

**Detection and Attribution of Climate Change  
and Human Activities Impacts on Water  
Resources in the Haihe River Basin of China**

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**2010.09.20**

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# 1. Introduction

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# 1.1 Background

- The Haihe River Basin (320,000 km<sup>2</sup>, 120 million persons) may be the most water-stressed basin in China. Water issues like drought, urban flood and water pollution became very serious since 1980s.
- Many observational facts and studies have shown water resources in the basin decreased significantly over last half of the 20th century. The reduction extent of runoff ranked first among China's major rivers. Simultaneously, groundwater was seriously over-exploited, aquatic ecosystems were overdrawn, and water security suffered severe crises

How to attribute the observed water resources changes to various factors (natural variation, global warming, local human activities)?



## 1.1 Background

➤ Current attribution methods are mostly based on the fingerprint method (Hasselmann,1997). Attribution studies have been conducted for a number of measures of atmospheric and oceanic climatic conditions. A review of previous attribution studies is available from the International Ad Hoc Detection and Attribution Group. Most of the previous studies examined global or continental scale quantities

- This study differs from the existed studies by attempting to perform attribution on a regional scale, which is generally more difficult.
- **Different from some exploratory work in western United States (Barnett et al.,2008), we attribute water resources amount changes at a basin level in this study.**

## 1.2 Aim

The aim of this study is to quantitatively distinguish impacts of various factors - natural variation, global warming and human activities impacts on water resources changes in the Haihe River Basin in past 40 years.

- Firstly, the temporal variation of water resources amount in the basin is analyzed using moving-average method, linear regression method and Mann-Kendall method. In addition, the spatial variation is analyzed using EOF (Empirical Orthogonal Function) method
- Secondly, through setting different scenarios, water resources amount affected by different factors including natural variability, global climate change as well as human activities are analyzed separately
- Finally, fingerprint-based method is used to calculate the signal strengths of water resources changes under different scenarios, thus the changes can be attributed to different factors by comparing the signal strengths



## **2. Methods, models and data sources**

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➤ **To investigate possible attribution of water resources in the basin to different factors, we employ a climate model PCM and its two model simulations including no forcing run and anthropogenic forcing run, a downscaling model SDSM to downscale the PCM output, a distributed hydrological model WEP-L to obtain water resources amount, the fingerprint-based method, a set of observed meteorological data over the basin and observed river flow data at main hydrological gauge stations**

## 2.1 Methods

### *Detection method of temporal variation of hydro-meteorological factors and water resources*

- There are several methods commonly used in trend analysis for hydro-meteorological time series, such as linear regression, cumulative average, moving-average, second smooth, cubic spline function and Mann-Kendall rank correlation method.
- In this study, trend analysis of the time series of water resources amount is conducted by combining linear regression, moving-average and Mann-Kendall rank correlation method. Since these methods are widely used, the details of these methods will not be explained here

## 2.1 Methods

### *Spatial variation analysis method*

- The EOF (Empirical Orthogonal Function) method is the method chosen for analyzing the variability of variables and finds the spatial patterns of variability which are referred to as the “EOFs”.
- Given the matrix  $F$  including measurements of some variable at several locations taken at several times, we form the covariance matrix of  $F$  by calculating  $R = F^t F$ , then we solve the eigenvalue problem  $RC = C\Lambda$
- For each eigenvalue chosen we find the corresponding eigenvector, and these eigenvectors are the EOFs we are looking for. In what follows we always assume that the eigenvectors are ordered according to the size of the eigenvalues. Thus, EOF1, which is the eigenvector associated with the biggest eigenvalue, explains the variance most

## 2.1 Methods

### *Fingerprint-based attribution method*

➤ The fingerprint is defined as the leading EOF of the data set. Given the fingerprint, the signal strength  $S$  is calculated as the least-squares linear trend of the projection of a data set onto the fingerprint.

$$S = \text{trend}(F(x) \bullet D(x, t))$$

➤ Attribution of the variable changes can be conducted through comparing the signal strengths of different scenarios with the actual signal strength.

## 2.2 Models

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### *Climate model*

- The PCM (Washington et al. 2000) has been used widely in hydrological studies and realistically portrays important features of observed climate and the amplitude of natural internal variability.
- Based on the simulation results of the two run (B07.20, B06.22), we can obtain precipitation and temperature data under natural variability and anthropogenic forcing scenarios, after downscaled and interpolated, the data can be supplied as input to hydrological model to obtain water resources amount data.
- The details of the model and two runs are referred to website:  
<http://www.earthsystemgrid.org/>.

## 2.2 Models

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### *Statistical downscaling model*

➤ The statistical downscaling model SDSM enables the construction of climate change scenarios for individual sites at daily time-scales using grid resolution GCM output, and is the first tool of this type offered to the broader climate change impacts community.

➤ SDSM couples multiple regressions with stochastic weather generator. The statistical relationship between large scale climatic factors (predictors) and local variables (predictands) is firstly established, then local change information can be simulated and climate change scenarios in the future can be obtained.

➤ Details of the model and application are referred to in Wilby (2007)

## 2.2 Models

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### *Hydrological model*

- The distributed hydrological model WEP-L (Jia et al 2006) was developed in a national key basic research project of China. The WEP-L model is based on the WEP model (Jia et al 2001) which has been successfully applied in several watersheds in Japan, Korean and China with different climate and geographic conditions. The model adopts the contour bands as the calculation units to fit for large basins.
- The WEP-L model can not only simulate natural water cycle but also artificial water cycle, and therefore could reflect local human activity impacts on water resources. Thus we consider that once validated by observed discharge data, the WEP-L model is applicable to the attribution study.

