Teleconnection patterns of precipitation in the Three-River Headwaters region, China

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Keywords: precipitation, large-scale atmospheric circulation, Three-River Headwater region, spatiotemporal variation, empirical orthogonal functions analysis, wavelet transform coherence

Abstract

With the intensification of global warming, spatiotemporal variations in the climate and their mechanisms have received increasing attention. Currently, the relationship between regional precipitation regime, large-scale circulation, and topography, particularly in high-altitude areas such as the Qinghai–Tibet Plateau, are not well understood. Herein, the spatial and temporal variability in the annual and intra-annual (wet and dry periods) precipitation at 33 stations in the Three-River Headwaters (TRH) region from 1967 to 2016 are analysed. Moreover, the empirical orthogonal function and wavelet transform coherence methods are used to analyse the relationships between the different modes of precipitation change and 14 atmospheric circulation indices. The following results were obtained. (1) The mean annual precipitation and mean dry period precipitation significantly increased over the studied period. Annual and intra-annual precipitation showed a spatial southeast-to-northwest decreasing trend. (2) Two main patterns of precipitation were observed during the studied period: a dominant pattern with high- and low-value centres located in southeast and northwest TRH, respectively, and a dipole pattern with more precipitation over southwest TRH and less precipitation over northeast TRH. (3) Precipitation had a negative correlation with latitude, positive correlation with longitude, and nonlinear relationship with elevation. (4) Precipitation changes over various parts of the studied domain were determined based on changes in the weather systems affecting the area, with different indices being correlated with different components during different times of the year.

1. Introduction

Precipitation is considered the most basic link in the water cycle process and a key parameter in equations of water quantity and energy balance, evaluations of climate change, water resources, crop water demand, flood and drought monitoring and early warning systems, ecological environment protection, and other fields. In the last few decades, the observed global mean observations of precipitation have shown a widespread statistically significant increase accompanying global climate change (Alexander et al 2006, IPCC 2013, Asadieh and Krakauer 2015, Du et al 2019), resulting in an increase in global surface runoff and flooding risks (Trenberth 2011). This has seriously damaged regional ecological environments, affected industrial and agricultural production, caused great economic losses, and threatened human lives. Research on precipitation change and its impacts under climate change has become a hot issue (Shi et al 2017, Sun et al 2017, 2018, Lee et al 2018, Ding et al 2019).

For decades, global changes in precipitation have been extensively investigated using long-term observational data (Alexander et al 2006). Inconsistent changes in global precipitation have also been
observed (Alexander et al 2006, Trenberth 2011, Sun et al 2017, Tan et al 2020). The Intergovernmental Panel on Climate Change (IPCC) suggested that high latitudes, the equatorial Pacific Ocean, and many midlatitude wet regions are expected to experience an increase in mean annual precipitation (MAP), while that in many midlatitude and subtropical dry regions will likely decrease by the end of this century under the RCP8.5 scenario (IPCC 2013). As precipitation continues to change significantly, numerous studies on precipitation have been conducted from the perspective of climate change. In addition, research in the United States, Canada, Europe, and East Asian, Indian, North American, and Asian-Pacific regions has confirmed that precipitation changes do not have the same global consistency as temperature changes (Wang and Linho 2002, Kurtzman and Scanlon 2007, Ghosh et al 2011, Sohn et al 2012, Jiang et al 2013, Tošić et al 2016, Barlow et al 2019). This indicates that there are dissimilarities in precipitation trends in different regions. Further, Sun et al (2017) reached similar conclusions concerning changes in precipitation at different time scales in China. Simultaneously, they pointed out that temperature, the East Asian summer monsoon, and related large-scale atmospheric circulation patterns are important factors affecting the spatial and temporal variability of precipitation in China, especially at the decadal scale, and other factors, such as urbanization, land use, and topographic heterogeneity, can significantly influence local microclimates and the formation of precipitation.

Precipitation studies in the Three-River Headwaters (TRH) region, northwest arid zone, southwestern region, Yangtze River Basin, Loess Plateau, and Qinghai–Tibet Plateau (QTP) in China have further illustrated the patterns and features of the spatial and temporal distribution of precipitation in China under climate change. They have improved our understanding of the spatiotemporal characteristics of precipitation at different regional scales in China, which has its own unique distribution pattern and evolutionary trend (Liu et al 2015, Shi et al 2017, Yang et al 2017, Xi et al 2018, Gao et al 2020, Wei et al 2019). In particular, the TRH region (including the Yellow River, Yangtze River, and Lantsang River Headwaters region) is a vulnerable ecological environment and has regions with complex climatic environmental backgrounds (it is located in the hinterland of the QTP and is significantly affected by monsoon) with characteristics that are sensitive to climate change. This makes the region ideal for researchers to study modern climate change (Hu et al 2011, Yuan et al 2016, Tang et al 2018, Xi et al 2018). Precipitation studies in the TRH region have also received increasing attention (Liang et al 2013, Yi et al 2013, Shi et al 2016, 2017, Xi et al 2018). Previous studies indicate that there has been a significant increasing trend in the annual precipitation over the past half century and a southeast-to-northwest decreasing trend in the TRH region (Yi et al 2013, Shi et al 2016, 2017, Xi et al 2018). These studies demonstrate that the terrain and topography of the TRH region are complex and that this area has significant temporal and spatial variation characteristics in its precipitation. However, the reasons behind the precipitation changes in the TRH region are still largely unclear, which warrants further study.

Regional precipitation change is primarily affected by natural and human activities (Yi et al 2013). However, the regional population is relatively small in the TRH region (Yi et al 2013), which therefore experiences a limited impact from human activities on precipitation. The regional precipitation change is increased owing to various factors within the climate system and distinct local characteristics (Yi et al 2013, Shi et al 2017, Tang et al 2018, Xi et al 2018, Wei et al 2019). Moreover, local precipitation changes are primarily affected by climate system changes (Liu et al 2015, Kukulies et al 2019). Further, the South Asian and East Asian monsoons and the midlatitude westerlies have combined and competitive effects on the QTP climate (Ding 1992, Webster et al 1998, Schiemann et al 2009, Yu et al 2009, Cuo et al 2013, Liu et al 2015). Kukulies et al (2019) found that the spatial variations of precipitation in three subregions in QTP are affected by different dominant large-scale atmospheric circulation patterns and moisture sources (i.e. the westerly-dominated domain, transition zone, and monsoon-dominated domain). In particular, precipitation in the TRH region is closely related to atmospheric circulation anomalies in the North Atlantic/European sector (Liu and Yin 2001, Bothe et al 2011, Liu et al 2015) and is also influenced by the Pacific Decadal Oscillation, the El Niño–Southern Oscillation (ENSO), and the East Asian summer monsoon (Liu et al 2015, Sun et al 2017, Xi et al 2018, Wei et al 2019). Nevertheless, thus far, studies have only focused on the associations between a few circulation types, for example, some predefined circulation indices with the variability of the TRH precipitation; however, the explanations for these associations remain insufficient. Comprehensive investigations considering all types of atmospheric circulation patterns are necessary but have currently been insufficiently studied in the TRH region.

Significant intra-annual variation in precipitation in the TRH region has been reported (Yi et al 2013, Kukulies et al 2020). In general, the period from June to September in a given year has relatively higher precipitation (known as the wet period), whereas precipitation is lower from October to the following May (known as the dry period) (Li et al 2016b). Furthermore, Kukulies et al (2020) found a spatial dipole pattern with two distinct seasonalities in the precipitation variations in the study area. Precipitation variations at annual and seasonal
scales have multiple components and are marked by different dominant large-scale atmospheric circulations and moisture sources (Feng and Zhou 2012, Zhang et al. 2017, Chen et al. 2019). However, studies on the dominant patterns of precipitation at annual and seasonal scales and the influence of large-scale atmospheric circulation patterns in the TRH region are relatively scarce. Therefore, it is necessary to systematically detect the dominant patterns of precipitation and analyze the interactions of these patterns with large-scale atmospheric circulation patterns. Moreover, few studies have focused on the influence of regional geographic factors, such as longitude, latitude, and altitude, on precipitation in the TRH region (Yin et al. 2004, Shi et al. 2016, 2017, Tang et al. 2018). Spatial variabilities in precipitation are attributable to the combined effects of the monsoon system and topography (Shi et al. 2017, Kukulies et al. 2020). It is important to study the principal components of the TRH precipitation variations and the potential atmospheric and geographic factors, which are helpful for obtaining a deeper understanding of the regional precipitation regime and for empirical precipitation projections and related adaptation activities.

