

# Analysis of the evolution of precipitation in the Haihe river basin of China under changing environment

Xiangyi Ding<sup>1,2</sup>, Jiahong Liu<sup>1,2,3</sup> and Jianguo Gong<sup>1,2</sup>

<sup>1</sup> State Key Laboratory of Simulation and Regulation of the River Basin Water Cycle, China Institute of Water Resources and Hydropower Research (IWHR), Beijing, 100038, China;

<sup>2</sup> Department of Water Resources, China Institute of Water Resources and Hydropower Research (IWHR), Beijing, 100038, China.

<sup>3</sup> liujiahong00@sohu.com

**Abstract.** Precipitation is one of the important factors of water cycle and main sources of regional water resources. It is of great significance to analyze the evolution of precipitation under changing environment for identifying the evolution law of water resources, thus can provide a scientific reference for the sustainable utilization of water resources and the formulation of related policies and measures. Generally, analysis of the evolution of precipitation consists of three levels: analysis the observed precipitation change based on measured data, explore the possible factors responsible for the precipitation change, and estimate the change trend of precipitation under changing environment. As the political and cultural centre of China, the climatic conditions in the Haihe river basin have greatly changed in recent decades. This study analyses the evolution of precipitation in the basin under changing environment based on observed meteorological data, GCMs and statistical methods. Firstly, based on the observed precipitation data during 1961-2000 at 26 meteorological stations in the basin, the actual precipitation change in the basin is analyzed. Secondly, the observed precipitation change in the basin is attributed using the fingerprint-based attribution method, and the causes of the observed precipitation change is identified. Finally, the change trend of precipitation in the basin under climate change in the future is predicted based on GCMs and a statistical downscaling model. The results indicate that: 1) during 1961-2000, the precipitation in the basin showed a decreasing trend, and the possible mutation time was 1965; 2) natural variability may be the factor responsible for the observed precipitation change in the basin; 3) under climate change in the future, precipitation in the basin will slightly increase by 4.8% comparing with the average, and the extremes will not vary significantly.

## 1. Introduction

Precipitation is an important element of water cycle as well as a major source of local water resources. Precipitation change directly affects the condition of local water resources. Thus, scientific problems related to precipitation are commonly concerned by hydrologists and meteorologists. Among so many scientific problems about precipitation, it is a fundamental problem to analyze the precipitation change based on measured data, find out the possible causes of observed precipitation change and forecast the trend of precipitation under changing environment in the future.

The Haihe River Basin is the political and cultural center of China. The Basin is located at 35°~43°N and 112°~120°E, and neighbors the Inner Mongolian Plateau to the north, the Yellow River



to the south, the Bohai Sea to the east and Shanxi Plateau to the west. The basin belongs to the warm temperate zone and has a semi-humid and semi-arid climate. The winters are dry and cold, and there is low rainfall in the spring and heavy rainfall in the summer. The average annual precipitation is 548 mm, about 80% of which falls from June to September. The basin has an area of 317,800 km<sup>2</sup>, of which 189,000 km<sup>2</sup> is mountainous and the remainder is plains. Main rivers in the basin include the Luanhe River, the Haihe River and the Tuhaimajia River. In 2010, the total population in the basin is 152 million, and the GDP of the basin is \$496 million. In recent decades, climatic and environmental conditions in the basin have significantly changed. Many observations and studies have shown that precipitation in the basin decreased over the last half of 20th century [1]. Related studies in the basin showed that the precipitation during 1980-2000 decreased by 11% comparing with the precipitation during 1956-1979 [2]. As the major source of water resources, precipitation is particularly important for the sustainable development of the basin. Based on the understanding of what the observed precipitation change in the basin is, we consider why the precipitation changed this way and how the precipitation will change in the future.

Current attribution methods are mostly based on the fingerprint-based method [3]. Many studies researched the attribution of the changes for atmospheric and oceanic climatic variables on a global or continental scale [4-8]. This study differs by performing attribution analysis on a regional scale. In this study, we attempt to attribute the observed precipitation changes in the basin over a recent 40-year interval (1961-2000) to some internal and external factors, including the natural variability of climate system (hereinafter referred to as natural variability), climate change induced by anthropogenic forcing of greenhouse gas emissions (hereinafter referred to as anthropogenic forcing), and volcanic eruptions and solar radiation changes (hereinafter referred to as solar radiation) using the fingerprint-based attribution method based on several simulations of GCM (General Circulation Model) and observed meteorological data.