## 2.3 Data sources

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- Observed meteorological data of long time series (1961-2000) including precipitation and temperature is provided by China Meteorological Administration
- River runoff data of long time series (1961-2000) which is used for the validation of hydrological model is provided by main hydro-stations in the basin
- The downscaling model SDSM can be obtained at <https://co-public.lboro.ac.uk/cocwd/SDSM/> ; SDSM calibration data is from NCEP reanalysis data which can be obtained at: <http://www.cdc.noaa.gov/>. The output of two runs can be obtained at <http://www.ipcc-data.org>
- Land use data can be obtained at <http://www.geodata.cn/Portal/mdsearch/listMetadata.jsp?category=185&pn=2&isCookieChecked=true>.



## **3. Results and Discussions**

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## 3.1 Scenarios

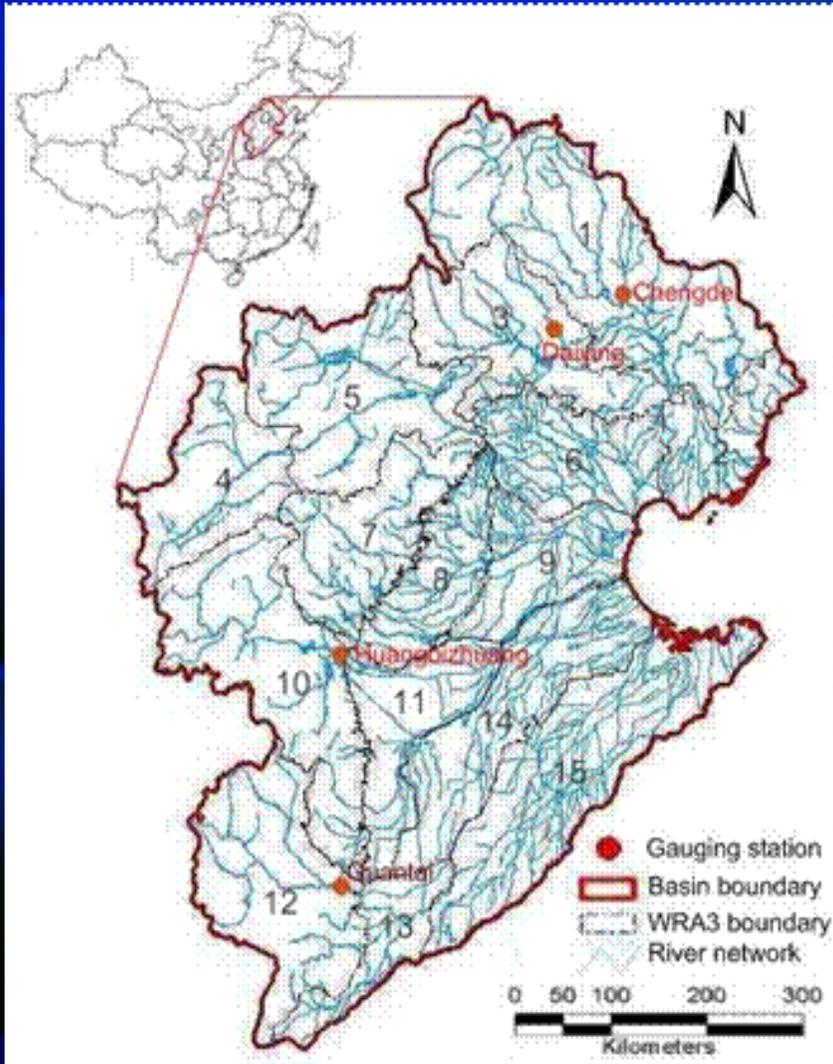
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### *Scenarios setting*

➤ For the attribution of water resources change, we set five scenarios including natural variation, global warming forcing, water use, land use change and human activities (combining water use and land use change)

## 3.2 WEP-L model application

### *Description of study area*



➤ Located between  $35^{\circ}$  ~  $43^{\circ}$  N and  $112^{\circ}$  ~  $120^{\circ}$  E

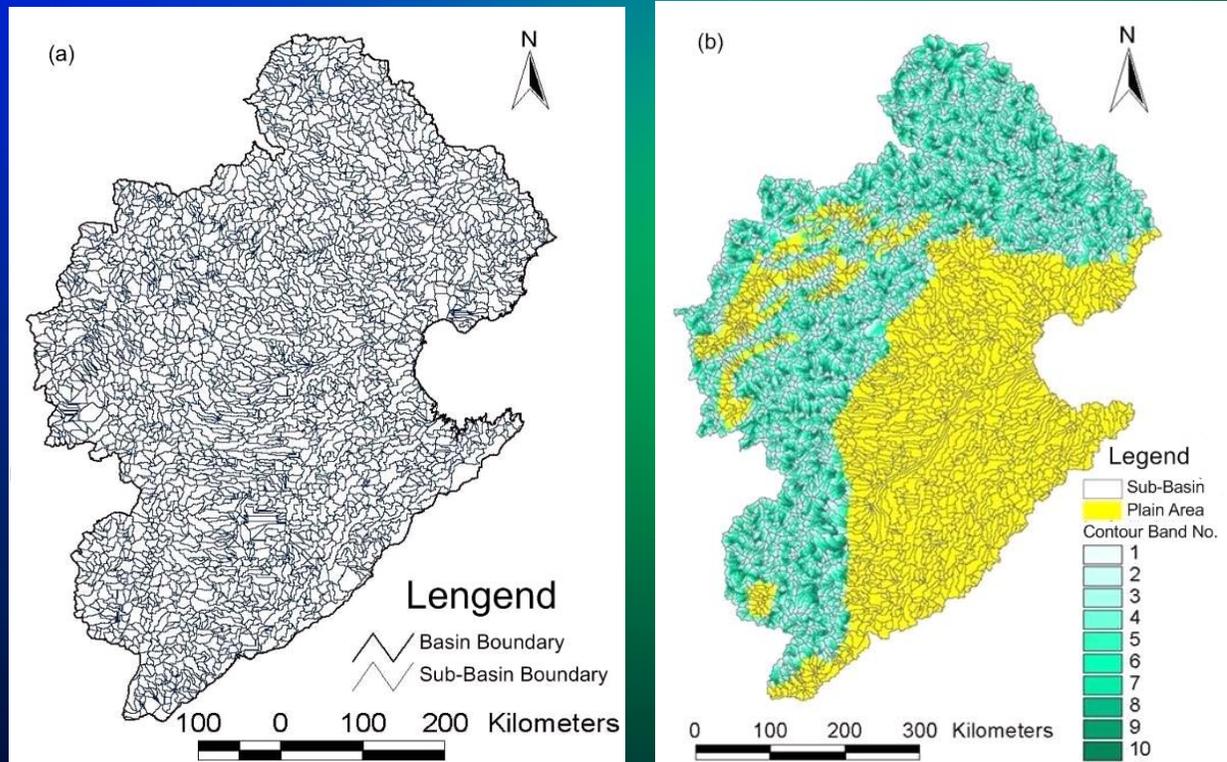
➤ The average annual precipitation is 548 mm, about 80 percent of which falls during June to September