In this study, we focused on the following: (1) investigation of the temporal trends and spatial distribution characteristics of precipitation changes at annual and intra-annual scales in the TRH region during the period of 1967–2016, (2) presenting dominant patterns of regional precipitation over the last 50 years using the empirical orthogonal function method, and (3) exploring the relationships between longitude, latitude, altitude, the ocean–atmosphere interaction circulation patterns, and precipitation using wavelet transform coherence and Spearman’s correlation coefficient analysis method. The results will help reveal the characteristics of precipitation in the TRH region and provide a clearer understanding of the factors influencing precipitation change, which offer the potential possibility of using ocean–atmosphere interaction circulation patterns and geographical information to model and predict precipitation.

2. Materials and methods

2.1. Study area

The TRH region (31°39′–36°16′N, 89°24′–102°23′E), located in the hinterland of the QTP, also known as the ‘Water Tower of Asia’, is the source of the Yellow River, Yangtze River, and Lantsang River (figure 1). The TRH region not only forms a natural barrier within the ecological environment in China but is also one of the most sensitive and vulnerable ecological environments on the planet. It has an area of 318,000 km² with elevations ranging from 1713 to 6766 m and an average elevation of 4200 m (Wang et al. 2016). This region lies in the temperate zone and is primarily dominated by a typical plateau continental monsoon climate with strong radiation, low cloud cover, and seasonal variations in the temperature and rainfall. The annual mean temperature ranges from −5.38 °C to 4.14 °C (Ding et al. 2018). The annual mean precipitation ranges from 395.78 to 544.87 mm and is primarily concentrated between June and September, when the majority of the annual precipitation (75%) occurs.

2.2. Data sources and quality control

Daily meteorological data were downloaded from the National Meteorological Administration of China (http://data.cma.cn). These datasets are publicly available and have been processed for quality control, including time consistency and homogeneity tests, which were performed using the RHtest V4 package. Daily precipitation was obtained from 33 stations in the TRH region from the first service date of the stations (spanning the period of January 1, 1951–1967) to December 31, 2016, and the precipitation data at all stations are available from 1967 to 2016. The station information is presented in table 1, and the geographical locations of the stations are shown in figure 1.

According to existing research results and current controversies, we selected 14 atmospheric circulation indices. All the selected atmospheric circulation indices, which have a month-scale resolution, are publicly available for download from the websites of different authorities and research centres. The selected indices include the large-scale oceanic and atmospheric circulation patterns of the North Atlantic Oscillation (NAO), Southern Oscillation Index (SOI), Western Pacific Index (WPI), Pacific North American Index (PNA), East Pacific/North Pacific Oscillation (EP/NP), Pacific Decadal Oscillation (PDO), Arctic Oscillation (AO), Atlantic Multidecadal Oscillation (AMO), Multivariate ENSO Index (MEI), and East Central Tropical Pacific sea surface temperature (SST) Niño 3.4 (5°N–5°S, 170–120°W), which were obtained from the Earth System Research Laboratory of the Physical Sciences Division of the United States National Oceanic and Atmospheric Administration (https://www.esrl.noaa.gov/psd/data/climateindices/list/). In addition, the Antarctic Oscillation (AAO), East Asian Summer Monsoon Index (EASMI), South Asian Summer Monsoon Index (SASMI), and South China Sea Summer Monsoon Index (SCSSMI) were obtained from Professor Jianping Li’s homepage hosted by Beijing Normal University (http://ljp.gcess.cn/dct/page/1). The credibility of these datasets has been confirmed (Li and Zeng 2002, Wang et al. 2008).
Table 1. Parameters and raw data for the 33 meteorological stations.

| Station name | Latitude (° N) | Longitude (° N) | Elevation (m) | Maximum precipitation (mm) | Minimum precipitation (mm) | Annual mean precipitation (mm) | Time series |
|--------------|----------------|----------------|---------------|----------------------------|----------------------------|--------------------------------|-------------|
| Gangcha      | 37.33          | 100.13         | 3301          | Value 572.65 2014          | Value 262.25 1990          | 390.54                         | 1958–2016  |
| Geermu       | 36.42          | 94.90          | 2807          | Value 104.60 1967          | Value 13.20 1965           | 44.43                          | 1956–2016  |
| Nuomuhong    | 36.43          | 96.42          | 2790          | Value 146.15 2010          | Value 19.35 1965           | 47.65                          | 1957–2016  |
| Chaka        | 36.78          | 99.08          | 3087          | Value 428.85 1989          | Value 125.40 1956          | 218.38                         | 1956–2016  |
| Qiaobugia    | 36.27          | 100.62         | 2835          | Value 524.90 1967          | Value 160.75 1956          | 320.65                         | 1953–2016  |
| Guizhou      | 36.03          | 101.43         | 2237          | Value 389.70 1961          | Value 136.70 2000          | 256.97                         | 1957–2016  |
| Minhe        | 36.32          | 102.85         | 1813          | Value 575.40 1967          | Value 202.30 1965          | 349.62                         | 1957–2016  |
| Wudaoliang   | 35.22          | 93.08          | 4612          | Value 430.90 2009          | Value 140.25 1984          | 295.54                         | 1957–2016  |
| Xinghai      | 35.58          | 99.98          | 3323          | Value 531.90 2005          | Value 216.05 1977          | 367.06                         | 1960–2016  |
| Linxia       | 35.58          | 103.18         | 1917          | Value 766.35 1967          | Value 329.55 1969          | 504.28                         | 1951–2016  |
| Anduo        | 32.35          | 91.10          | 4800          | Value 628.65 2003          | Value 282.40 2015          | 447.93                         | 1966–2016  |
| Tuotuohu     | 34.22          | 92.43          | 4533          | Value 504.75 2009          | Value 166.65 1994          | 295.42                         | 1957–2016  |
| Zaduo        | 32.90          | 95.30          | 4066          | Value 701.55 2008          | Value 365.50 1959          | 531.34                         | 1957–2016  |
| Qumalai      | 34.13          | 95.78          | 4175          | Value 567.40 2012          | Value 276.30 2015          | 414.80                         | 1957–2016  |
| Yushu        | 33.02          | 97.02          | 3681          | Value 751.35 1952          | Value 325.00 1984          | 490.15                         | 1952–2016  |
| Maduo        | 34.92          | 98.22          | 4272          | Value 489.70 1975          | Value 188.85 1962          | 325.72                         | 1953–2016  |
| Qingshuide   | 33.80          | 97.13          | 4415          | Value 672.45 1989          | Value 345.25 1990          | 519.66                         | 1957–2016  |
| Shiqu        | 32.98          | 98.10          | 4200          | Value 817.25 2014          | Value 367.20 2002          | 516.95                         | 1959–2016  |
| Guoluo       | 34.47          | 100.25         | 3719          | Value 690.05 1989          | Value 382.75 2006          | 516.95                         | 1960–2016  |
| Henan        | 34.73          | 101.60         | 3500          | Value 891.55 1967          | Value 386.30 2002          | 585.59                         | 1960–2016  |
| Jiuzhi       | 33.43          | 101.48         | 3628          | Value 1033.15 1981         | Value 565.55 2000          | 749.11                         | 1959–2016  |
| Maqiu        | 34.00          | 102.08         | 3471          | Value 812.50 1981          | Value 451.20 1996          | 604.95                         | 1967–2016  |
| Ruogai       | 33.58          | 102.97         | 3439          | Value 865.25 1984          | Value 466.75 2008          | 650.76                         | 1957–2016  |
| Dingqing     | 31.42          | 95.60          | 3873          | Value 888.85 1960          | Value 382.85 1973          | 648.62                         | 1954–2016  |
| Nangqian     | 32.20          | 96.48          | 3643          | Value 740.40 2003          | Value 374.20 1997          | 538.59                         | 1957–2016  |
| Chandu       | 31.15          | 97.17          | 3306          | Value 707.25 1998          | Value 292.00 1994          | 486.13                         | 1954–2016  |
| Dege         | 31.80          | 98.58          | 3184          | Value 788.80 2012          | Value 427.65 1973          | 625.63                         | 1957–2016  |
| Banma        | 32.93          | 100.75         | 3530          | Value 836.25 1989          | Value 445.15 2002          | 664.60                         | 1961–2016  |
| Seda         | 32.28          | 100.33         | 3893          | Value 855.70 2005          | Value 463.85 2002          | 664.87                         | 1961–2016  |
| Maerkang     | 31.90          | 102.23         | 2664          | Value 1059.75 1993         | Value 559.90 2002          | 781.62                         | 1954–2016  |
| Hongyuan     | 32.80          | 102.55         | 3491          | Value 999.45 1983          | Value 510.95 2002          | 754.25                         | 1961–2016  |
| Songpan      | 32.65          | 103.57         | 2850          | Value 978.10 1954          | Value 517.15 1959          | 723.99                         | 1951–2016  |
| Xiaozhuang   | 36.80          | 93.00          | 2767          | Value 67.90 2012           | Value 8.30 1965            | 29.56                          | 1961–2016  |
| Average      | –              | –              | –             | Value 661.20 –             | Value 307.80 –              | 467.29                         | –           |
2.3. Analytical methods