GCMs play an important role and are widely used in predicting precipitation change under climate change in the future. This study attempts to predict the trend of precipitation change in the basin under climate change based on GCMs dataset and a statistical downscaling model.

## **2. Methodology and data sources**

The general outline of the methodology is evaluating the precipitation change, attributing the observed precipitation change using the fingerprint-based method, and predicting the precipitation trend under climate change based on the GCMs dataset and a statistical downscaling model. The methods and data mentioned above are each described in the following sections.

### *2.1. Trend analysis method*

To evaluate the temporal variations of the precipitation during 1961-2000 in the basin, we employ a trend analysis method combining moving-average, linear regression with Mann-Kendall method [9]. Since these methods are widely used, their details are not given here.

### *2.2. Instrumental analysis*

Two kinds of GCMs are employed in this study. One is for the attribution of precipitation change during past 40 years, the other is for the prediction of precipitation trend in the future.

For the attribution of observed precipitation change in this study, the factors affecting the evolution of precipitation consist of natural variability, anthropogenic forcing and solar radiation. The precipitation series under the scenarios of natural variability, anthropogenic forcing and solar radiation can be deduced from the outputs of GCM. The GCM selected in this study is the PCM version 2.1 at a resolution of T42L26 [10], which has been widely used in hydrological studies and realistically reflects main characteristics of actual climate and the amplitude of natural climate variability [11]. The precipitation under the scenarios of natural variability, anthropogenic forcing and solar radiation are characterized by run B07.20, B06.22 and B06.69 respectively. Details of the model and the three runs are given at <http://www.earthsystemgrid.org/>.

For the prediction of precipitation trend in the future, the WCRP's (World Climate Research Programme's) CMIP3 (Coupled Model Intercomparison Project Phase 3) multi-model dataset, which includes estimation results of more than 20 climate models provided by the PCMDI (Program for Climate Model Diagnosis and Intercomparison), are employed. GCMs perform differently in different regions. Many studies show that ensemble averages of climate models perform better than a single model [12]. Based on the dataset, the multi-model average dataset under three emission scenarios A1B, A2 and B1, which were provided by the IPCC (Intergovernmental Panel on Climate Change) in 2000, can be obtained employing the REA (Reliability Ensemble Average) method [12]. Finally, the climate change projections of the multi-model average dataset at a particular station are produced by National Climate Centre of China [13]. For more details about the dataset and methods, please refer to [14]. It should be noted that, the CMIP5 data with RCP scenarios are not used in this study. Actually, this study was based on a research project which had been finished several years before, and we have not updated the whole research progress yet, in the next step of research, we will consider updating the results.

### *2.3. Fingerprint-based attribution method*

Fingerprint-based attribution method is a kind of technology for the attribution analysis of variable changes in meteorology [15], which uses fingerprint and signal strength as the quantitative evaluation indexes of variable changes. Fingerprint refers to the leading EOF (Empirical Orthogonal Function) of the dataset (model or observation). The EOF analysis is the method of choice for analyzing the variability of variables and finding the spatial patterns of variability that are referred to as the EOFs. Given the fingerprint, the signal strength is calculated as the least-squares linear trend of the projection of a dataset onto the fingerprint.

The general idea for attributing variable changes is to reduce the problem of multiple dimensions to a low dimensional problem. This operation can also be understood as applying a filter to the observations or simulations. This has advantages compared with the two extremes of trying to assess a significant variable change in the full variable space or simply using a mean value. In the low dimensional space, observed variable changes can be attributed to different factors by comparing the signal strengths under different scenarios with the signal strength calculated from observations. Details of the method are given by [4,5].

### *2.4. Statistical downscaling model*

GCMs simulate the climate conditions at global and regional scales under different emission scenarios and hence play an important role in evaluation studies of climate change. However, for evaluating the impacts of climate change on water cycle and water resources at basin or smaller scale, the application of GCMs are restricted due to their coarse spatial resolution. Generally, there are two kinds of methods for downscaling the GCM outputs, dynamical downscaling method and statistical downscaling method. Statistical downscaling methodologies have several practical advantages over dynamical downscaling approaches. In situations where low-cost, rapid assessments of localized climate change impacts are required, statistical downscaling represents the more promising option currently [16]. Therefore, in this study, we select the statistical downscaling methodology, concretely the SDSM (Statistical Down-Scaling Model), to downscale the GCMs output.