➤ Its area is 317,800 km<sup>2</sup>, of which 189,000 km<sup>2</sup> is mountainous and the remained is plain

## 3.2 WEP-L model application

### *Subdivision of calculation units*

➤ The basin in WEP-L model is divided into 3,067 sub-watersheds (a), each of which is assigned with a Pfafstetter code. Each sub-watershed in hilly and tableland areas is further divided into 1-10 contour bands, thus the basin is discretized into 11,752 calculation units (b)



## 3.2 WEP-L model application

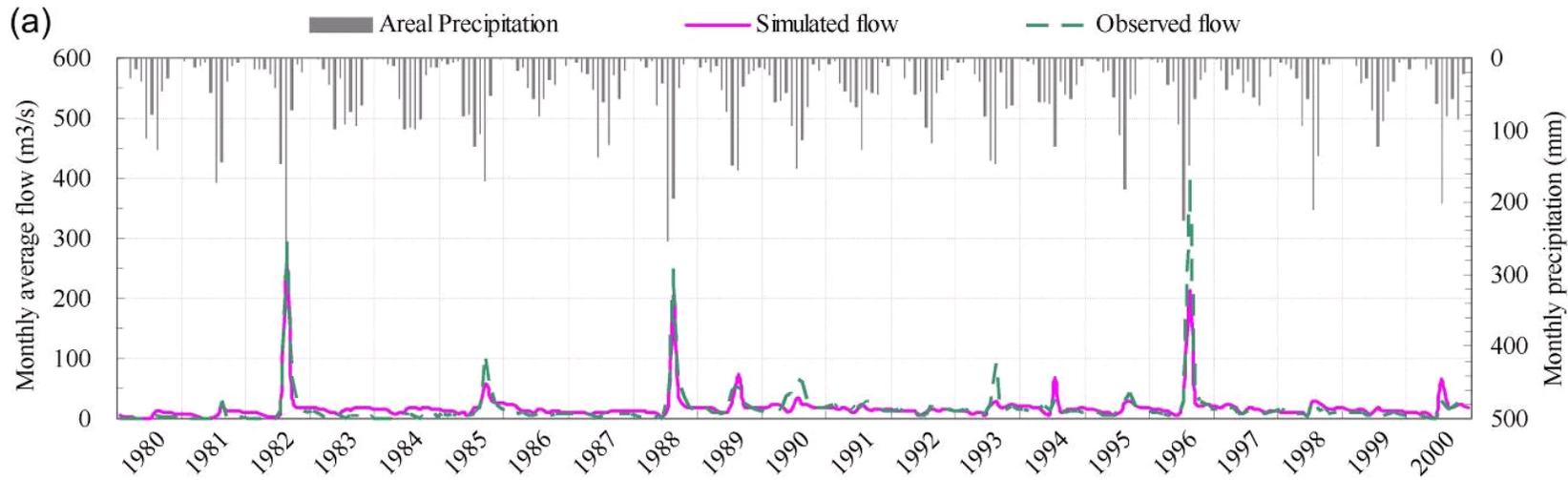
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### *Model calibration and validation*