2.3.1. Trend analysis
The Mann–Kendall (MK) test has commonly been used to assess the monotonic trends in time series of hydrological and climatic data, such as precipitation, temperature, streamflow, and water quality, in different parts of the world (Wang et al. 2016, Ding et al. 2018, 2019). A brief mathematical background of the Mann–Kendall test is provided in appendix Method 1. Furthermore, the influence of elevation on precipitation may be nonlinear. To explore the correlation between precipitation and elevation, we used the segmented regression model to detect abrupt change points (Shao and Campbell 2002). Previous studies have applied this method in the Shiyang River Basin and Hanjiang River Basin in China (Timo et al. 2002, Shao et al. 2009, She et al. 2017). More details, including the definition and calculation method can be found in a previous study (Shao and Campbell 2002).

2.3.2. Empirical orthogonal function analysis
Hydroclimatological data usually have nonlinear and high-dimensional characteristics. Therefore, it is crucial to identify methods to reduce the dimensionality of the system to the least number of possible modes by expressing the data in such a way as to highlight their similarities and differences. Empirical orthogonal function (EOF), also known as eigenvector analysis or principal component analysis, is frequently used to simplify the interpretation of complex data in the space–time domain (Hannachi et al. 2007). Lorenz (1956) first introduced EOF to examine the spatiotemporal structures of long-term variations in seasonal precipitation. One of the main objectives of EOF is to identify the dominant spatial pattern according to the spatial modes (EOFs) and obtain the corresponding time coefficients (PCs) that reflect the weight change in the corresponding spatial mode of the precipitation with time. To distinguish the physical signal from the noise in the EOF, the North criterion (North et al. 1982) significance test was performed. This test is used here to derive the dominant signals of precipitation from the 33 meteorological stations in the TRH region. The leading principal components that contained most of the original variance were selected as substitutions to investigate the relationships between precipitation and the atmospheric circulation indices. For details concerning EOF, several previous studies can be referred to (Jiang et al. 2013, Yao et al. 2015, Fujinami et al. 2016, Tosić et al. 2016, Gong et al. 2018).

2.3.3. Correlation analysis
To explore the relationship between the mean annual, wet, and dry period precipitation leading EOFs in the TRH region and the large-scale atmospheric circulation indices, correlation analyses were performed between the PCs and atmospheric circulation indices. Wavelet transform coherence (WTC) is a new signal-analysis technology that combines wavelet
transform with cross-spectrum analysis. It is widely used in the field of Earth sciences to effectively analyse the correlation between two time series and can be used to study the co-varying relationship between hydrometeorological factors and their potential drivers in the time–frequency domain at multiple time scales (Torrence and Compo 1998, Jevrejeva et al 2003, Asong et al 2018, Su et al 2019). WTC is a correlation coefficient localized in time and frequency space that can be used to quantify the degree of the linear relationship between two non-stationary series in the time and frequency domains (Torrence and Compo 1998, Su et al 2017, Jiang et al 2019). A brief mathematical background of WTC is provided in appendix Method 2. Spearman’s correlation test, a nonparametric test, has been widely used in correlation analyses of two time series (Wang et al 2019). To identify the factors influencing precipitation, Spearman’s correlation analysis was performed between precipitation and location, elevation, and primary atmospheric circulation patterns in the TRH region. A brief mathematical background of Spearman’s correlation analysis is provided in appendix Method 3.

In this study, the regional averages of annual and seasonal precipitation were calculated as the arithmetic mean of the values at all selected stations. The annual precipitation was computed from January to December. The intra-annual periods were defined as follows: the period from October to the following May is the dry period and that from June to September is the wet period. Based on the obtained monthly mean values of the large-scale atmospheric circulation indices, we calculated the corresponding annual and seasonal large-scale atmospheric circulation indices according to the annual and seasonal precipitation time series.

3. Results and discussion

3.1. Precipitation trends

Change trends were analysed at the 0.01 and 0.05 significance levels using Mann–Kendall analysis. For example, 6, 4, and 14 stations were found to have positive trends at \( \alpha = 0.05 \) for MAP, wet period precipitation (MWP), and dry period precipitation (MDP), respectively (table 2). At this significance level, no station showed a negative trend during the annual, dry, and wet periods. Using all the station data, the absolute change rate (ACR) values of MAP, MWP, and MDP were 3.76, 0, and 4.01 mm decade\(^{-1}\), respectively. The relative change rate (RCR) was 1.42% for MAP, 0.54% for MWP, and 0.89% for MDP (table 2), which indicates that the increasing trend in MDP was much more pronounced than that in MWP. In fact, the increase in MAP in the TRH region could be caused by global warming, which strengthens ocean evaporation and terrestrial evapotranspiration. This intensifies the hydrologic cycle over large regions (Brutsaert and Parlange 1998, IPCC 2013) and further recycles the local moisture to increase precipitation (Zhang et al 2017). The increase in MDP is closely related to the weaker westerlies and stronger southerly winds, which are conducive to northward water vapour transport (WVT) from the Indian Ocean and the Western Pacific Ocean (Zhang et al 2017, Chen et al 2019, Xu et al 2020). In addition, MWP and MDP were 339.33 and 127.92 mm, respectively, indicating that MWP accounted for more than 70% of MAP and was 2.7 times as large as MDP (figure 2). The RCR averaged an approximately 1.42% increase in MAP, irrespective of whether the precipitation occurred during the wet or dry periods (table 2). Over the entire region, precipitation primarily showed an increasing trend. As mentioned above, previous studies (Yi et al 2013, Shi et al 2016, 2017) have reported that MAP showed a significant increasing trend. However, the apparent differences in the trends between this study and those of Shi et al (2016) and Li et al (2016a) may be attributed to the selected stations and time series in the area.

3.2. Spatial variations

The spatial distributions of MAP, MWP, and MDP are shown in figure 3. MAP, MWP, and MDP exhibit a decreasing trend from southeast to northwest (figures 3(a)–(c)). The highest MAP, MWP, and MDP values were 781.6, 520.0, and 315.8 mm at the Maerkang, Jiuzhi, and Songpan stations, respectively. The MWP values in the southern and eastern TRH were generally more than 380.0 mm, while the MDP values were generally less than 200.0 mm. The lowest MAP, MWP, and MDP values were 29.6, 23.2, and 6.7 mm, respectively, at Xiaozaohuo station. A strong spatial variability was observed for the ACR (figures 3(d)–(f)). For MAP, large increase rates occurred primarily in the western and middle regions, with the largest ACR value of 17.64 mm decade\(^{-1}\) at Anduo station, but decreasing trends were observed in the eastern TRH, with the largest ACR value being –11.22 mm decade\(^{-1}\) at Henan station (figure 3(d)). For MWP, the precipitation totals in the northwest TRH exhibited a large increase rate, with the largest ACR value being 10.08 mm decade\(^{-1}\) at Anduo station, while there were significant decreasing trends in the southeast TRH, with the largest ACR value being –14.32 mm decade\(^{-1}\) at Henan station (figure 3(e)). In addition, the increasing ACR trends for MDP occurred primarily in the southwest region, with the largest ACR value being 14.36 mm decade\(^{-1}\) at Shiqu station, whereas the ACR for MDP showed relatively tight decreasing trends in the northeast TRH (figure 3(f)). For MAP, MWP, and MDP, the variations in the RCR spatial patterns were similar to those observed for the ACR distribution (figures 3(g)–(i)). In particular, compared with ACR, the regional scope for the increasing and decreasing RCR trends were more obvious.
Table 2. Trend analysis of precipitation during the annual, wet, and dry periods.

