global large-scale atmospheric-oceanic circulation patterns (Shi et al., 2017; Zhang et al., 2017; Ding et al., 2019; Chen et al., 2020; Irannezhad et al., 2021; Ma et al., 2020; Zhang et al., 2020a), human activities (Min et al., 2011; Ficher et al., 2015; Gudmundsson et al., 2021; Konapala et al., 2017), the regional geographical characteristics (Ding et al., 2019; Li et al., 2020a; Ma et al., 2020; Wang et al., 2021) and so on. Specifically, the main factors such as the solar activity (Zhang et al., 2021), the dew point temperature (Ali et al., 2018), the latitude, longitude, altitude (Ding et al., 2019; Wang et al., 2021) and the anthropogenic forcing (Ficher et al., 2015; Konapala et al., 2017), etc. Perlwitz et al. (2017) have indicated
that regional climate variability cannot be understood without considering the role of large-scale atmospheric circulation. Lots of considerable previous research have paid attention to the potential linkage of EP and associated large-scale climate teleconnection patterns (Shi et al., 2017; Ding et al., 2019; Chen et al., 2020; Zhang et al., 2021; Wang et al., 2021). As an instance, Wang et al. (2019) indicated that the eastward wind field anomalies at 850 hPa over the Eurasian continent, together with enhanced anticyclonic circulation near 47°N and 100°E, provided favorable conditions for the occurrence of EP events over Northwest China. Ning et al. (2021) also demonstrated that summer extreme precipitation events in arid Northwest China are significantly dominated by a deep zonal wave pattern associated with the deepening of the western Siberian trough, central Asian high, and Mongolian high. The Arctic polar vortex, East Asian trough, and circulation at 850 hPa have a great impact on EP in winter in Northeast China (Zhang et al., 2020a). The strength and location of western North Pacific subtropical high are closely related to the variation of summer precipitation in Eastern China (Zhang et al., 2017). El Niño/Southern Oscillation (ENSO) is an important factor driving the internal variability of climate (Trenberth et al., 2014). Zhang et al. (2021) demonstrated that ENSO is one of main drivers for annual precipitation or EP periodic variation in Xinjiang, an arid-semiarid region of China. Chen et al. (2020) showed that the close linkage between the weaken East Asian summer monsoon and the increasing summer precipitation in arid Central Asia. Thus, we can clearly conclude that the EP variability associated large-scale climate teleconnection factors across different regions shows obvious disparities.

The Tienshan Mountains known as the “water tower” of Central Asia (Chen et al., 2016; Yu et al., 2020) are located in the hinterland of Eurasia, far from any sea. They lie adjacent to the Central Asian nations of Kazakhstan, Uzbekistan, Tajikistan, Kyrgyzstan and Xinjiang (in China). Since the past half a century, the warming rate in Central Asia is significantly higher
than that in the global or northern hemisphere, which is bound to lead to changes in the
spatiotemporal distribution and form of precipitation (Chen et al., 2017). Moreover, extreme
precipitation indices such as total summer precipitation and persistent precipitation extreme
have been significantly augmented in Central Asia (Ma et al., 2020; Yao et al., 2021; Zhang
et al., 2018a; Zou et al., 2021). Generally, several kinds of natural and secondary disasters
caused by extreme climate events are reported in Central Asia, leading to significant damage
to the economy and society (Zhang et al., 2018a; Zou et al., 2021). For example, natural
disasters such as floods, landslides, and debris flow have affected 13.5% of the total land area
of Kazakhstan, while 85% of the total land area of Tajikistan is at risk of debris flow, and the
formation area of strong debris flow accounts for 32%. Additionally, about 50,000 signs of
landslides were recorded in the country, of which 1500 threaten residential areas (Zhang et
al., 2018a). Still, with the disintegration of the Soviet Union in the last century, complex
issues such as multiple political entities, transboundary rivers, and lack of hydro-
meteorological data have become intertwined, making the handling of water-related issues a
challenging task. Therefore, understanding the spatiotemporal variability of EP and its related
large-scale climate teleconnections mechanism in such politically volatile but ecologically
fragile region is essential hence to comprehend the response of extreme events to global
warming and finding better strategies to cope with water resources management.

The present study investigates extreme precipitation events and associated large-scale
climate teleconnections of the TMCA for the past approximately 60 years (1951-2014).
Based on APHRODITE (Asian Precipitation-Highly Resolved Observational Data Integration
Towards Evaluation of Water Resources) data, this work detected changes in 25 EP indices
including the number of consecutive dry days (CDD), the number of continuous wet days
(CWD), and the total precipitation (PRCPTOT). The study also investigates the
corresponding relationship with different climatic teleconnections factors. And, the specific
objectives of this work are: (1) to clarify the temporal and spatial changes of EP in the
TMCA during 1951-2014; and (2) to determine the degree of influence of climatic
teleconnections factors on EP events, and explain the associated large-scale climatic
circulation mechanisms.

2. Data and Methods

2.1. Study Area

The Tienshan Mountains region in Central Asia (TMCA) sprawls across the nations of
Kazakhstan, Uzbekistan, Tajikistan and Kyrgyzstan, as well as the Xinjiang Uygur
Autonomous Region in northwest China. The mountains span over 2,500 km from east to
west and around 250-350 km from north to south (Chen et al., 2016, 2017; Li et al., 2020c).
As shown in Figure 1, the TMCA is subdivided into the sub-regions of West Tienshan
Mountains, Middle Tienshan Mountains, North Tienshan Mountains, and East Tienshan
Mountains. The altitude of the mountains ranges from 284 m to 7126 m, and includes valleys
and lowlands below 1,500 m (low altitude), shrub forest distribution areas at 1,500-3,000 m
(medium altitude), and glaciers above 3,000 m (high altitude). The present study mainly
refers to the mountain areas in the middle and high altitude (Deng et al., 2018).