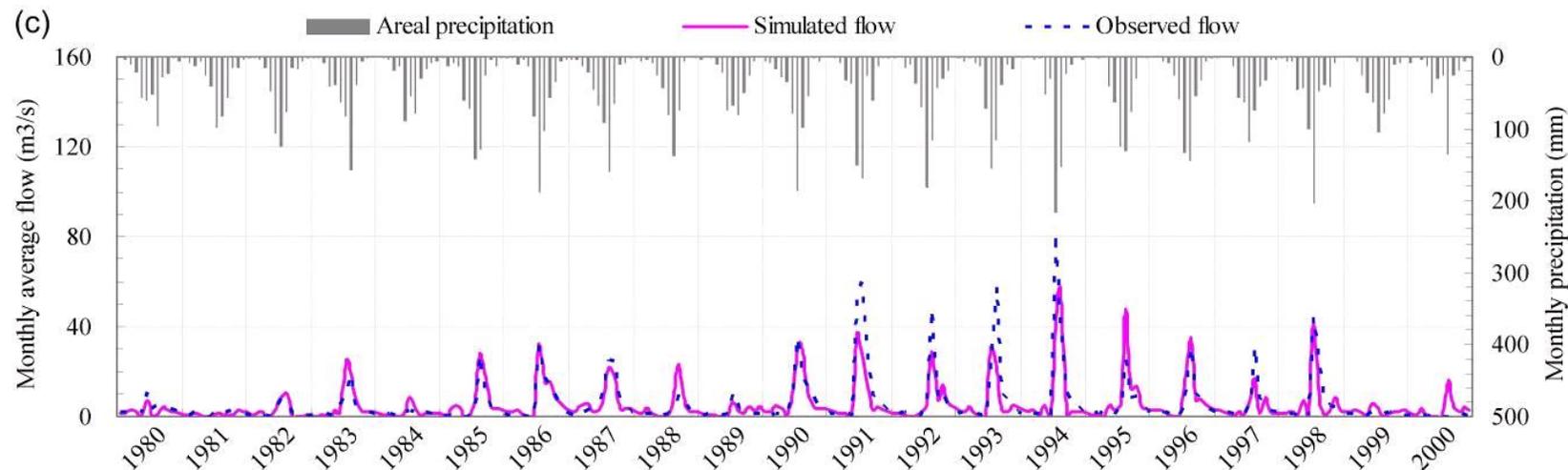
- The main parameters include soil parameters, groundwater aquifer hydraulic conductivity and specific yield, vegetation parameters, roughness of overland and river channel and infiltration coefficient of river bed
- 11 years (1990-2000) is selected as calibration period. After model calibration, continuous simulation from 1980-2000 are performed to verify the model by using observed monthly discharges at 23 main stations.
- Simulation results indicate that average errors of annually runoff are less than 10%, Nash-Sutcliffe efficiency of monthly runoff at main stations is over 60%, and correlation coefficients exceed 80%.

## 3.2 WEP-L model application

### *Model calibration and validation*



**Guantai  
station**



**Chengde  
station**