| Station name | ACR (mm/decade) | RCR (%) |
|--------------|-----------------|---------|
|              | Annual | Wet period | Dry period | Annual | Wet period | Dry period |
| Gangcha      | 9.75\textsuperscript{b} | 8.69\textsuperscript{b} | –1.88 | 2.50 | 2.22 | –0.48 |
| Geermu       | 2.55\textsuperscript{b} | 1.69 | 0.72 | 5.75 | 3.80 | 1.62 |
| Nuomuhong    | 2.38 | 1.42 | 1.01 | 4.98 | 2.98 | 2.12 |
| Chaka        | 7.86\textsuperscript{b} | 8.67\textsuperscript{b} | –1.76 | 3.60 | 3.97 | –0.81 |
| Qibaquja     | 6.10 | 2.05 | 1.67 | 1.90 | 0.64 | 0.52 |
| Guizhou      | 3.10 | 0.92 | –0.50 | 1.21 | 0.36 | –0.20 |
| Minhe        | –3.15 | –3.37 | 1.12 | –0.90 | –0.97 | 0.32 |
| Wudaoliang   | 12.91\textsuperscript{b} | 9.63\textsuperscript{b} | 4.74\textsuperscript{a} | 4.37 | 3.26 | 1.60 |
| Xinghai      | 10.9 | 7.92 | 0.54 | 2.99 | 2.16 | 0.15 |
| Linxia       | 1.19 | –2.29 | 2.30 | 0.24 | –0.45 | 0.46 |
| Anduo        | 17.64\textsuperscript{b} | 10.08 | 5.19\textsuperscript{b} | 3.94 | 2.25 | 1.16 |
| Tuotuohe     | 8.34 | 5.48 | 3.82\textsuperscript{b} | 2.82 | 1.86 | 1.29 |
| Zaduo        | 5.43 | 0.18 | 8.22\textsuperscript{a} | 1.02 | 0.03 | 1.55 |
| Qumalai      | 9.30 | 8.61 | 3.66\textsuperscript{b} | 2.24 | 2.08 | 0.88 |
| Yushu        | –0.28 | –6.02 | 5.40\textsuperscript{a} | –0.06 | –1.228 | 1.10 |
| Maduo        | 10.29\textsuperscript{b} | 5.37 | 3.94\textsuperscript{b} | 3.16 | 1.65 | 1.21 |
| Qingshuihe   | 3.51 | –0.07 | 6.91\textsuperscript{a} | 0.68 | –0.01 | 1.33 |
| Shiqu        | 5.39 | –10.20 | 14.36\textsuperscript{b} | 0.94 | –1.77 | 2.50 |
| Guoluo       | 2.13 | –0.54 | 3.50 | 0.41 | –0.11 | 0.68 |
| Henan        | –11.22 | –14.32\textsuperscript{b} | 0.43 | –1.92 | –2.45 | 0.07 |
| Jiuzhi       | –7.95 | –13.39 | 7.35\textsuperscript{a} | –1.06 | –1.79 | 0.98 |
| Maqu         | –2.02 | 0.07 | –0.14 | –0.33 | 0.01 | –0.02 |
| Ruoergai     | –1.43 | –0.45 | –0.60 | –0.22 | –0.07 | –0.09 |
| Dingqing     | 2.74 | –6.48 | 9.26\textsuperscript{b} | 0.42 | –0.10 | 1.43 |
| Nangqian     | 7.10 | 1.28 | 8.85\textsuperscript{a} | 1.32 | 0.24 | 1.64 |
| Changdu      | 4.33 | –0.03 | 4.98\textsuperscript{b} | 0.89 | –0.01 | 1.03 |
| Dege         | 4.75 | 1.49 | 4.39 | 0.76 | 0.237 | 0.702 |
| Banma        | 0.44 | –5.98 | 9.11\textsuperscript{b} | 0.07 | –0.90 | 1.37 |
| Seda         | 5.16 | 0.10 | 6.74 | 0.78 | 0.01 | 1.01 |
| Maerkang     | 9.24 | –0.56 | 8.67 | 1.18 | –0.07 | 1.11 |
| Hongyuan     | –2.76 | –6.02 | 6.13 | –0.37 | –0.80 | 0.81 |
| Songpan      | –0.86 | –4.53 | 3.54 | –0.12 | –0.63 | 0.49 |
| Xiaozaozhuo  | 1.06 | 0.72 | 0.50 | 3.59 | 2.45 | 1.69 |
| Average      | 3.76 | 0.00 | 4.01 | 1.42 | 0.54 | 0.89 |

\textsuperscript{a}If trend at ≤0.01 level of significance.
\textsuperscript{b}If trend at ≤0.05 level of significance.

Figure 2. Mean yearly precipitation totals during the wet and dry periods.

The MAP, MWP, and MDP patterns exhibit a southeast-to-northwest decreasing trend over this region. The reason for this is as follows: the TRH region lies in a typical plateau continental monsoon...
region where precipitation is primarily dominated by the South Asian Monsoon (SAM), East Asian Monsoon (EAM), and westerlies system (Yu et al. 2009, Boos and Kuang 2010, Liang et al. 2013, Cao and Pan 2014, Shi et al. 2017). The warm and humid water vapor from the Bay of Bengal and the mountainous topography, which may also play an important role in blocking some of the moisture delivered by SAM from the Indian Ocean and EAM from the Pacific Ocean under the uplift and thermal effect of the terrain, leads to relatively sparse and unstable precipitation in the northern TRH. Topography, in which information can be acquired from the elevation and geographical location (i.e. the longitude and latitude) to some extent, is an important factor affecting the spatial distribution of precipitation. In addition, previous studies have found a close correlation between precipitation and longitude, latitude, and elevation in similar regions (Yin et al. 2004, Shi et al. 2016, 2017).

3.3. Dominant patterns of precipitation

Table 3 presents the explained variances of the varimax components. The first five EOFs account for 69% of the total variance, while the error ranges of the first two characteristic roots do not overlap and pass the North significance test (North et al. 1982). The first two EOFs, accounting for 50% of the total variance, can appropriately explain the dominant patterns of precipitation in the TRH region. They were therefore identified for subsequent discussion and analysis.

Figure 4 shows the spatial patterns of the two main components (EOF1 and EOF2) for MAP, MWP, and MDP. The EOF1 components of the annual, wet, and dry periods explain 28.99%, 28.46%, and 34.37% of the total variance, respectively, highlighting the primary patterns of precipitation in the TRH region. Negative EOF1 values of the annual and wet periods are spread widely over the TRH region with a negative centre around southeast TRH (figures 4(a) and (c)); meanwhile, positive EOF1 values of the dry period occur (figure 4(e)). The high-value centre is located in southeast TRH, which reflects the large amount of precipitation change, and the low-value centre is located in northwest TRH. The spatial patterns of EOF1 of the annual, wet, and dry periods are similar to those of the precipitation trend shown in figure 3, indicating that the precipitation trends in the TRH region were highly consistent; specifically, the precipitation distribution characteristics of the entire region were either rainier or drier. The EOF2 of the annual, wet, and dry periods exhibits a dipole precipitation anomaly pattern, demonstrating reverse precipitation anomalies over the southwest and northeast parts of the TRH region (figures 4(b), (d) and (f)). Here the explained variances are 19.70%, 20.92%, and 14.93%, respectively, less than those of EOF1. The positive EOF2 centre appears in southern TRH, and the negative centre appears in northeast TRH, showing a southwest–northeast reverse distribution pattern, that is, precipitation increases in southwest TRH and decreases in northeast TRH, or precipitation decreases in southwest TRH and increases in northeast TRH. In summary, the above analyses suggest that the first two EOFs can represent the dominant patterns of precipitation in the TRH region.

The PC trends of EOF1 and EOF2 for the three periods from 1967 to 2016 are depicted in figure 5. PC1 experienced a negative-to-positive-to-negative trend starting in the mid-1960s, 1970s, and mid-1970s, respectively, which displays an interannual variability with a timescale of ~8–9 years (figures 5(a)–(c)). PC1 of MDP is opposite to that of...
Table 3. Percentage of variance explained by the first five varimax loadings (EOFs) of precipitation in the three periods.

| EOF  | Annual (%) | Wet period (%) | Dry period (%) |
|------|------------|----------------|----------------|
| EOF1 | 28.99      | 28.46          | 34.37          |
| EOF2 | 19.70      | 20.92          | 14.93          |
| EOF3 | 9.2        | 9.8            | 9.0            |
| EOF4 | 6.8        | 7.3            | 6.4            |
| EOF5 | 4.7        | 4.8            | 5.3            |
| Cumulative value | 69.4 | 71.3 | 70.0 |

Figure 4. Spatial patterns of EOF1 and EOF2 over the TRH region during 1967–2016.