The complex and diverse topography of the TMCA results in large differences in the
temporal and spatial distribution of precipitation and snowfall. The annual precipitation in the
study area is 280 mm and shows a slight increasing trend from 1960 to 2017 (Li et al.,
2020c). However, the northern portion of the study area shows a significant increase in
annual precipitation, while most areas in western TMCA show a decreasing trend (Li et al.,
Figure 1. Sketch map of Tienshan Mountains, Central Asia. (a) Temperature anomaly (1951-2014); (b) precipitation anomaly (1951-2014); (c) geographical location. The letters “W”, “M”, “N” and “E” stand for West, Middle, North, and East Tienshan Mountains, respectively. The map is based on the standard map number GS (2016) 1666 downloaded from the standard map service website of the National Bureau of Mapping Geographic Information, and the base map is not modified.

2.2. Datasets

2.2.1 Observed Data

Generally, most of the studies relied on meteorological station data, but traditional station data has some limitations in time series and data integrity. These limitations are especially pronounced in mountain regions, making it difficult for researchers to discern long-term changes (Kidd et al., 2017). The APHRODITE water resources project, jointly carried out by the Research Institute for Human and Nature and the Meteorological Research Institute of the...
Japan Meteorological Agency provide a set of highly-resolved daily grid precipitation data over Monsoon Asian, Middle East, and Russia/Northern Eurasia (Yatagai et al., 2008, 2012) (http://aphrodite.st.hirosaki-u.ac.jp/download/). The gridded fields of daily precipitation are defined by interpolating rain-gauge observations obtained from meteorological and hydrological stations across the region, in combination with the intelligent interpolation algorithm of a digital elevation model. Compared with other grid data, APHRODITE takes into consideration the influence of terrain on precipitation and also has a more uniform spatial distribution. It is often used as observational data for evaluating the performance of global climate models (Yatagai et al., 2008, 2012; Samuels et al., 2018; Kim et al., 2019; Gusain et al., 2020). However, it has to be admitted that the author reluctantly regridded the raw spatial resolution (0.05-degree) data to 0.25- and 0.5-degree products due to the data policy, this process potentially influences extreme values (Yatagai et al., 2008, 2012).

Furthermore, APHRODITE has been applied in the mountainous areas of Central Asia (Fang et al., 2016), the eastern Mediterranean (Samuels et al., 2018), and the Asian summer monsoon region (Kim et al., 2019; Irannezhad et al., 2021) concerning extreme climate and water resource evaluations and other research fields (Yatagai et al., 2008, 2012; Han et al., 2012; Fang et al., 2015; Samuels et al., 2018; Kim et al., 2019; Luo et al., 2019; Li et al., 2020d). The observation data sets selected in this paper are: APHRO_MA_025deg_V1101 (1951-2007) and APHRO_MA_025deg_V1101_EXR1 (2007-2014). The algorithms and resolutions of these datasets are the same, and the use of splicing in time series is acceptable (Yatagai et al., 2008, 2012; Luo et al., 2019).

2.2.2 CLIMATE TELECONNECTIONS AND SUMMER MONSOONS

Considering regional atmospheric circulation background and existing research results (Berg et al., 2009; Deng et al., 2014; Ding et al., 2019; Chen et al., 2020; Ma et al., 2020;
Irannezhad et al., 2021; Zhang et al., 2021), 16 atmospheric teleconnections indices with month-long scale resolutions were selected to explore the relationship between regional EP and associated large-scale climate teleconnections in the TMCA (Table S1). These indices include 14 large-scale ocean-atmosphere circulation patterns of the Northern Hemisphere Subtropical High Intensity (NSI), Arctic Oscillation (AO), North Atlantic Oscillation (NAO), 30hPa Zonal Wind (30ZW), 50hPa Zonal Wind (50ZW), NINO3.4 area sea surface temperature anomaly (NINO 3.4), NINO B area sea surface temperature anomaly (NINO B), ENSO Modoki Index (EMI), Multivariate ENSO Index (MEI), Total Sunspot Number (TSN), Solar Flux (SF), Atlantic Multidecadal Oscillation (AMO), Asian Zonal Circulation Index (AZI), Tropic Indian Ocean Dipole (IOD), which were obtained from the collection of 100 climate system indices of the National Climate Center of China Meteorological Administration (https://cmdp.nccma.net/Monitoring/cn_index_130.php). In addition, there are 2 summer monsoon indices, including the South Asian Summer Monsoon Index (SAM) and East Asian Summer Monsoon Index (EAM), which were obtained from collaborative work environment kit (http://ljp.gcess.cn/dct/page/1).

2.3. Methods

2.3.1 Extreme Precipitation Diagnosis

The proxy climate indicator is one of the most commonly used methods for diagnosing EP characteristics. At present, the 27 core extreme climate indices proposed by the International Expert Group on Climate Change Detection and Indicators (ETCCDI/CRD) are widely applied in identifying hydro-climate extremes, among which 11 indices are related to EP (Ding et al., 2019; Irannezhad et al., 2017, 2021; Zhang et al., 2020a; Wang et al., 2021; Zhang et al., 2021). However artificial and misleading conclusions may be produced if we calculate precipitation percentiles while ignoring the changes in the frequency of the number
of wet days (Schar et al., 2016). Therefore, another 14 extended indices based on different percentage thresholds of wet-day and all-day precipitation have been added to the original group. For example, counting annual total precipitation determining the threshold according to the 95%, 99%, 99.9%, and 99.95% percentiles based on the all-day precipitation [1961-1990], that is R95pALL, R99pALL, R99.9pALL, R99.95pALL. The above indices can describe the temporal and spatial changes in EP from the perspective of duration, frequency, and intensity. The determination method of indices threshold can be divided into the two categories of absolute threshold indices and relative threshold indices. Table S2 presents the specific meanings and calculation formulas for these indices.

2.3.2 Determination of Impact Factor

The geographical detector method (GDM) is a set of statistical methods for detecting spatial stratified heterogeneity and revealing the driving forces behind them (Wang et al., 2017; Xie et al., 2020). Generally, based on the q value of the single driving factor and the two driving factors, we can quantify the contribution of a single driving factor to the dependent variable (attribute or phenomenon) and judge whether there is interaction between the two factors. Please check the details about the GDM from Wang et al. (2017).

Nevertheless, since this method has a clear physical mechanism and does not need a linear hypothesis, it is widely used in the fields of medicine, health, regional construction, ecology, atmospheric science, and geosciences (Liao et al., 2017; Xu et al., 2017; Zhang et al., 2020b; Zhao et al., 2020). Therefore, the strategy can be used to quantify the impacts of different large-scale climate teleconnections on EP.