### 3.3 SDSM application

➤ **SDSM: establish the statistical relation between climate predictors of large scale and local predictands, and then downscale the climate model outputs based on the relationship and predictors**

- ◆ The predictors for selected in SDSM are from the reanalysis data provided by NCEP and NCAR, including 23 variables which may be obtained at <http://www.cics.uvic.ca/scenarios/sdsm/select.cgi>.
- ◆ The observed daily precipitation and temperature data at 26 meteorological stations in 1961-2000, which are the predictands of SDSM, are provided by China Meteorological Administration

### **3.3 SDSM application**

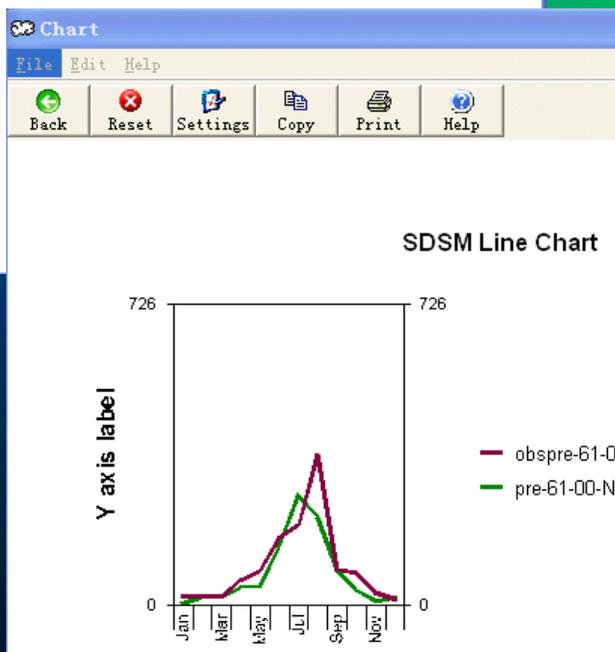
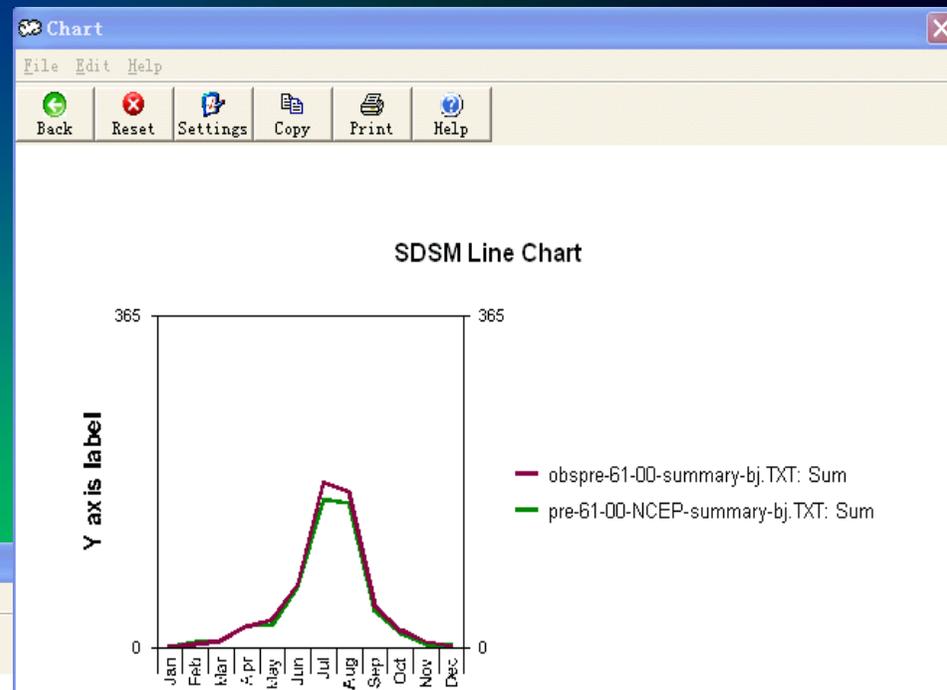
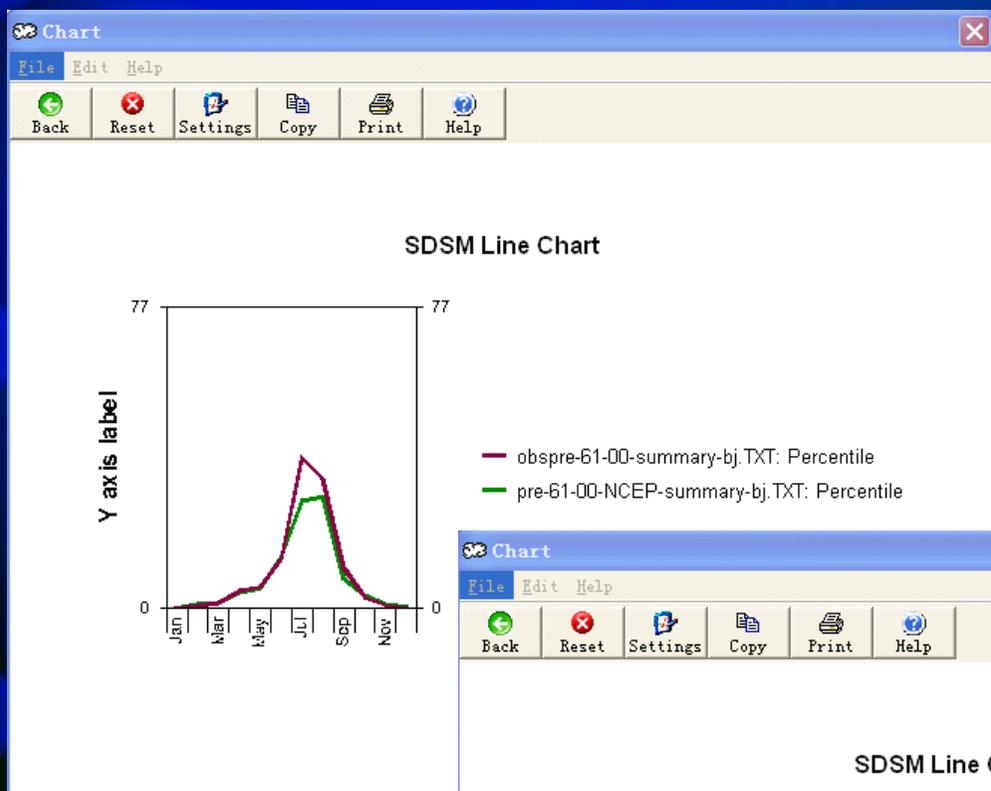
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#### *Model calibration and validation*