MAP and MWP. The trend slope of PC1 for MAP is less than zero, and the corresponding EOF1 value is negative, which indicates that the TRH region has an increasing trend of precipitation to some extent. These precipitation changes correspond well with the findings of Shi et al. (2017) and Xi et al. (2018), who identified an increasing trend for MAP. The trend slopes of PC1 for MWP and MDP are slightly greater than zero, and the corresponding EOF1 values are negative and positive, respectively (figures 4(c) and (e)), which indicates that precipitation has decreased and increased, respectively, for these periods from 1967 to 2016.

The PC2 trend slope for MDP is the opposite of those for MAP and MWP (figures 5(d)–(f)). PC2 indicates that there is more precipitation in western TRH and less precipitation in northeast TRH, or less precipitation in southern TRH and more precipitation in northeast TRH. The trend slope of annual PC2 is greater than zero, indicating that the amount of precipitation is decreasing in northeast TRH and increasing in southwest TRH (figure 5(d)). The trend slope of the wet period PC2 is greater than zero, which is consistent with the observed MAP change. The trend slope of the dry period PC2 is slightly less than zero, indicating that the precipitation has increased in northeast TRH and decreased in southwest TRH (figure 5(f)). It can be seen from figure 3 that the degree of the typical precipitation field reflected by the time coefficient is consistent with that reflected by the feature vector. The spatiotemporal structure according to EOF2 and PC2 resembles the precipitation fluctuation pattern between southwest and northeast TRH, as reported by Shi et al. (2017) and Xi et al. (2018).

3.4. Factors influencing precipitation change

3.4.1. Relationship between precipitation, location, and elevation

Precipitation is primarily affected by atmospheric circulation, topography, the underlying surface, and other climate factors (Yi et al. 2013, Kukulies et al...
For the TRH region, the factors of regional and seasonal differences influencing precipitation may be inextricably linked to location, topography, and the large-scale circulation patterns. To explore the links between precipitation, location, topography, and large-scale circulation patterns, we calculated their correlations through a correlation analysis. Precipitation had significant negative and positive correlations with latitude and longitude, respectively (table 4). The absolute value of the correlation coefficient between MWP and latitude was up to 0.81, and it was the smallest (0.63) between MDP and latitude. The absolute values of the correlation coefficient between precipitation and latitude were mostly lower than those between precipitation and longitude, except for MDP, which had a range from 0.36 to 0.67. This is consistent with the findings of Shi et al. (2016, 2017), who suggested that the geographical location (i.e. longitude and latitude) is an important factor influencing precipitation. In addition, precipitation changes corresponding to elevation changes have been reported in previous studies (Yin et al. 2004, Chu 2012, Shi et al. 2016, 2017, Li et al. 2017). However, precipitation had no correlation with elevation according to Spearman’s correlation coefficient analysis (table 4), which is used to reflect the linear correlation degree between two variables. In fact, the influence of elevation on precipitation may be nonlinear (Shi et al. 2016, 2017). Using the segmented regression model, abrupt change points were found at altitudes of 2800 and 3500 m for the relationship between precipitation and elevation (figure 6). Because the $R^2$ values were not low (i.e. >0.80 for <2800 m, >0.70 for 2800–3500 m, and >0.40 for >3500 m), dramatic correlations were found. However, precipitation at the two stations (Maerkang and Songpan) located in low-altitude valleys was obviously higher. This was because the summer monsoon, with a large amount of water vapour blowing from the southeast direction, significantly increased precipitation. Shi et al. (2016, 2017) suggested that the relationship between MAP and the elevation could be divided into two groups and that the cutoff value should be 3800 m in the TRH region. The apparent differences in these results may be attributable to the low station density and the different data series lengths in areas that can introduce higher uncertainty. Admittedly, more in situ observations at high elevations are required to further evaluate the elevation dependence of the trends in the region. Furthermore, Li et al. (2017) showed that large-scale atmospheric circulation patterns represent another possible factor influencing the elevation dependence of the precipitation trends, which requires further investigation. Changes in precipitation over the TRH region could be related to large-scale atmospheric circulation systems that directly or indirectly affect the region, as will be examined below.

3.4.2. Relationship between the PCs of precipitation and large-scale atmospheric circulation patterns

Figures 7 and S1 illustrate the WTC results for the first two PCs (PC1 and PC2) of MAP and the 14 large-scale circulation patterns with phase lags between components, as illustrated by the black arrows. To simplify and limit the length of this paper, only the results for the large-scale climate indices with the strongest correlations with the PCs are depicted. Other results are included as supplementary material.

For PC1, it is apparent that WPI had a significant anti-phase (negative) relationship with PC1 primarily concentrated in the 6–9-year band from 1967 to 1977 and in the 5–7-year band from 1987 to 2003, while a significant in-phase (positive) correlation was observed in the 1–3-year band after 2005 (figure 7(a1)). In addition, a strong coherence between PC1 and PDO, AO, AAO, SOI, MEI, and SST occurred at the 2–6-year scale spanning 1967–1977 and 1987–2003 (figures 7(b1)–(g1)). A significant positive correlation between PDO, MEI, SST, and PC1 (figures 7(b1), (f1) and (g1)) and significant negative correlation with AO, AAO, and SOI...
Table 4. Correlation coefficients between precipitation, location, and elevation.

| Location  | Maximum precipitation (mm) | Minimum precipitation (mm) | MAP (mm) | MWP (mm) | MDP (mm) |
|-----------|-----------------------------|-----------------------------|----------|----------|----------|
| Latitude  | $-0.72^a$                   | $-0.72^a$                   | $-0.76^a$| $-0.81^a$| $-0.63^a$|
| Longitude | $0.56^a$                    | $0.55^a$                    | $0.52^a$ | $0.36^b$ | $0.67^a$ |
| Elevation | $0.10$                      | $0.15$                      | $0.16$   | $0.27$   | $-0.04$  |

$^a$If trend at $\leq 0.01$ level of significance.

$^b$If trend at $\leq 0.05$ level of significance.

were found; in particular, the relationship between SOI and PC1 was opposite to that between MEI and SST (figures 7(c1)–(e1)). The dominant high-energy anti-phase coherence between PC1 and AO occurred at the 7–10-year scale spanning 1967–1993. In other frequency bands, the resonance energy of PC1 and the large-scale circulation patterns is weak and only scattered areas pass the significance test. In particular, PC1 has a 16-year band of high wavelet power with EASMI for 1967–2016 and has a rather stable mean phase angle ($0^\circ$) both inside and outside the cone of influence (COI) over the past 50 years. In theory (Jevrejeva et al 2003), the wavelet power outside the COI does not pass the Monte Carlo test, indicating that these coherences may not be reliable (Grinsted et al 2004). Nevertheless, the significance regions in the large-scale circulation patterns are so extensive and consistent that it is unlikely to be an accident (Grinsted et al 2004), which possibly indicates an approximately 16-year

Figure 6. Relationship between precipitation and elevation.
The relationships between the first two PCs of MWP and the 14 large-scale circulation patterns are shown in figures 8 and S2. In the case of WPI–PC1, discontinuous in-phase coherence patterns were detected in the 6–8-year bands from 1967 to 1977, in the 4–8-year bands from 1990 to 2010 with a significant negative correlation, and in the 12–16-year bands from 1967 to 2003 with an obvious negative correlation (figure 8(b1)). It is clear that PC1 has a significant correlation pattern with ENSO (SOI, MEI, and SST) (figures 8(e1)–(g1)). Therefore, significant positive correlations with MEI and SST were observed, primarily distributed in the 4–8-year band and spanning 1967–1977, while a significant negative coherence was noticed at a higher frequency, ranging between 8 and 11 years and primarily concentrated over 1998–2015. For EN/NP (figure 8(c1)), a significant 3–6-year anti-phase coherence also existed from 1988 to 2013. Relationships between PC1 and PDO were found from 1978 to 1985 and from 1998 to 2015, where the significant coherence was primarily concentrated in the 1–2-year and 5–6-year bands,
For the other large-scale circulation patterns within the COI zone, scattered interannual periodicities occurred in the period from the 1970s to the 2000s (figures 8(a1), (h1) and S2(a1)–(f1)). For PC2, figures 8(a2)–(h2) depicts that significant coherences are primarily observed with NAO, EP/NP, AO, AAO, SOI, MEI, SST, and SCSSMI and occurred between 8 and 16 years over the period from the 1980s to the 2010s. Positive coherences between PC2 and AO, AAO, and SOI occurred, while negative coherences with NAO, EP/NP, MEI, SST, and SCSSMI occurred; sporadic significant coherence was noted with a scattered distribution on other periodic scales from the 1980s to the 2010s. In particular, the strongest relationship between PC2 and AO occurred over the period of 1967–2015 (figure 8(c2)). Other large-scale circulation patterns have relationships with PC2 ranging between 1 and 8 years and are primarily concentrated in the period from the 1970s to the 2000s (for SASMI ranging between 1 and 8 years in the period from the 1980s to the 2010s) (figures s2(a2)–(f2)).