Since the explanatory variables required to be input in the model must be a certain type of quantity, we discretized 16 climate factors through the natural breaks (Jenks) classification. The factor contribution is measured by the following formula:
\[ q = 1 - \frac{SSW}{SST} \]  
\[ SSW = \sum_{h=1}^{l} N_h \delta_h^2 \]  
\[ SST = N \delta^2 \]

where \( q \) is the degree of explanation (contribution) of a specific factor to the dependent variable, with a value range of \([0,1]\); \( SSW \) is the sum of variance within the strata; \( SST \) is the total variance of the whole region; \( h \) is the stratification number of the factor; \( N, N_h \) represent the number of units in the whole area and layer \( h \), respectively; and \( \delta^2, \delta_h^2 \) refer to the variances of the dependent variables within the whole area and layer \( h \), respectively. The larger the value of \( q \), the higher the degree of factor that explains the dependent variable.

3. Results

3.1. Temporal Changes of Extreme Precipitation

We calculated EP indices over each grid box, and then calculated the average over the region. The mean values of CDD and CWD were 82.94 d and 4.18 d, indicating that CDD has been continuously decreasing at a rate of -3.70 d/decade (p<0.01), while CWD has significantly increased at rates of 0.15 d/decade (p<0.01), (Figure 2a, Table 1). Besides, the number of days with daily precipitation higher than 5 mm, 10 mm, 20 mm (R5mm, R10mm, R20mm) showed slightly decreasing trends. As well, the maximum precipitation per day (Rx1day) and maximum precipitation for 5 consecutive days (Rx5day) decreased slightly although PRCPTOT showed increased rates of 18.43 mm/decade. However, R95pALL, R99pALL, R99.9pALL, R99.95pALL showed increasing trend, and the significant levels of trend in R99.9pALL, R99.95pALL are above 5%. These changes indicate that the trend of extreme precipitation in the TMCA toward humidification is mainly caused by less frequent of dry days and intensified in extremely strong precipitation (Figure 2, Figure 3b, Table 1).
Moreover, around 1998, EP underwent an obvious change (Figure 2, Figure 3, Table 1). To put into perspective, the mean values of CDD, PRCPTOT, and frequency of R95p ALL (R95pFALL) in 1951-1997 were 86.89 d, 169.65 mm and 18.17 d, respectively; these changed to 71.99 d, 171.64 mm, and 28.42 d, respectively (1998-2014). This informs that the frequency and intensity of EP in the TMCA had increased in recent years. Moreover, it is obvious that the frequency change rates of EP events increase according to their rarity. Specifically, the frequency change rates that occurred once every 20 days, 100days, 1000days, and 2000days based on the wet period (1961-1990) (R95pFWET, R99pFWET, R99.9pFWET, R99.95pFWET) was on average 34.46%, 96.58%, 597.58% and 853.98%, respectively (Figure 3c).

**Figure 2.** Changes in absolute threshold precipitation indicators in TMCA from 1951 to 2014. (a) CDD/CWD; (b)Rx1day/Rx5day; (c) R5mm/R10mm/R20mm; (d) PRCPTOT/SDII. The red line represents the trend line fitted by the 7th order polynomial, while the red shaded area represents the ±1 standard error range of fitted trend line.
Figure 3. Changes in relative threshold indicators in TMCA from 1951 to 2014. (a) From top to bottom, the intensity changes of $R_{95\% \text{WET}}$, $R_{99\% \text{WET}}$, $R_{99.9\% \text{WET}}$, and $R_{99.95\% \text{WET}}$ respectively, with WET representing the determination of the threshold according to the 95%, 99%, 99.9%, and 99.95% percentiles based on wet day precipitation from 1961 to 1990. (b) From top to bottom, the intensity changes of $R_{95\% \text{ALL}}$, $R_{99\% \text{ALL}}$, $R_{99.9\% \text{ALL}}$, and $R_{99.95\% \text{ALL}}$, with ALL representing the determination of the threshold according to the 95%, 99%, 99.9%, and 99.95% percentiles on annual day precipitation from 1961 to 1990 (intensity is obtained by the cumulative sum of precipitation exceeding a certain percentile in the reference period). (c/d) From top to bottom, the frequency (referring to the number of precipitation events exceeding a certain percentile threshold in the reference period) corresponding to (a/b); a 95% quantile means that extreme precipitation events occur once every 20 days on average, a 99% quantile once every 100 days on average, while 99.9% and 99.95% once every 1000 days and 2000 days on average respectively. The red line indicates the trend line fitted by a 7th order polynomial. The red shaded area indicates the ±1 standard error range of the fitted trend line.

Table 1. Regional decadal changes (regional mean trend and regional mean) in extreme precipitation

<table>
<thead>
<tr>
<th>Indices</th>
<th>Unit</th>
<th>Region trend</th>
<th>Region mean in</th>
<th>Region mean in</th>
<th>Region mean in</th>
</tr>
</thead>
</table>