- Firstly, the correlation coefficient between the predictors and each predictand at each station is calculated, and the predictors are selected if the correlation is significant at 95% confidence level
- 30 years (1961-1990) is selected as the calibration period, 10 years (1991-2000) is selected as the validation period, the model is calibrated and validated at each station based on the selected predictors, observed data and NCEP reanalysis data
- The model performs well comparing the statistical indexes including average, maximum, minimum, percentile of downscaled values with observed

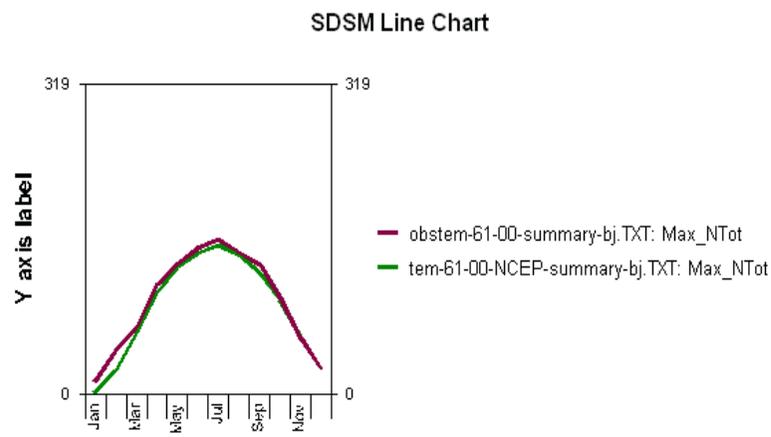
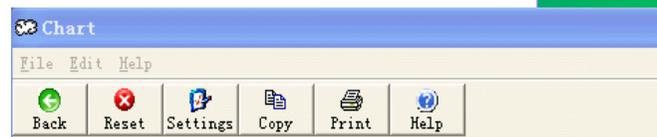
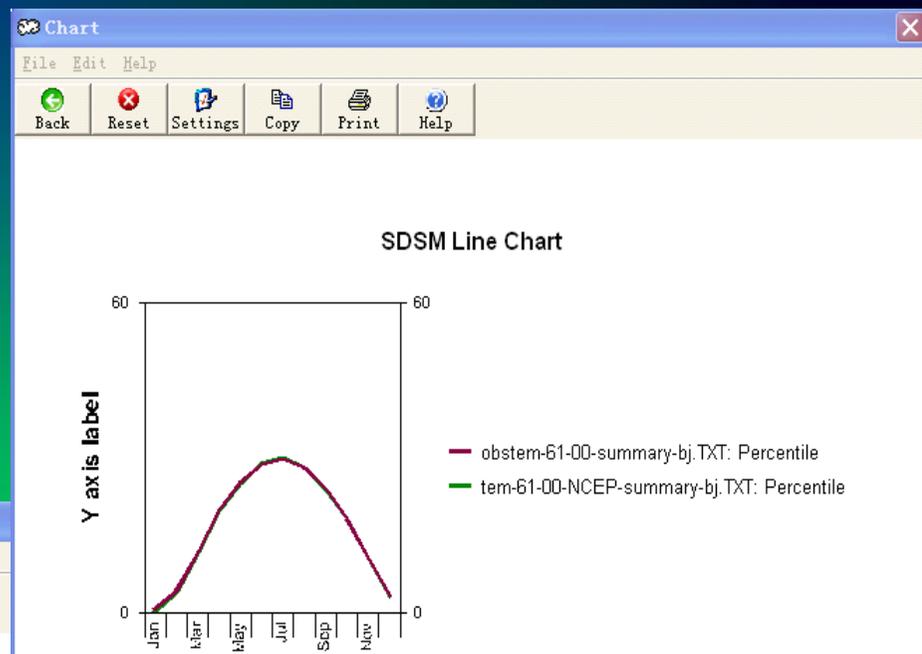
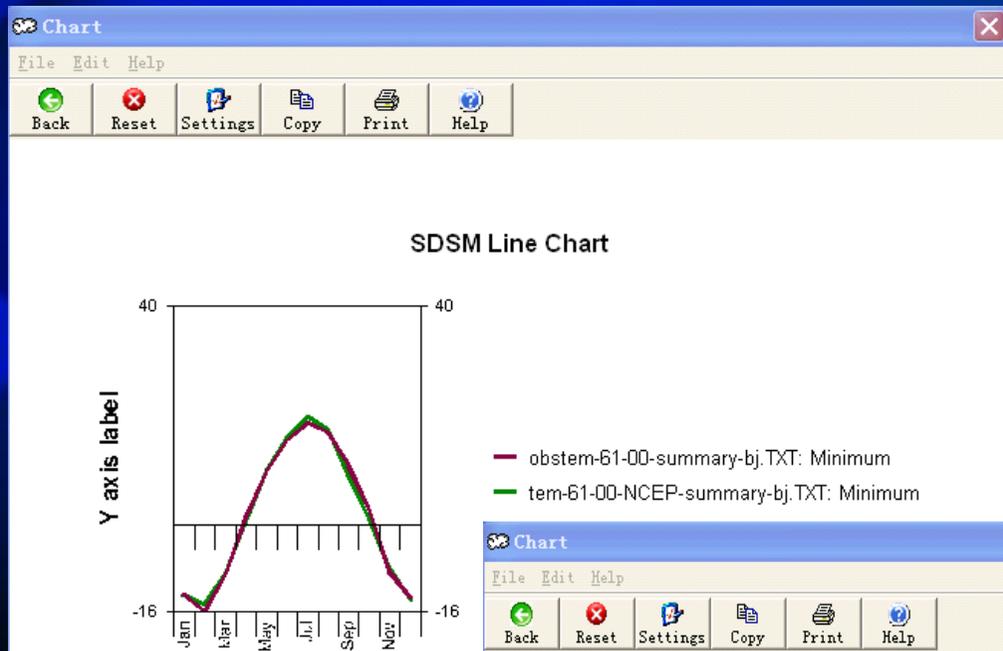
# 3.3 SDSM application

## Downscaled precipitation at Beijing station



# 3.3 SDSM application

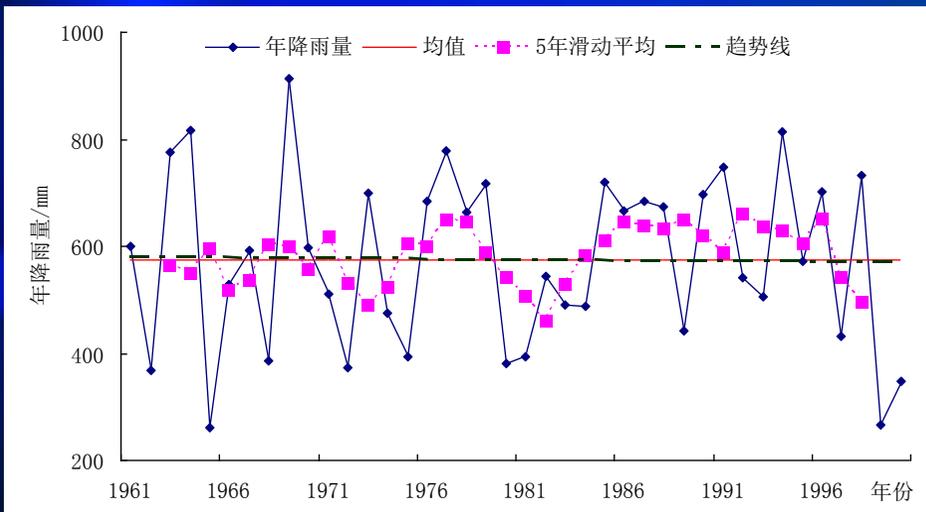
## Downscaled temperature at Beijing station



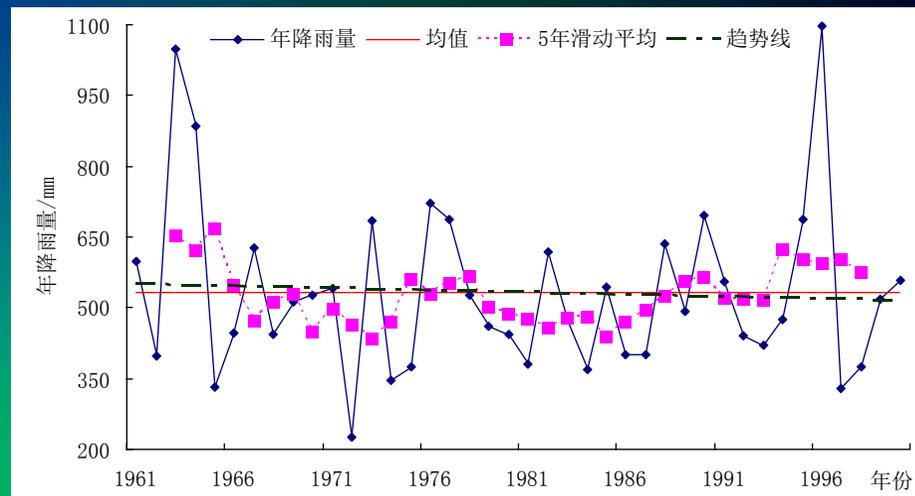
# 3.4 Detection of temporal and spatial variation