SDSM is a widely used statistical downscaling model in the world. In recent years, many studies have shown that SDSM model is of superior performance and easy to use and its application becomes more widely [17]. SDSM allows the construction of climate change scenarios for individual sites at daily time scales using the gridded output of the GCM. The statistical relationship between large scale predictors and local predictands is firstly established, and then local climate information is simulated and future climate scenarios can be obtained. Details of the model and application are given by [18].

### 2.5. Data sources

Time series (1961-2000) of observed precipitation at 26 national standard meteorological stations in the basin are provided by the CMA (China Meteorological Administration). It should be noted that, we have obtained the time series of 1961-2015 at 26 stations, however, the PCM outputs are from 1961 to 2000. To be consistent with the PCM outputs series, the meteorological series of 1961-2000 was used in this study.

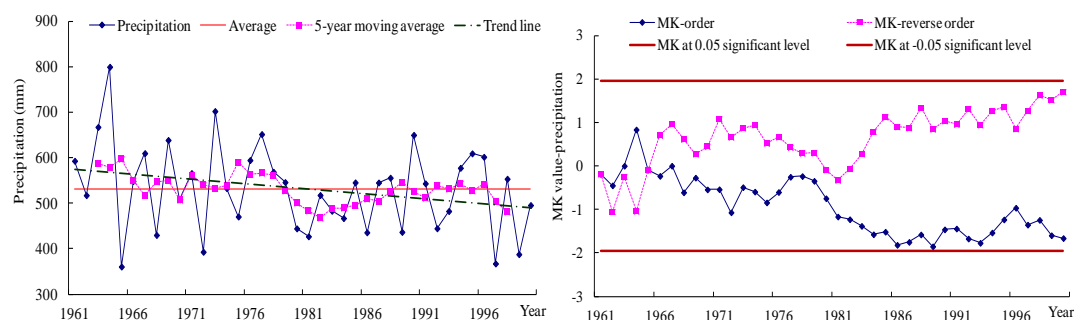
The SDSM is obtained from <https://co-public.lboro.ac.uk/cocwd/SDSM/>. SDSM calibration data are taken from NCEP reanalysis data, which are obtained from <http://www.cdc.noaa.gov/>.

The CMIP3 outputs are obtained from <http://ncc.cma.gov.cn/cn/>. The PCM outputs of three runs (B07.20, B06.22 and B06.69) are obtained from <http://www.ipcc-data.org>.

## 3. Results and analysis

### 3.1. Observed precipitation change

Based on the observed time series (1961-2000) of annual precipitation at 26 meteorological stations, the precipitation for the whole basin can be obtained through spatial interpolation using the IDW (Inverse Distance Weighting) method and the Thiessen polygon method [19]. The temporal variations of precipitation for the whole basin as well as the Kendall's tau (hereafter called MK) values which are used for statistical significance test and sudden change test during 1961-2000 are shown in Figure 1.



**Figure 1.** Temporal variation and MK values of observed precipitation during 1961-2000.

It can be seen from Figure 1 that, during 1961-2000 in the basin, the precipitation decreased but the trend was not significant at 0.05 level since the MK value is -1.35 which is less than the threshold value -1.96. According to the Mann-Kendall method, the cross-over point of the positive and inverted sequence curve of MK was 1965, thus the estimated sudden change time which referred to the time annual precipitation might begin to statistically change was 1965.

### 3.2. Application of SDSM

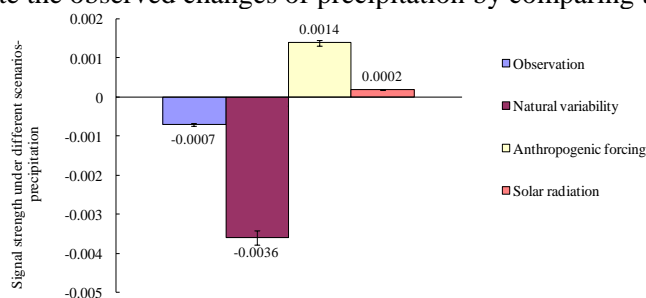
The applicability of the SDSM and GCM to the Hai River Basin is affirmed by comparing the annual statistical characteristics of downscaled historical precipitation simulated by PCM with those of observations (1961-2000) at 26 selected meteorological stations. In addition, monthly statistical characteristics of downscaled precipitation with those of observations at 26 stations are also compared.