14
<table>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>CDD</td>
<td>d</td>
<td>-3.70**</td>
<td>82.94</td>
<td>86.89</td>
<td>71.99</td>
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<tr>
<td>CWD</td>
<td>d</td>
<td>0.15**</td>
<td>4.18</td>
<td>4.05</td>
<td>4.56</td>
</tr>
<tr>
<td>Rx1day</td>
<td>mm</td>
<td>-0.33</td>
<td>12.53</td>
<td>12.86</td>
<td>11.62</td>
</tr>
<tr>
<td>Rx5day</td>
<td>mm</td>
<td>-0.14</td>
<td>22.62</td>
<td>22.89</td>
<td>21.86</td>
</tr>
<tr>
<td>R5mm</td>
<td>d</td>
<td>-0.24</td>
<td>9.71</td>
<td>9.91</td>
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</tr>
<tr>
<td>R10mm</td>
<td>d</td>
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<td>2.88</td>
<td>3.09</td>
<td>2.30</td>
</tr>
<tr>
<td>R20mm</td>
<td>d</td>
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<td>0.45</td>
<td>0.51</td>
<td>0.29</td>
</tr>
<tr>
<td>PRCPTOT</td>
<td>mm</td>
<td>18.43</td>
<td>170.18</td>
<td>169.65</td>
<td>171.64</td>
</tr>
<tr>
<td>SDII</td>
<td>mm/day</td>
<td>-0.004</td>
<td>2.24</td>
<td>2.24</td>
<td>2.23</td>
</tr>
<tr>
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<td>31.65</td>
<td>32.04</td>
<td>30.56</td>
</tr>
<tr>
<td>R95pALL</td>
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<td>101.89</td>
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<tr>
<td>R99pWET</td>
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<td>9.39</td>
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<tr>
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<td>1.73</td>
<td>1.38</td>
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<tr>
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<td>3.66</td>
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<td>0.52</td>
<td>0.41</td>
<td>0.81</td>
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<td>0.15</td>
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</tr>
<tr>
<td>R99.9pFALL</td>
<td>d</td>
<td>0.23**</td>
<td>0.64</td>
<td>0.36</td>
<td>1.39</td>
</tr>
<tr>
<td>R99.95pFWET</td>
<td>d</td>
<td>0.08**</td>
<td>0.13</td>
<td>0.03</td>
<td>0.41</td>
</tr>
<tr>
<td>R99.95pFALL</td>
<td>d</td>
<td>0.18**</td>
<td>0.40</td>
<td>0.18</td>
<td>1.00</td>
</tr>
</tbody>
</table>
Note: The “−” sign before each of these numbers indicates a decreasing trend; significance levels above 5% are marked with “*” and above 1% are marked with “**”.

3.2. Spatial Distribution of Extreme Precipitation Indices

The characters of EP indices in the TMCA have strong heterogeneity. Generally, EP in the West Tienshan Mountains and Middle Tienshan Mountains differs from that in the North and East Tienshans, with the latter two areas showing an increasing trend (Figure 4, Figure 5, Table S3). For example, from 1951 to 2014, the tendencies of PRCPTOT range from -10.08 to 18.43 mm/decade (Figure 4c, Table S3). The results of the linear tendencies show that 65.03%, 34.70%, 0%, and 1.36% of grids have decreasing trends in the West, Middle, North, and East Tienshan Mountains, whereas 34.97%, 65.30%, 100%, and 98.64% of grids exhibit increasing trends (Table S3). Meanwhile, 24.32%, 59.56%, 100%, 63.27% of grids indicate significant increasing trends (p<0.05) in the West, Middle, North, and East Tienshans, whereas only 51.91% and 21.58% of the grids have significant decreasing trends (p<0.05) in the West and Middle Tienshans.

In terms of R5mm, R10mm and R20mm in the TMCA, the trends essentially remained the same. The West Tienshan Mountains mainly showed a decreasing trend, while all of the North and East Tienshan Mountains and most of the Middle Tienshan Mountains showed an increasing trend (Figures 4d, g, h). Over the past 64 years, R5mm, R10mm and R20mm ranged from -0.93 to 0.97 d/decade, -0.52 to 0.20 d/decade, and -0.12 to 0.01 d/decade, respectively (Table S3).

The R95pWET/R95pALL series indices (with the threshold determined based on the WET/ALL period from 1961 to 1990) also revealed the same spatial distribution characteristics. This is characterized by a decreasing trend in the West Tienshan Mountains and western regions of the Middle Tienshan Mountains and an increasing trend in the North
and East Tienshans, as well as in the northern and eastern regions of the Middle Tienshans (Figure 5). Additionally, the trend change of the R95pALL series indices is stronger than that of the R95pWET.

As presented in Table S3, the change trend intensity for the R95pALL series indices is approximately 1.86~6.67 times that of the R95pWET series indices. More specifically, ALL days demonstrate a less strict selection threshold compared to WET days.

Figure 4. (a) CDD, (b) CWD, (c) PRCPTOT, (d) R5mm, (e) Rx1day, (f) Rx5day, (g) R10mm and (h) R20mm show spatial trend changes in the TMCA during 1951-2014. (Note that the black dot in the figure indicates that the trend change at this point has passed the 95% confidence test.)
Figure 5. Spatial trends of (a/b) R95p, (c/d) R99p, (e/f) R99.9p and (g/h) R99.95p in the TMCA from 1951 to 2014, based on different threshold methods. (Note that the black dot in the figure indicates that the trend change at this point passes the 95% confidence test.)

3.3. Changes in Extreme Precipitation Indices at Different Altitudes

As mentioned previously, the terrain in the TMCA is highly complex. Most of the region is located at middle altitudes (1500~3500 m), while about 20% is located at low altitudes (<1500 m) and 16% at high altitudes (>3500 m) (Li et al., 2020c). To reflect the changes in EP at different altitudes, we calculated the changes in EP indices for low, middle, and high-altitude areas. The results show that EP indices have good dependency with altitude (Figure 6). For example, the mean value of CDD in 1951-2014 decreases according to elevation, with 95.84, 88.86 d, and 79.58 d at low, middle, and high altitudes. Meanwhile, Rx1day increases
from 10.42 mm, to 11.86 mm and 12.43 mm and the R95pFWET also rises from 1.72 d at low altitudes to 2.01 d and 2.22 d at middle and high altitudes, respectively (Figures 6a, b, f).

Series indices for areas of different altitudes, an interesting phenomenon is noticed where the rate of frequency/intensity change of EP events in middle altitude areas is stronger than that in high and low altitude areas. We also noted that the rarer the extreme precipitation events were, the greater the change rate of frequency/intensity became (Figures 7a, b). For example, the increasing rate of R95pALL (EP events occurring once every 20 days) at middle altitudes was 21.62%, whereas it was in high- and low-altitude area it was 15.81%, and 12.02 %, respectively. Additionally, the changing rates of R99.95pALL events (EP events occurring once every 2,000 days) were 112.21%, 72.19% and 5.61% in middle-, high- and low-altitude regions, respectively (Figure 7a).
**Figure 6.** Extreme precipitation indices at different altitude areas. (a) From left to right, CDD and PRCPTOT. (b) From left to right, CWD, R5mm, R10mm, R20mm, Rx1day, Rx5day, and SDII. (c/e) From left to right, the intensity/frequency of R95p WET series indices determined by WET. (d/f) From left to right, the intensity/frequency of R95p ALL series indices determined by ALL. The upper edge, middle red line, and lower edge of each box correspond to the 75th quantile, median, and 25th quantile of the variable, respectively. The upper and lower extensions indicate the acceptable range of normal values. The outliers are indicated by "+", and L, M, and H represent low, medium, and high altitudes, respectively.