## Annual Precipitation

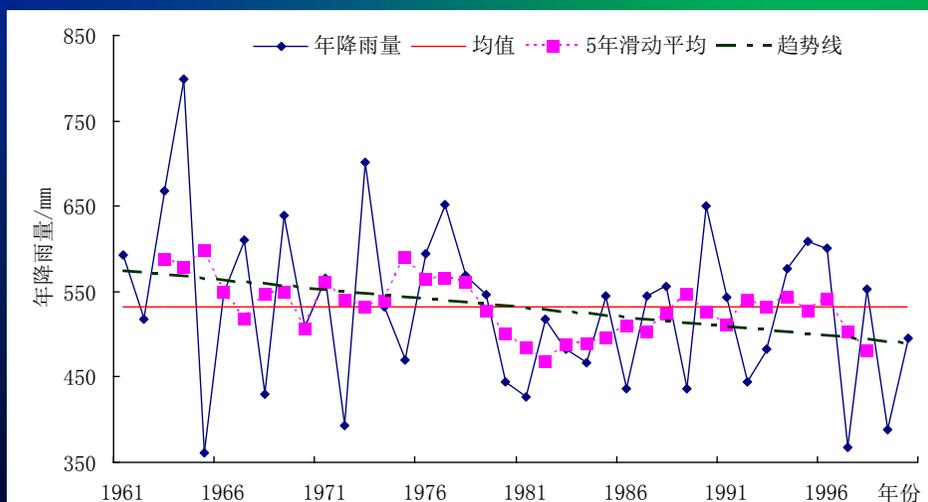
### Beijing



### Shijiazhuang



### Basin average

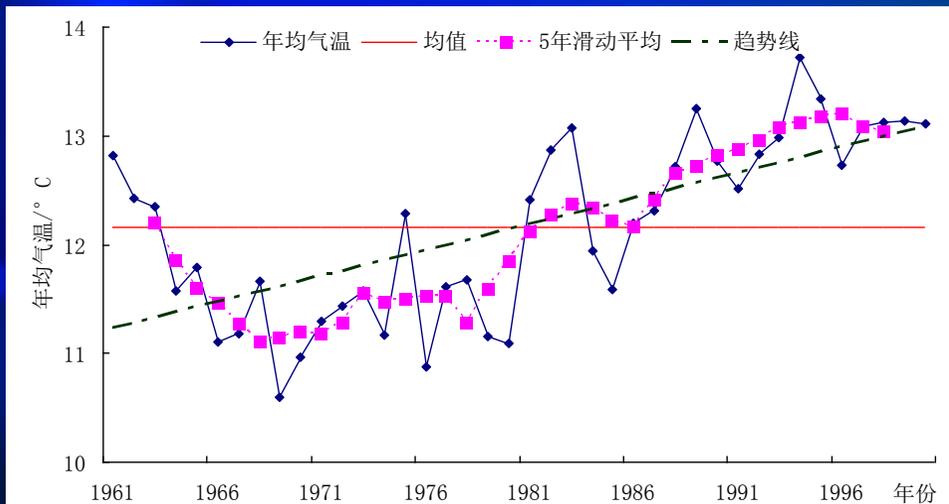


The decrease trend is not significant at 95% confidence level

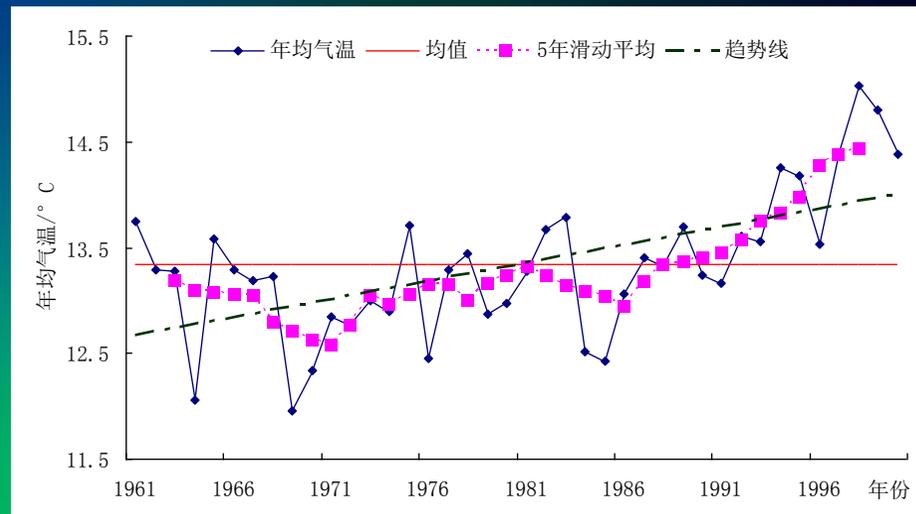
# 3.4 Detection of temporal and spatial variation