Based on the verification of PCM performance on characterizing local climate, precipitation during 1961-2000 in the basin under three simulations B07.20, B06.22 and B06.69 could be obtained. Comparing with the historical average during 1961-2000 in the basin, the precipitation under the scenario of natural variability might be underestimated by 2.7%, while the precipitation under the scenario of anthropogenic forcing might be overestimated by 5.3%, and the precipitation under the scenario of solar radiation might be overestimated by 1.3%.

Limited to the paper length, details of the application of SDSM can be referred in [9].

### 3.3. Attribution analysis

Using the fingerprint-based attribution method and the 1961-2000 time series of precipitation for the whole basin, the fingerprints of precipitation changes under different scenarios could be obtained. We then further calculate the signal strengths of precipitation changes under different scenarios as shown in Figure 2, thus attribute the observed changes of precipitation by comparing the signal strengths.



**Figure 2.** Signal strengths of precipitation under different scenarios.

As can be seen from Figure 2, the signal strengths of precipitation change under anthropogenic forcing and solar radiation scenario are inconsistent with the observed, and thus we consider that these two factors may be not the factors responsible for the observed precipitation change during the past 40 years in the basin. While the signal strength of precipitation change under natural variability scenario is consistent with the observed and is larger than the observed, thus we consider that natural variability is the factor responsible for the observed precipitation change during the past 40 years in the basin.

### 3.4. Prediction of precipitation trend under climate change

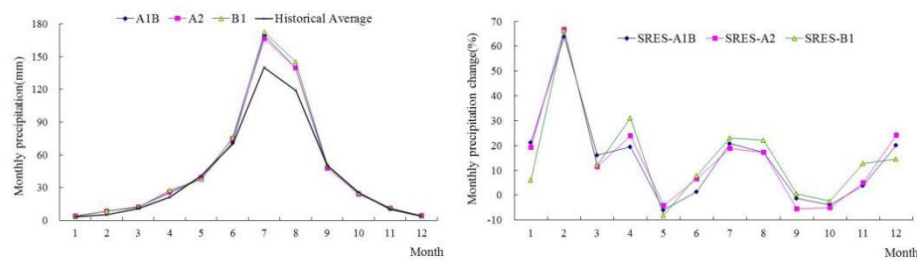
Prediction of precipitation in the basin for the future 30 years (2021-2050) under three scenarios is shown in this section. A comparison of the average annual characteristics values of precipitation under historical conditions (1961-2000) as well as three scenarios in the future is shown in Table 1.

**Table 1.** Comparison of average annual characteristics values of precipitation under historical conditions as well as three scenarios in the future.

Scenario	Average (mm)	Maximum (mm)	Minimum (mm)
History	532.5	799.4	360.5
A1B	552.2	770.9	352.5
A2	552.9	785.8	369.2
B1	568.6	806.1	381.8

As can be seen from Table 1 that, from the view of average annual change, comparing with the historical average, in the future 30 years under A1B, A2 and B1 scenarios, the precipitation will appreciably increase by 3.7%, 3.8% and 6.8% (the trend is not statistically significant at 0.05 level), respectively, and will averagely increase by 4.8%. Additionally, the extremes will not obviously vary.

The average monthly changes of precipitation are shown in Figure 3. From the view of monthly average change, except for the precipitation in May, September and October will slightly decrease, precipitation in the other months will increase, especially in February and April.

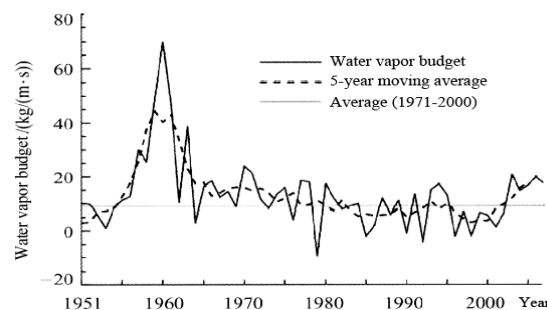


**Figure 3.** Average monthly change of precipitation in the Hai River basin in 2021-2050.

### 3.5. Water vapor flux

As the main factor affecting precipitation, water vapor flux change has a significant positive correlation with precipitation change [20]. The attribution results in this study are generally consistent with the actual conditions in the basin. The inter-annual variation of water vapor transport in summer in the basin is shown in Figure 4 [21].