Figures 9 and S3 show the WTC results for the first two PCs of MDP and the 14 large-scale circulation patterns. For PC1, sporadic but anti-phase significant coherence is observed intermittently between 1 and 4 years over the period of 1967–1987 and between 6 and 10 years over the period of 1993–2015 with NAO (figure 9(a1)); PC1 also has a similar relationship with SCSSMI (figure s3(f1)). For PNA, dominant strong anti-phase coherence occurred between 13 and 16 years over the period of 1967–2003, whereas fluctuations were intermittently observed between 1967 and 2006 ranging from 1 to 6 years (figure 8(b1)). In addition, ENSO (SOI, MEI, and SST) was sporadic but co-varied with PC1 during the period of 1967–1997 at the 3–6-year band and during the period of 1967–2015 at the 8–12-year band (figures 9(e1)–(g1)). EASM1 had a significant anti-phase coherence with PC1 primarily concentrated in the 4–6-year band from 1967 to 2003 (figure 9(h1)). For other circulation patterns within the COI zone, coherence occurred with scattered interannual periodicities or had no correlation from the 1970s to the 2000s (figure s3). Figures 9(a2)–(h2) shows that sporadic but significant coherence is observed intermittently from year to year. In the case of PC2–PNA, discontinuous in-phase coherence patterns were detected in the 1–16-year bands. The dominant high-energy coherence occurred at the 14–16-year scale, spanning the period of 1967–2015 (figure 9(c2)). For AMO, dominant strong in-phase coherence occurred between 8 and 16 years over the period of 1967–2015 (figure 9(f2)). EP/NP showed a strong in-phase relationship with PC2 only over the 8–16-year scale, from the later 1960s to the early 1990s (figure 9(d2)). Moreover, NAO, AO, and WPI co-varied significantly with PC2 during the study period and most of these indices are outside the COI, suggesting that this relationship may be robust (figures 9(a2), (h2) and (e2)). Significant coherence was scarce between other large-scale atmospheric circulation indices and PC2 (figures 9(g2), (h2) and S3).

Furthermore, to comprehensively examine the correlation results between MAP, MWP, and MDP and the large-scale climate circulations, the Spearman’s correlation coefficients were calculated for the precipitation, PCs, and the 14 large-scale climate indices (tables s1 and s2). The results are shown in figure S4. There are some differences between the results of WTC and Spearman’s correlation coefficient analysis. One possible reason for this is that the Spearman’s correlation coefficient analysis is linear, while WTC is nonlinear. Both indicate that precipitation in the TRH region is likely controlled by different circulation patterns.

The impacts of the large-scale climate indices on EOF1 and EOF2 for MAP, MWP, and MDP over the TRH region are different. NAO exerts a strong influence on the spatial EOF2 pattern of MAP over the entire domain during 1977–2015, while AO appears to affect the spatial EOF1 pattern from 1967 to 2015. NAO and AO exert similar effects on the spatial EOF2 pattern of MWP over the entire TRH region. Previous studies have shown that NAO and AO appear to be internally related (Cuo et al 2013). Moreover, the effects of NAO and AO on the dominant patterns of MDP are primarily on EOF1 (1967–1987 and 1993–2015) and EOF2 (1967–2000), respectively. It is possible that the associated teleconnection patterns differ between the seasons, consistent with the fact that NAO and AO are most pronounced in winter despite their year-round presence (Cuo et al 2013). In addition, AMO primarily affected the EOF1 (1967–1993) and EOF2 (1967–2015) of MDP, while it scarcely affected the dominant patterns of MWP.

AAO has an important effect on the EOF2 of MAP (1977–2015) and primarily affects EOF2 of MWP (1977–2015). The EOF1 of MDP (1993–2010) is weakly affected by AAO, while the EOF2 of MDP (1967–1987) shows a shift in the effect of AAO.

SASMI and SCSSMI primarily affect the EOF2 of MAP (1977–2015) and MWP (1977–2015), and the corresponding impact area is southern TRH. This is in line with a previous study by Xi et al (2018), indicating that the correlations between precipitation and the teleconnection indices over the northern regions are small and insignificant. Moreover, the influence of SASMI and SCSSMI over the TRH region exhibits a strong subregional preference in the summer months, with a generally larger impact over the southern domain than the northern domain. EASM1 significantly affects the EOF1 of MAP and MDP (1977–2015) in southeast TRH. This is consistent with the work of Shi (1996), who considered the winter climate in China to be closely related to the interannual and interdecadal changes in EASM1. Furthermore, PNA
Figure 8. Same as figure 7, but for the large-scale atmospheric circulation indices and the first two EOF modes of the mean wet period precipitation (MWP).

is another major factor in East Asian winter atmospheric circulation and has a significant effect on the EOF1 (1967–2003) and EOF2 (1967–2015) of MDP. Moreover, PNA has weaker effects on MWP but its effect abruptly changes in 1977 and 1987. The effect of PDO on TRH precipitation is similar to that of PNA, and its influence range is larger.

The seasonal effects of AAO versus EASMI, PNA, and PDO on precipitation are contrary, which is consistent with the finding that AAO has a significant inverse correlation with atmospheric circulation from low to high latitudes in the North Pacific (Shi 1996).

EP/NP significantly affects the EOF2 of MAP (1987–2015) and MWP (1977–2015), while it has a small effect on the EOF2 of MDP (1967–1987) in southeast TRH. In addition, WPI significantly affects the EOF1 values of MAP (1967–1977 and 1987–2003) and MWP (1967–2003 and 1977–2015), while it has a small effect on the EOF2 of MDP (1967–1987) in northeast TRH.

ENSO is usually reflected by SOI, MEI, and SST, which exert a similar influence over the TRH region. The effects of SOI versus MEI and SST on precipitation are contrary. ENSO produces an effect on the EOF1 (1967–1977 and 1987–2003) and EOF2 (1977–2015) of MAP, with anti-phase and in-phase changes occurring in 1977, 1990, and 2003. For MWP, ENSO primarily affects EOF2 in the Yellow River region, consistent with the findings of Cu et al (2013), who suggested that ENSO primarily affects northern QTP during the summer months. Additionally, the EOF1 of MDP is affected by ENSO in the Yangtze River region and Lantsang River region. Therefore, the effect of ENSO on precipitation is comparatively strong regardless of the season or region.

The precipitation is determined by regional water vapour sources, and the amount and direction of the WVT are closely related to atmospheric circulation (Li et al 2009a, Zhang et al 2011; Li et al 2016a, Sun and Wang 2018, Zhang et al 2019). The southwest warm and humid air from the Bay of Bengal, Indian Ocean, and South China Sea is the main source of water vapour in the TRH, followed by the northwest dry and cold air from the Aral Sea, Caspian Sea in Central Asia, and high-latitude areas (Li et al 2009a).
These two types of large-scale circulation background flows converge to the TRH, forming a special water vapour structure and WVT characteristics. During the dry period, the anomalous northwesterly WVT branch crossing the western and northern boundary of the TRH is critical to the interannual variability of the MDP and the anomalous southwesterly WVT branch toward the TRH region plays a secondary role. During the wet period, the southwesterly WVT associated with the South Asian summer monsoon (SASM) and East Asian summer monsoon (EASM) is the main water source for the MWP, indicating the important role of these two monsoons in climatology of the TRH (Li et al. 2009a, Sun and Wang 2018, Zhang et al. 2019). Moreover, there is a significant correlation between the two Asian summer monsoon subsystems; this is primarily reflected in the interactions of water vapour sources and transport pathways and may also be reflected in the teleconnection on a larger scale. Previous studies have shown that the interannual and interdecadal variability of the EAM is influenced by various factors, including the NAO, ENSO, Pacific and Indian Ocean SSTs, PDO, and AMO (Wang et al. 2000, Zhang et al. 2004; Ding et al. 2009; Zhu et al. 2011, Ouyang et al. 2014, Sun 2015, Xiao et al. 2015). Overall, the relationships of the indices are complicated and require further in-depth investigation (Wu et al. 2011, Ye et al. 2018).