**Figure 7.** Change rate of the extreme precipitation events (R95pWET/ALL series of indices) in different altitude areas from the 1950s to the beginning of this century, in % units. (a) The change rate of extreme precipitation events in intensity. (b) The change rate of extreme precipitation events in frequency. L, M, and H represent low, medium, and high altitudes, respectively.
3.4. Analysis of Large-Scale climatic teleconnections Affecting Extreme Precipitation

3.4.1 QUANTITATIVE ASSESSMENT OF LARGE-SCALE CLIMATIC TELECONNECTIONS

CONTRIBUTION RATE

The above analysis shows that the increase in EP in the TMCA is the result of the comprehensive effect of intensity, frequency and duration of precipitation. However, there is a strong correlation among the selected 25 EP indices (Figure S1). For that, 8 EP indices (CDD, PRCPTOT, R10mm, Rx1day, R95pWET, R95pALL, R99.95pFWET, and R99.95pFALL), taking into account the type and independence of indices used for exploring the influence of large-scale climatic teleconnections by the GDM.

This study quantified the magnitude of the effect of each factor on EP by calculating the $q$ values, which is a kind of detector in GDM (Table S4). Based on these values, the order of influence of all the large-scale climatic teleconnections is shown in Figure 8. Although there are differences in the influence of large-scale climatic teleconnections factors on EP indices, SAM, AMO, NINO B, NSI, SF, AO, and 30ZW are the most important ones. SAM has the largest impact on EP, with an average contribution rate of 23%, while the average contribution of AMO, NINO B, NSI, SF, AO, and 30ZW is 22%, 21%, 19%, 11%, 10% and 9% respectively (Figure 8).

The contribution of all factors to EP also showed differences in sub-regions. For CDD, the largest driving factor in the Middle, North and East Tienshan Mountains is NINO B, with contribution rates of 35%, 40% and 34%, respectively, while the largest driving factor in the West Tienshan Mountains is SAM, with a contribution rate of 24%. Meanwhile for R10mm, AO and SAM are the main driving factors in the West and Middle Tienshan Mountains, with contribution rates of 38% and 37%, respectively. The main driving factors in the North Tienshans are AMO and NSI.
3.4.2 INFLUENCE OF INTERACTIONS BETWEEN LARGE-SCALE CLIMATIC TELECONNECTIONS

Shi et al. (2017) found that the occurrence of EP is often the result of comprehensive effects of multiple factors. To analyze the influence of interaction between various climatic teleconnections factors on the occurrence of EP, we used an interaction detector (a kind of detector in GDM) to quantitatively evaluate the explanatory power when two factors simultaneously act on EP.

As shown in Figure 9 and Figure S2, the factors of all sub-regions had an interactive effect on EP. The interaction of various factors was divided into two types: bivariate enhancement ($q(X_1 \cap X_2) > q(X_1)$ and $q(X_2)$) and nonlinear enhancement ($q(X_1 \cap X_2) > q(X_1) + q(X_2)$). It is worth noting that in bivariate enhancement, the explanatory power of the interaction of the two proxy variables is greater than that of any variable prior to the interaction, and that different manifestations.

Highlighting CDD as an example, all interactions are nonlinear enhancement except TSN∩SF in the West Tienshan Mountains, while the interactions of TSN∩SF denote nonlinear enhancement in the Middle, North, and East Tienshan Mountains (Figures 9a~d).

From a spatial perspective, there are differences in large-scale climatic teleconnections.
factors associated with EP in different regions. For R10mm, the interaction of SF∩AZI has the strongest explanatory power in the West and Middle Tienshan Mountains, while SAM∩NSI, SAM∩30ZW have the strongest in the North and East Tienshans, respectively (Figures 9i~l).

Moreover, the same two factors can have different interaction results in different sub-regions. Taking R95pWET as an example, the interaction of SAM∩NSI has the strongest explanatory power in the Middle and North Tienshan Mountains, at 65% and 92%, respectively, while, the interaction result in the West and East Tienshan Mountains is only 59% and 61%, respectively (Figures S2a~d).

**Figure 9.** Interaction detection results of large-scale climatic teleconnections factors on different EP indices in each sub-region. The letters A–P on the abscissa and ordinate indicate the selected 16 atmospheric circulation indices, while the yellow rectangle and value indicate the greatest contributions of two factors simultaneously acting on extreme precipitation. For example, the yellow rectangle and the value in (a) indicate that the interaction between SAM and NSI (SAM∩NSI) can explain 78% of CDD changes in the West Tienshan Mountains.
4. Discussion

4.1. Obvious Spatial Heterogeneity of Extreme Precipitation Indices

The current investigations on the changes of EP indicate a wet tendency in the TMCA, especially in recent years. These results are strongly supported by previous studies (Chen et al., 2016; Chen et al., 2020; Ma et al., 2020; Ning et al., 2021; Yao et al., 2021; Zhang et al., 2018; Zhang et al., 2012a; Zhang et al., 2012c; Zhang et al., 2013; Zou et al., 2021). For example, we concluded that the consecutive wet days show a significant increase trend, with a multi-year average of 4.18 days, from 1951 to 2014 in TMCA, and extended to 4.56 days in 1998-2014, based on APHRODITE data (Table 1). The results are consistent with those results in Xinjiang of China (Zhang et al., 2012a) and Central Asia (CA) (Ma et al., 2020). According to meteorological observations, the annual maximum consecutive wet days are mostly 2-4 days, and are lengthened after 1987 in Xinjiang (Zhang et al., 2012a). In CA, maximum number of consecutive wet days in summer are 0-6 days during 1979-2018, increasing at rate of 0.02d/a during 1978-2018, and 2.66 days/a in 1996-2018 (Ma et al., 2020). According to the changes of 25 EP indices, we found that EP in the TMCA toward humidification is mainly caused by less frequent dry days and intensified extremely strong precipitation (Figure 2, Figure 3 and Table 1). A similar phenomenon is also identified in Xinjiang, China (Zhang et al., 2012c) and CA (Yao et al., 2021) that a wetting tendency was mainly attributed to increasing high precipitation. There behaviors indicate the wettest days become more frequent, at the expense of days with light or no precipitation (Fischer et al., 2016). Moreover, changes in EP across the TMCA seem to be inherent with the climate change around the world. An increasing trend of EP is also identified in the world’s dry and wet regions (Donat et al., 2016), Europe and the US (Fischer et al., 2016), Southeast Asia (Ge et al., 2019; Irannezhad et al., 2021), Central Asia (Ma et al., 2020; Yao et al., 2021; Zou et
al., 2021), eastern China (Zhang et al., 2017), arid northwest China (Ning et al., 2021; Zhang et al., 2012c), etc.