As can be seen from Figure 4, comparing with the multi-year average, water vapor budget in the basin from the mid-1950s to the early 1960s showed a significant positive anomaly, which indicated that water vapor income during this period in the basin significantly exceeded the expenses and water vapor amount was abundant. However, from the mid-1960s to the late 1970s, water vapor budget gradually decreased, even less than 0 from the 1980s to the early 21st century, indicating that water vapor income in the basin was less than expenses and the available precipitation amount in the atmosphere was less. In recent years, water vapor budget in the basin began showing an increasing trend. Therefore, we think that the decreasing trend in precipitation in the basin is related to the trend in water vapor flux.



**Figure 4.** Annual variation of water vapor transport in summer in the basin during 1951-2008.

## 4. Conclusion

This study attempts to find out the possible causes of observed precipitation change in the Hai River Basin and predict the possible trend of precipitation under climate change in the future. The research results indicate that: 1) during 1961-2000, the precipitation in the basin decreased but the trend was not statistically significant at 0.05 level; 2) natural variability may be the factor responsible for the observed precipitation change during 1961-2000 in the basin; 3) comparing with the historical average, the precipitation in the basin will increase by 4.8% in the future 30 years, and the extremes will not obviously vary.

The attribution results also show that anthropogenic forcing and solar radiation may not responsible for the observed precipitation change. The effects of these factors are not a simply algebraic addition and subtraction, thus the signal strength of observation is not equal to the simple algebraic sum of the contribution of natural variability, anthropogenic forcing and solar radiation. The relation between them needs to be further studied in the following studies.



It should be noted that uncertainties arising from the GCMs as well as SDSM may affect the results. These aforementioned issues will be listed as our major focal areas of future researches.

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### References

- [1] Zhang JY, Wang GQ 2007 *Science Press*, Beijing
- [2] Yu YD, Yang ZY, Liu YP, Qin DY, Liu JH 2010 *J. China Hydrol.* 30(4):32-35
- [3] Hasselmann K 1997 *Climate Dyn.* 13(9): 6101-611
- [4] Barnett TP, Pierce DW, Schnur R 2001 *Science*, 292: 270-274
- [5] Barnett TP, Pierce DW, Achutarao KM, Gleckler PJ, Santer BD, Gregory JM, Washington WM 2005 *Science*, 309: 284-28
- [6] Thorne PW, Jones PD, Tett SFB, Allen MR, Parker DE, Stott PA, Jones GS, Osborn TJ, Davies TD 2003 *Clim. Dynam.* 21: 573-591
- [7] Lambert FH, Stott PA, Allen MR, Palmer MA 2004 *Geophys Res Lett.* 31 L10203: 4
- [8] Gillett N.P., Allen RJ, Ansell TJ 2005 *Geophys Res Lett.* 32 L19714: 4
- [9] Ding X Y 2010 Beijing: China Institute of Water Resources & Hydropower Research
- [10] Washington WM, Weatherly JW, Meehl GA 2000 *Climate Dyn.* 16: 755-774
- [11] Barnett TP, Pierce DW, Hidalgo HG, Bonfils C, Santer BD, Das T, Bala G, Wood AW, Nozawa T, Mirin AA, Cayan DR, Dettinger MD 2008 *Science*, 319: 1080-1083
- [12] Giorgi F, Mearns LO 2003 *Geophys Res Lett.* 30(12):1629
- [13] Xu Y, Gao XJ, Giorgi F 2010 *Clim. Res.* 12, doi:10.3554/cr00835
- [14] National Climate Centre 2009 Climate change estimation dataset in China, Version 2.0: Manual
- [15] Hegerl GC, Storch HV, Hasselmann KH, Jones PD 1996 *J. Climate* 9:2281-2306
- [16] Chu JT 2009 *Dissertation* of Graduate University of Chinese Academy of Sciences
- [17] Fowler HJ, Wilby RL 2007 *Int. J. Climatol.* 27, 1543-1545
- [18] Wilby RL, Dawson CW, Barrow EM 2002 *Environ Modell Softw.* 17: 147-159
- [19] Hou ZH, Jia YW, Wang H 2006 *J. China Hydrol.* 26, 6-11
- [20] Zhu L, Liu YX, Zuo HC 2011 *Advances in Climate Change Research* 7(3):184-188
- [21] Ding XY, Jia YW, Lu Q, Chou YQ, Zhang HT 2013 Proceedings of 2013 IAHR World Congress