After 1977, the relationship between precipitation and EASMI, SCSSMI, and SASMI in the TRH became significant. In particular, the precipitation in the source regions of the Yangtze River and Lancang River showed a strong correlation with these indices, while that in the source region of the Yellow River showed a weak correlation. This finding corresponds with a previous study by Li et al. (2016) and Ye et al. (2018). These correlations reflect the fact that the EAM experienced an abrupt change from strong to weak since the late 1970s (Tian et al. 2004, Zhang et al. 2011, Ye et al. 2018). The weakening of the EASM led to a decrease in the meridional WVT to the north, resulting in a decrease in precipitation in the northern TRH and an increase in precipitation in the southern TRH (Lv et al. 2004, Gao et al. 2014). Moreover, because the WVT of the SASM is primarily latitudinal, the transported WVT mainly

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**Figure 9.** Same as figure 7, but for the large-scale atmospheric circulation indices and the first two EOF modes of the mean dry period precipitation (MDP).

| Year | NAO-PC1 | PNA-PC1 | PDO-PC1 | AMO-PC1 |
|------|---------|---------|---------|---------|
| 1970 | 0.8     | 0.6     | 0.4     | 0.2     |
| 1980 | 0.7     | 0.5     | 0.3     | 0.1     |
| 1990 | 0.6     | 0.4     | 0.2     | 0.1     |
| 2000 | 0.5     | 0.3     | 0.1     | 0.0     |
| 2010 | 0.4     | 0.2     | 0.1     | 0.0     |

| Year | EASM-PC1 | ENNP-PC1 | WNP-PC1 | PNA-PC2 |
|------|----------|----------|---------|---------|
| 1970 | 0.8      | 0.6      | 0.4     | 0.2     |
| 1980 | 0.7      | 0.5      | 0.3     | 0.1     |
| 1990 | 0.6      | 0.4      | 0.2     | 0.1     |
| 2000 | 0.5      | 0.3      | 0.1     | 0.0     |
| 2010 | 0.4      | 0.2      | 0.1     | 0.0     |

| Year | SASM-PC1 | SCSSMI-PC1 | YR-PC2 |
|------|----------|------------|--------|
| 1970 | 0.8      | 0.6        | 0.4    |
| 1980 | 0.7      | 0.5        | 0.3    |
| 1990 | 0.6      | 0.4        | 0.2    |
| 2000 | 0.5      | 0.3        | 0.1    |
| 2010 | 0.4      | 0.2        | 0.1    |
affects the precipitation in the central and southwest border areas of South China (Tian et al 2004, Chen and Huang 2007). A strong SASM is more likely to carry a large amount of water vapour from the west to the east along the latitudinal direction to South China and brings a large amount of precipitation to the region; conversely, a weak SASM carries less water vapour in the latitudinal direction, extending to the upper reaches of the Yangtze River along the east side of the QTP and bringing precipitation to the TRH (Li et al 2016a).

The North Atlantic SST gradually entered a cooling stage from the 1960s to 1980s. Since the early 1990s, the North Atlantic SST has entered a warm period (Li et al 2009b), which is consistent with the abrupt change in the relationship between the AMO and precipitation in the TRH in 1993. The main AMO mechanism affecting the Asian climate may be that the AMO is a prominent mode of the multi-decadal variability in the Atlantic Ocean. The abnormal warming of the Atlantic SST heats up the middle and upper tropospheres of the Northern Hemisphere, thus increasing the temperature of Eurasia, strengthening the thermal difference between land and sea in summer, and enhancing the summer monsoon and weakening the winter monsoon. However, the relationship between AMO and MWP is weak in this study because the influence of AMO on MWP is revealed through the EASM. Moreover, the effect of NAO is similar to that of AMO (Goswami et al 2006, Lu et al 2006). Previous studies showed that NAO and AO appear to be internally related (Guo et al 2013); therefore, the effects of NAO and AO are similar. Moreover, AMO can modulate ENSO and warm-phase AMO tends to weaken the ENSO intensity (Li et al 2009b).

Another contributor to the southwesterly WVT anomalies toward the TRH is likely ENSO (Ouyang et al 2014, Xiao et al 2015). ENSO, as the strongest worldwide signal of the interaction between ocean and atmosphere, affects the climate in China via atmospheric circulation. During El Niño-decaying summers, warming in the Arabian Sea may have an important impact on the anomalous anticyclone over the Bay of Bengal. The strengthened convection over the Arabian Sea resulting from its warming can cause easterly wind anomalies over the Bay of Bengal and India and result in an anticyclonic wind shear north of the Bay of Bengal, pushing southwesterly WVT anomalies toward the TRH. This effect is responsible for the anticyclonic regime affecting the TRH (Wu et al 2009, Xie et al 2009, Sun and Wang 2018). ENSO can also affect the interannual precipitation variation by directing the WVT into the southern TRH branch during the dry period (Sun and Wang 2018). Three phases of significant interdecadal SST warming in the tropical central and eastern Pacific, which occurred in the late 1970s, and early 1990s, have been found. The above interdecadal variability of the heating fields over Asian land areas and neighbouring West Pacific oceanic regions has consistently reduced the land–sea thermal contrast in summer in the Asian monsoon region based on estimates of the atmospheric heating fields. This likely leads to weakening of the Asian summer monsoon. In such a case, the northward moisture WVT in East Asia is greatly weakened and cannot reach North China, resulting in less precipitation. Conversely, the Yangtze River Basin and South China receive a large amount of moisture and experience strong upward atmospheric motion, creating favourable conditions for increased precipitation (Sun and Wang 2018).

AAO anomalies can cause mean meridional circulation anomalies in the Southern Hemisphere and are closely related to the local meridional circulation anomalies in Eurasia and the North Pacific. The meridional teleconnection in these regions may connect the two hemispheres in winter (Fan and Wang 2006). For example, changes in the intensity of the Somali Jet directly affect the WVT across the equator to the SAM and EAM regions and subsequently result in changes in the water vapour supply and precipitation. Changes in the Somali Jet can also directly affect the southwest monsoon and subsequently the East Asian climate via these changes. Changes in the Somali low-level jet simultaneously lead to changes in the upper meridional flow, and these changes are associated with the South Asian high. Changes in the low-level southwest monsoon flow result in changes in the high-level divergence and convergence, affecting the climate of East Asia (Wang and Xue 2003). There is a meridional teleconnection pattern distributed from the Southern Hemisphere to the Northern Hemisphere in the Pacific region in spring. The spring AAO is closely related to the PNA, which is a major factor of the winter atmospheric circulation in East Asia, reflecting the atmospheric circulation connection from low latitude to high latitude in the North Pacific region (Fan and Wang 2006); therefore, PNA primarily affects MDP, which partly explains why AAO affects MDP. AAO affects the climates of South and East Asia via teleconnection, and then the South and East Asian monsoons affect the variation in precipitation by influencing the amount and direction of the WVT.

In summary, the degrees of influence of different indices on precipitation are different. This is consistent with the findings of Liu et al (2015), who suggested that the changes in precipitation in a region are primarily attributable to the combined effect of all the circulation types. However, the effects of local weather systems on precipitation are difficult to quantify owing to the lack of representative indices. Large-scale circulation patterns provide us with an ideal tool to understand circulation dynamics and its association with local climate variability. Furthermore, we found that the relationships between precipitation and large-scale atmospheric
circulation patterns in the TRH region exhibited significant abrupt changes in 1977, 1987, 1993, 2000, and 2003. Moreover, the abrupt changes in the covariance between MWP and the large-scale climate indices occurred primarily in the mid- to late-1970s, while the abrupt changes in MDP occurred primarily in the late 1980s, early 1990s, and early 2000s. Our results are in agreement with previous studies in the QTP (Cuo et al. 2013, Yi et al. 2013, Liu et al. 2015). The abrupt changes are the result of a shift in the background state of the coupled ocean–atmosphere system over the eastern tropical Pacific and the northern Pacific Ocean (Graham 1994) and the phase/intensity transitions of ENSO since 1976/1977 (Gilderson and Schrag 1998). However, the mechanism of these abrupt changes is not clear. The reasons for the occurrence of abrupt changes in the relationships of precipitation with the large-scale atmospheric circulation patterns in the TRH region are complex. This issue remains open and requires further investigation.