The trend of EP indices shows strong spatial heterogeneity in the TMCA (Figure 4, Figure 5). For instance, CWD in the North and East Tianshan Mountains shows an increasing trend, but a decreasing trend appears in the eastern part of the West Tianshan Mountains and the western part of the Middle Tianshan Mountains. Besides, R5mm, R10mm, and R20mm tend to decrease mainly in the West Tianshan Mountains but increasing in the North Tienshan Mountains and most areas of the East and Middle Tianshan Mountains. In fact, the obvious heterogeneity of EP in spatial pattern changes exists in many studies, showing the opposite trend in different regions (Donat et al., 2016; Fischer et al., 2016; IPCC, 2021; Zhang et al., 2012c; Zhang et al., 2018b).

Even in the same geographical area, the characteristics of different sub-regions may be different (Deng et al., 2014; Ding et al., 2019; Irannezhad et al., 2021; Zhang et al., 2012b; Zhang et al., 2012c; Zhang et al., 2013). For example, Zhang et al. (2012c) claimed that the strong extreme precipitation was more obvious in northern Xinjiang and western region, which weak extreme precipitation was more obvious in southern Xinjiang and eastern region, indicating that North Xinjiang was getting wetter compared with south Xinjiang. In the TMCA, we found that the spatial changes of temperature, precipitation, snowfall, snow area, glacier deceleration rate, and water storage also exhibit obvious heterogeneity besides extreme precipitation. Specifically, from 1961 to 2014, the temperature in most areas of the TMCA increased 0-0.4°C/10a. However, the temperature in the West and Middle Tianshan Mountains dropped about 0.2-0.5°C/10a (Deng et al., 2018). During the same period, precipitation in the Middle and East Tianshan Mountains showed an increasing trend at a rate between 0-15 mm/10a, while precipitation in the West Tienshan Mountains showed a
decreasing trend, with a maximum decreasing rate of about 20-60 mm/10a (Deng et al., 2018).

From associated large-scale climate teleconnections, we found that the factors affecting EP also vary across different sub-regions (Table S5). As for the absolute threshold indices of EP, SF∩AZI is the most critical factor in the West Tienshan Mountains. In addition to SF∩AZI, SAM∩NSI is important to EP in the Middle Tienshan Mountains, while SAM∩AMO, SAM∩NSI, and SAM∩30ZW are the main factors affecting EP in the North and East Tienshan Mountains. Regarding relative threshold indices, EP is mostly affected by SAM∩AMO and SAM∩NSI in the Middle, North and East Tienshan Mountains, while AMO∩NINO3.4 is important in the West Tienshan Mountains.

Moreover, Chen et al. (2020) noted two key water vapor sources in arid Central Asia: one is the westerly water vapor transport from the North Atlantic, and the other is the monsoon water vapor transport from the tropical Indian Ocean and the South China Sea via the eastern and northern periphery of the Tibetan Plateau. However, the contribution of the monsoon water vapor transport was increasing. With the continued weakening of the East Asian monsoon since 1958, it has become the dominant source for the lower troposphere in arid Central Asia. In our study, EP is more strongly influenced by AZI (westerly wind circulation) in the West Tienshan Mountains, while for SAM (monsoon water vapor), NSI contributes more to EP in the North and East Tienshan Mountains. These climatic teleconnections explain why there is such a large difference in EP between western and eastern TMCA.

We also noticed an interesting phenomenon, in that the rate of frequency/intensity change in EP events in the middle-altitude areas is stronger than that in the high- and low-altitude areas. Thus, the most sensitive change in the middle altitude may be related to the anti-EDM (anti-elevation dependent warming) in this region (Li et al., 2020a). Snow/ice albedo feedback is a key physical mechanism that leads to this phenomenon because mountains have
warmed at a higher rate than the rest of the land surface (Rangwala et al., 2012). However, Li et al. (2020b) found a general reduction in snow cover fraction from the high mountains to the low mountains from 2002 to 2017. Snow melts in middle-altitude areas decreases the surface albedo, and thus the surface absorbs more solar radiation, and strengthens atmospheric-surface feedback. Therefore, in our study, the middle-altitude areas are the most sensitive to the extreme precipitation variations.

4.2. Possible forcing factors of extreme precipitation variation

We first quantified the magnitude of effect on EP of each associated large-scale climatic teleconnections, and then analyzed the explanatory power of interaction of the above factors on EP events using the GDM. Our results unveiled that SAM, AMO, NINOB, NSI, SF, AO, and 30ZW are the most important factors impacting EP and that the interaction of multiple factors is more likely to cause an EP event. In general, SAM∩NSI, SAM∩30ZW, SF∩AZI, and AMO∩NINO 3.4 have the strongest explanatory power on EP.