4. Conclusions

This paper, using daily precipitation datasets in the TRH region during 1967–2016, investigated long-term temporal trends and spatial distributions of precipitation. Precipitation was decomposed into time-dependent time components and spatial characteristics that did not change with time using EOF. Then, based on the time component and the spatial characteristics of decomposition, the possible effects of 14 large-scale atmospheric circulation patterns on the seasonal and annual precipitation were analysed using WTC. Moreover, the relationships between precipitation and longitude, latitude, and elevation were calculated using Spearman’s correlation coefficient analysis. The obtained results were comprehensively compared and discussed. The significance of this study can be summarized as follows:

First, MAP exhibited a significant increasing trend at an average ACR of 6.7 mm decade$^{-1}$. The rate of increase was higher in the northwestern region than in the southeastern region. Moreover, MWP exhibited a decreasing trend, while MDP had a greater increasing trend. The spatial distribution of MAP over this region had a southeast-to-northwest decreasing trend.

Second, two dominant patterns of precipitation existed during this period. For the EOF1 of the annual, wet, and dry periods, the high- and low-value centres are located in southeast and northwest TRH, respectively, indicating that the precipitation distribution characteristics of the entire region were either rainier or drier. The EOF2 of the three periods shows a dipole pattern, with more precipitation over southwest TRH and less precipitation over northeast TRH.

Third, precipitation has a significant negative correlation with latitude but a prominently positive correlation with longitude. Moreover, elevation has a nonlinear effect of on precipitation and abrupt change points occur at altitudes of 2800 and 3500 m. Hence, precipitation has a significantly negative relationship with elevation below 2800 and above 3500 m but an inverse correlation with elevation from 2800 to 3500 m.

Finally, precipitation changes over the various parts of the domain were determined through changes in the weather systems that affected the areas in the TRH region. NAO, AO, AMO, EASMI, PDO, and PNA exert the strongest effects on precipitation during the dry period over the entire domain. NAO and EASMI exert strong effects on the EOF1 of MDP, while AO primarily affects the EOF2 of MDP, and AMO, PDO, and PNA simultaneously affect both EOFs of MDP. EP/NP, SASMI, and SCSSMI exert strong effects on the EOF2 of MWP, while WPI has apparently affects the EOF1 of MWP. In general, EP/NP, WPI, SASMI, and SCSSMI primarily affect the southeastern region during the wet period, while SASMI appears to affect the southern domain the most. AAO and ENSO exhibit a strong effect regardless of the season or region.

Furthermore, the regional precipitation changes are primarily attributable to the combined effect of all the circulation types, topography, and location. This study provided a detailed analysis of the factors affecting precipitation change in the TRH region, which will be useful for precipitation modelling/forecasting.

Acknowledgments

This research was supported by the Youth Program of National Natural Science Foundation of China (Grant No. 51809282), the International Science & Technology Cooperation Program of China (Grant No. 2018YFE0196000), the National Natural Science Foundation of China (Grant No. 51979284), and the Innovative Team project of China Institute of Water Resources and Hydropower Research (Grant No. WR0145B622017).

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary information files).

Appendix

Method 1. The rank-based nonparametric Mann–Kendall test (Mann 1945, Kendall 1975) was used to detect the precipitation trend. For a time series $x$ with $n$ samples, the Mann–Kendall test statistic $S$ is calculated as follows:
The standardized test statistic $Z$ was calculated as follows:

$$Z = \begin{cases} \frac{S+1}{\sqrt{\text{Var}(S)}} & S > 0 \\ 0 & S = 0 \\ -\frac{S-1}{\sqrt{\text{Var}(S)}} & S < 0 \end{cases}$$ (A2)

Positive values of $Z$ indicate a decreasing trend, and negative values indicate an increasing trend. $Z$ has a standard normal distribution. The trends were tested using a two-tailed test at a significance level of $\alpha$. When $|Z| > Z_{1-\alpha/2}$, $Z_{1-\alpha/2}$ is the standard normal deviation. In this study, the significance levels of 0.01 and 0.05 were used.

Sen’s estimator of slope (Gilbert 1987) was used to estimate the true slope of an existing trend in terms of the change per year. Sen’s method can be used if the trend is assumed to be linear. Then, changes in precipitation $f(t)$ with time can be expressed as

$$f(t) = Qt + B$$ (A3)

where $Q$ represents the absolute change rate (ACR) of precipitation and $B$ is a constant.

The trend magnitudes were estimated using Sen’s slope estimator $Q$ (equation (A4)), defined as the median of all possible pairs for the entire precipitation series:

$$Q = \text{Median}\left(\frac{x_j + x_k}{j-k}\right)$$ (A4)

where $j > k$.

The relative change rate (RCR) is defined in this study as

$$\text{RCR} = \frac{Q}{\bar{P}_{\text{mean}}}$$ (A5)

where $\bar{P}_{\text{mean}}$ represents the annual mean precipitation. RCR is a non-dimensional parameter that illustrates the significance of the ACR of the precipitation compared to the mean precipitation; it is therefore reported as a percentage (Zhong et al 2017).

**Method 2.** The WTC of two time series $X$ and $Y$ is defined as

$$R_n^2 = \frac{\left|S\left(s^{-1}W_n^{XY}\right)(s)\right|^2}{S\left(s^{-1}W_n^X(s)\right)^2} \cdot S\left(s^{-1}W_n^Y(s)\right)^2$$ (A6)

where $W_n^X$ and $W_n^Y$ are transformed in the time series by $X$ and $Y$, respectively, and $S$ is a smoothing operator, where the scales in time and frequency over which $S$ is smoothing define the scales of the covariance coherence measurements (Jevrejeva et al 2003). This definition is similar to the traditional expression of the correlation coefficient, which is the ratio of the cross product of the amplitudes of two time series at a certain frequency to the amplitude product of each vibration wave. $S$ can be written as

$$W_i^{XY}(s) = W_i^X(s) \cdot W_i^Y(s)$$ (A7)

where * denotes the complex conjugate. $R_n^2$ takes a value between 0 and 1, where 0 indicates no correlation between the two time series and 1 indicates that the two time series are perfectly correlated with each other. The significance level for the wavelet spectrum can be estimated by comparing the wavelet spectrum with a red noise spectrum, whereas the significance level of the wavelet coherence is determined using the Monte Carlo method. Then, the significance level for each scale is calculated using only values outside the cone of influence (Torrence and Compo 1998, Grinsted et al 2004). In this study, a 95% confidence level was used to detect significant periodic variations. In addition, WTC can eliminate the effects of high-frequency components on the analysis results of periodic variations at short time scales because the Fourier transform was used to obtain the low-filtering series of the hydrometeorological data, which do not necessarily have high power in the time series (Keener et al 2010, Peng et al 2018).

**Method 3.** The correlation coefficient $\rho$ can be calculated as

$$\rho = \frac{\sum_{i=1}^{n} \left( (R_x - \bar{R}_x) (R_y - \bar{R}_y) \right)}{\sqrt{\sum_{i=1}^{n} (R_x - \bar{R}_x)^2} \sqrt{\sum_{i=1}^{n} (R_y - \bar{R}_y)^2}}$$ (A8)

where $R_x$ and $R_y$ are the ranks of the $x$ and $y$ variables, respectively; $i$ is the data number; and $\bar{R}_x$ and $\bar{R}_y$ are the averages of the ranks of the $x$ and $y$ variables, respectively. The value of $\rho$ lies in the range from $-1$ to 1. $\rho > 0$ indicates a positive correlation, $\rho < 0$ indicates a negative correlation, and $\rho = 0$ indicates that no relationship exists. A two-tailed version of Student’s $t$-test at the 0.05 and 0.01 levels of significance was applied to detect the statistical significance of the correlation coefficients.

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