El Niño/Southern Oscillation (ENSO) is an important factor driving the internal variability of climate. It also has a significant impact on global dry and wet change through ocean-atmosphere interactions (Trenberth et al., 2014). Over the past 60 years, El Niño has charted an increasing trend (Figure 10b), and when it occurs, most of the low latitudes south of 40 °N in Central Asia are dominated by significant abnormal high pressure, while areas north of 40 °N experience abnormal low pressure. The low-pressure anomalies induced by ENSO strengthen the westerly and southwesterly winds from the North Atlantic and the Indian Ocean and further facilitate the transport of large amounts of water vapor to Central Asia (Hu et al., 2019). Ma et al. (2020) studying wind speeds and geopotential heights at the 500hpa altitude, also found that there were negative geopotential highs and abnormal cyclones over northern Central Asia after 1998, as well as positive geopotential highs and
abnormal anticyclones over Mongolia. In this situation, the westerly wind was strengthened, bringing a humid climate, which provided favorable precipitation conditions to northern Kazakhstan and the Tienshan Mountains in Central Asia.

![Figure 10](image)

**Figure 10.** (a) Nino 3.4 region on a map, and (b) the anomaly of Nino 3.4 index from 1951 to 2014. The thresholds of +/- 0.5°C are used to identify El Niño and La Niña periods.

The westerly index AZI is an indicator of the westerly wind component of the average geostrophic wind speed, which can quantitatively describe the strength of the zonal circulation (Shi et al., 2011). From Figure 11a, we can see that an increasing trend was detected. In general, when the AZI increases, the zonal circulation from west to east strengthens, and the movement of 45-60 °N airflow on the 500hPa isobaric surface speeds up. At the same time, the meridional circulation from north to south weakens, and the movement of 60-150 °E airflow on 500hPa isobaric surface slows down. Ning et al. (2021) concluded that summer extreme precipitation events in Xinjiang are characterized by zonal wave patterns, which strongly supported our results. It is generally believed that North Atlantic moisture carried by mid-latitude westerlies dominates precipitation changes in arid Central Asia, where monsoon moisture is beyond their reach (Chen et al., 2020). However, many studies have confirmed that monsoonal water vapour transport is affecting precipitation variations not only in arid Central Asia, but also in non-monsoon regions, including the northwest arid area of China (Chen et al., 2020; Chen et al., 2021; Ding et al., 2019).
Monsoonal transport is related to the weakening of the EAM, which is accompanied by the westward extension of the western Pacific subtropical high and the increase in Mongolian anticyclone activity (Chen et al., 2020). In recent decades, the EAM has the greatest influence on interannual variation of the first corresponding time coefficient (PC1s) of R95p, R10mm and R20mm through the Lancang-Mekong River Basin, where climate variability is strongly affected by monsoons (Irannezhad et al., 2021). We can see an obvious increasing trend in the NSI and a decreasing trend in the SAM and EAM for the past 60 years (Figures 11b, c, d). The increase in NSI is beneficial to the westward extension of the western Pacific subtropical high that promotes the westward transport of water vapor from the Indian and Pacific oceans and enhances summer precipitation in arid Central Asia (Chen et al., 2020).

The AMO shift in the warm and cold phases possibly had a profound impact on changes in extreme precipitation not only in and around the Atlantic Ocean but also in China. We can see that the AMO entered a warm phase at the end of the 1990s (Figure 11e). Ding et al. (2019) found that the change trend for all extreme precipitation indices is significantly greater when the AMO enters a warm phase in non-monsoon regions of China. Irannezhad et al. (2021) concluded that the strongest teleconnection associated wet/dry spells was AMO in the Lancang-Mekong River Basin. In our study, AMO is another climatic teleconnection factor which has the greatest influence on EP besides SAM. The contribution rate of AMO to the number of consecutive dry days in the West, Middle, North, and East Tianshan Mountains is 13%, 30%, 36%, 30%, respectively.

Meanwhile, an increasing trend was detected in the AO, with most of these trends in recent years being a positive phase (Figure 11f). The positive phase of AO brings low pressure to the Arctic surface, along with enhanced zonal circulation and weakened meridional circulation, which increases the surface temperature in the middle latitudes. Generally, the zonal circulation at the 500hPa and 1,000hPa potential height increases while
the meridional circulation weakens, accelerating the movement of air flow from west to east and bringing sufficient exogenous water vapor from the North Atlantic. The weakening of the EAM is accompanied by the westward extension of the western Pacific subtropical high and an increase in Mongolian anticyclone activity, which benefits monsoonal water vapour transport from the tropical Indian Ocean and South China Sea. On the other hand, rising temperatures lead to greater evaporation, resulting in an increase in water vapor molecules in the air, which undoubtedly provides favorable conditions for the formation of regional precipitation.

**Figure 11.** Illustration showing (a) variations of the Asia Zonal Circulation Index anomaly, (b) Northern Hemisphere Subtropical High Intensity anomaly, (c) South Asian Summer Monsoon Index anomaly, (d) East Asian Summer Monsoon Index anomaly, (e) Atlantic Multi-decadal Oscillation anomaly, and (f) Arctic Oscillation Index anomaly from 1951 to 2014.

### 4.3. Uncertainty analysis and future prospects

There are two main uncertainties or limitations encountered in this study. The first is the selection of the dataset. Due to the sparsity of *in situ* stations and limitations in time series, we had to choose precipitation data sets in the TMCA, despite major variations in topography, altitude, and glacial distribution. Therefore, to make the results more convincing, we also referred to the National Oceanic and Atmosphere Administration (NOAA) Climate Prediction Center (CPC) precipitation dataset, which has good agreement with GPCP and TRMM 3B42-V7 in depicting the precipitation in Central Asia during 1997/8-2018, with the
correlation coefficients of 0.89 and 0.91, respectively (Ma et al., 2020). The selected
APHRODITE data shows a coincident trend, and the correlation coefficient achieves 0.85
(P<0.001) with the CPC during 1979-2014 (Figure S3). We chose the APHRODITE dataset
to depict EP in the TMCA with its advantage in high spatial resolution and long spatial
extension.

Secondly, the driving mechanism of EP change is highly complex owing to numerous
factors affecting regional precipitation variability. These include climate system variability,
large-scale atmospheric circulation patterns, regional environment characteristics, human
activities, and so on (Ding et al., 2019; Irannezhad et al., 2021). In this investigation, we only
analyzed the influence of associated large-scale climatic teleconnections. Therefore, further
research could involve a comprehensive physical mechanisms analysis.

As the climate warms, the water cycle accelerates and the intensity of precipitation and
risk of flooding increases, posing serious threats to arid regions (Donat et al., 2016), yet
heavy precipitation events do not occur frequently in arid areas. Most flood control projects
and water conservancy infrastructure are designed according to the intensity-time-frequency
(IDF) curve of EP in historical periods. However, under increasingly erratic climate change
conditions, the frequency and intensity of EP events have significantly altered. If no
corresponding measures are taken, even small changes in EP will have a sizeable impact on
society (Donat et al., 2016; Pfahl et al., 2017; Parisa et al., 2020).

There is no doubt that human activities warm the atmosphere, oceans and land, and this
warming is unprecedented over many centuries to thousands of years (IPCC, 2021). Global
Climate Models project that global surface temperatures will continue to rise, and the global
average surface temperature over 2081-2100 is very likely to be 3.3°C to 5.7°C higher than in
the pre-industrial period, taking into account the very high greenhouse gas emissions scenario
(IPCC, 2021). Under this background, changes in frequency and intensity of extreme
precipitation become larger. At the global scale, extreme daily precipitation events are projected to intensify by about 7% for every 1°C of global warming (IPCC, 2021). In Central Asia, Rx1day and Rx5day are expected to increase robustly at a rate of 6.30% and 5.71% for each 1°C of global warming (Peng et al., 2020). Additional 0.5°C warmer (from 1.5°C to 2.0°C global warming) targets can double increase of extreme precipitation in China (Wang et al., 2020). R20mm is also projected to increase by 8.6% in Southeast Asia (Ge et al., 2019). What’s more, the vulnerability or exposures of human society and natural ecosystems to climate extreme change will be greatly increased in the future. In the global monsoon region, the areal and population exposures of dangerous extreme precipitation would increase consistently with warming (Zhang et al., 2018c). Most regions of China will have a higher occurrence rate of extreme precipitation in a warmer climate, and exposures of land and population to Rx5day in the western arid (semi-arid) region and the Qinghai-Tibet Plateau are the most sensitive to climate warming (Wang et al., 2020). Therefore, in the next work, we should not only consider the credibility of the data, but also pay attention to the changes and risk prediction of extreme precipitation under different warming levels and different emission scenarios.

5. Conclusion

This paper assessed the temporal and spatial changes of EP in the Tienshan Mountains region of Central Asia, from 1951 to 2014. It also determined the climate system factors affecting EP based on GMD. In our investigations, we found the following:

(1) From 1951 to 2014, the CDD in the TMCA decreased at a rate of -3.70 d/10a (P<0.001) and the CWD increased at a rate of 0.15 d/10a (P<0.001). Further, R5mm, R10mm and R20 mm showed a slight decrease.
(2) The rarer that extreme precipitation events are, the greater the change rate of frequency/intensity becomes. Across different altitude areas, EP indices show good elevation-dependence. Meanwhile, the increasing trend of EP in the eastern part of the TMCA was stronger than that in the western region.

(3) Finally, GMD found that SAM, AMO, NINOB, NSI, SF, AO and 30ZW were the most important factors affecting EP during the study period. Overall, the joint contribution of multi-factors to EP events was larger than the contribution of single factors, and the enhancement of zonal circulation at 500hPa and 1,000hPa accelerated the airflow from west to east. Finally, the weakening of the EAM accompanied by the westward extension of the western Pacific subtropical high and the increase in Mongolian anticyclone activity were shown to bring sufficient exogenous water vapor from the North Atlantic and Indian Ocean to the TMCA.

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Data Availability Statement.

All data used in this study are publicly available and listed in the datasets.

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Highlights
• Insightful viewpoint about frequency of extreme precipitation (EP) increases with event rareness is confirmed.
• Changing rate of EP in middle altitude areas (1,500~3,500 m) is most sensitive to climate change.
• New finding about explanatory power of multiple teleconnections interaction on EP.

Dear Sir/Ma’am

Prof. Dr. Yaning Chen (Corresponding author) certifies that:

- The manuscript is being submitted by me (Corresponding author) on behalf of all the authors.
- The manuscript is original work of all authors.
- All authors made a significant contribution to this study.
- This manuscript has not been submitted for publication; it has not been accepted for publication and has not been published in any other journals.
- All authors have read and approved the final version of the manuscript.

Thank you

Sincerely,
Yaning Chen

ABSTRACT

Under global warming, extreme hydrological events are experiencing increasingly violent fluctuations. Investigating changes in the intensity and frequency of extreme precipitation (EP) events is particularly critical for understanding the hydrological response to climate change. Based on high-precision and long-term daily grid precipitation data obtained from Asian Precipitation-Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), 25 EP indices were examined for the Tienshan Mountains region of Central Asia (TMCA). Here, the relationship between EP and associated large-scale
climate teleconnections is revealed by using a series of approaches such as trend analysis and
the geographical detector method (GMD), a statistical tool to measure and attribute spatial
stratified heterogeneity. The results show an overall increase in EP during 1951-2014, as
reflected in the 25 indices. Furthermore, the number of consecutive dry days (CDD)
decreased from 87.02 to 69.35 while the number of continuous wet days (CWD) increased
from 3.89 to 4.61. Meanwhile, the increasing trend of total precipitation (PRCPTOT) was
18.43 mm/10a, and changes in EP frequency were shown to increase with event rareness. For
R95p, the observed changes in frequency are 34.46%, but these jump to 96.58% for R99p.
Moreover, the study also notes that changes in EP are elevation-dependent, with middle
altitude areas (1,500~3,500 m) being most sensitive to change rates. As well, the study
reveals that the occurrence of EP responds non-linearly to climatic teleconnections, and that
the combined effect of two factors generally make much larger contributions to EP than the
summation of individual factors. Further analyses indicate strong zonal circulation at 500hPa,
1,000hPa potential height increases airflow from west to east. And the weakening of the East
Asian Summer Monsoon accompanied by the westward extension of the western Pacific
subtropical high and the increase in Mongolian anticyclone activity all bring sufficient
exogenous water vapor from the North Atlantic and Indian Ocean to the TMCA.
Keywords: global warming, extreme precipitation, large-scale climate teleconnections,
Tienshan Mountains, Central Asia