## Annual Precipitation

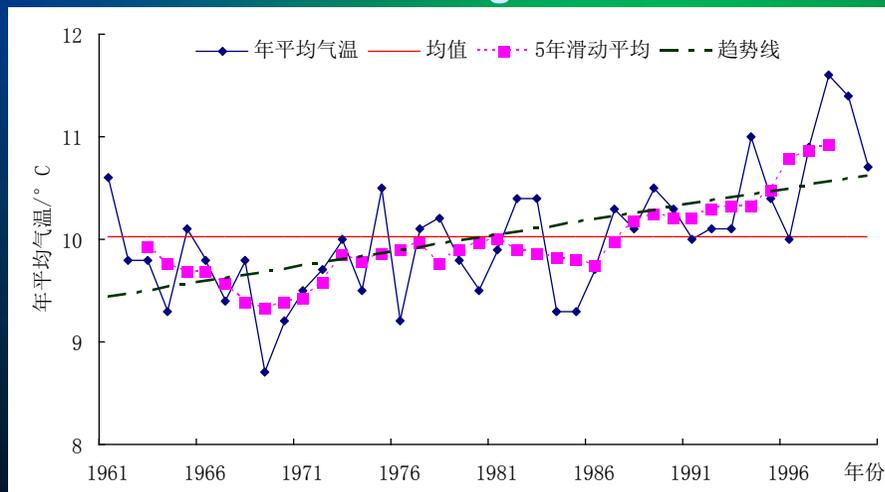
### Beijing



### Shijiazhuang



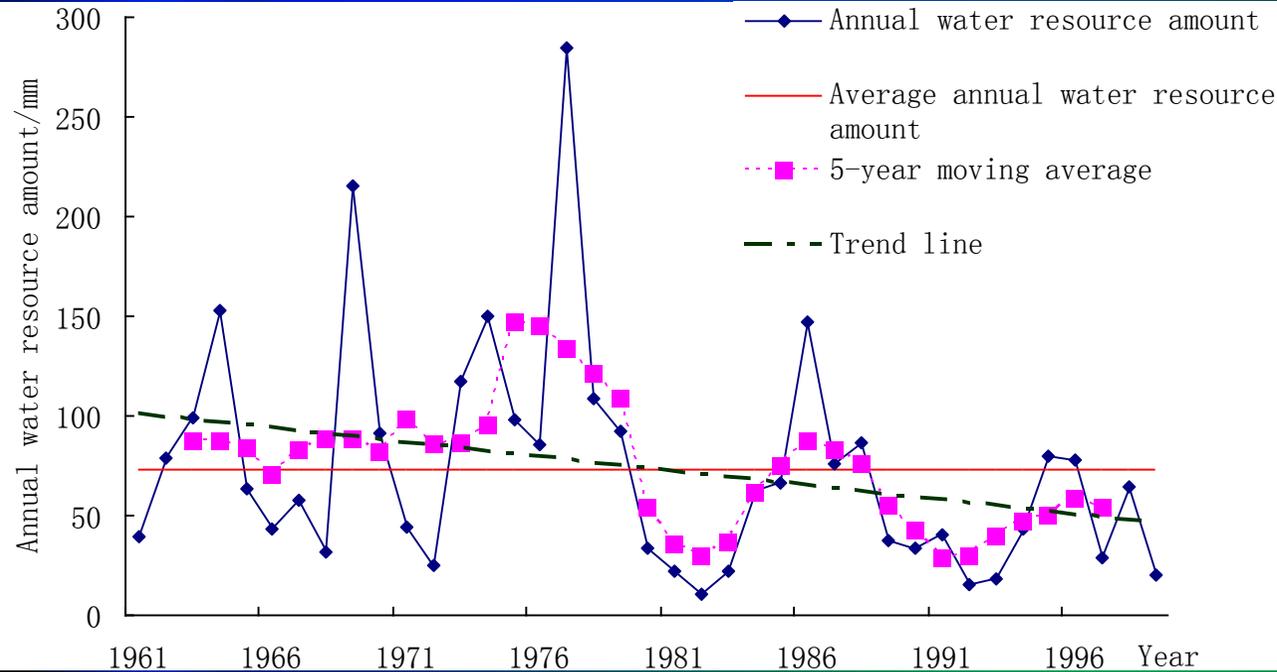
### Basin average



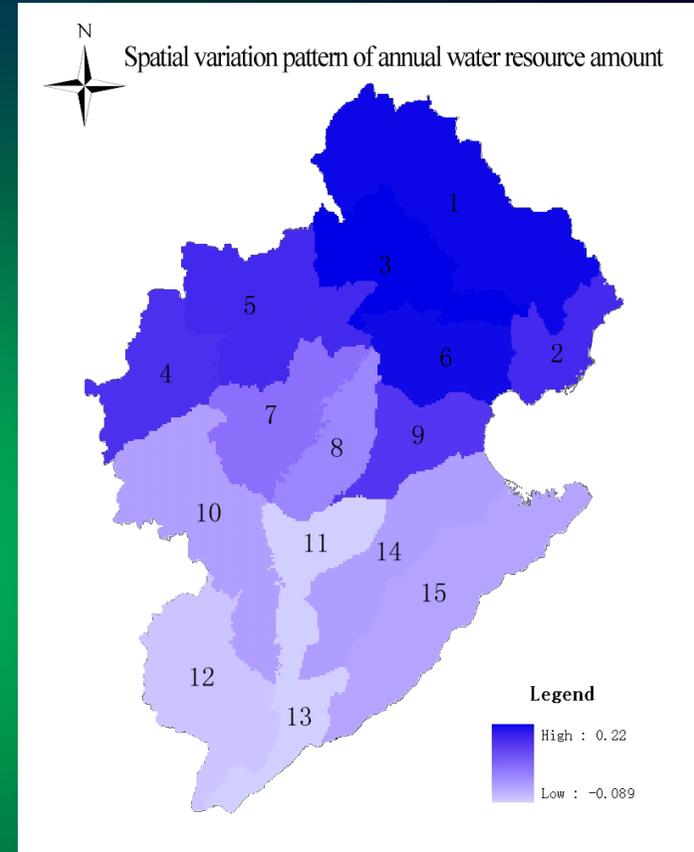
The increase trend is significant at 95% confidence level

# 3.4 Detection of temporal and spatial variation

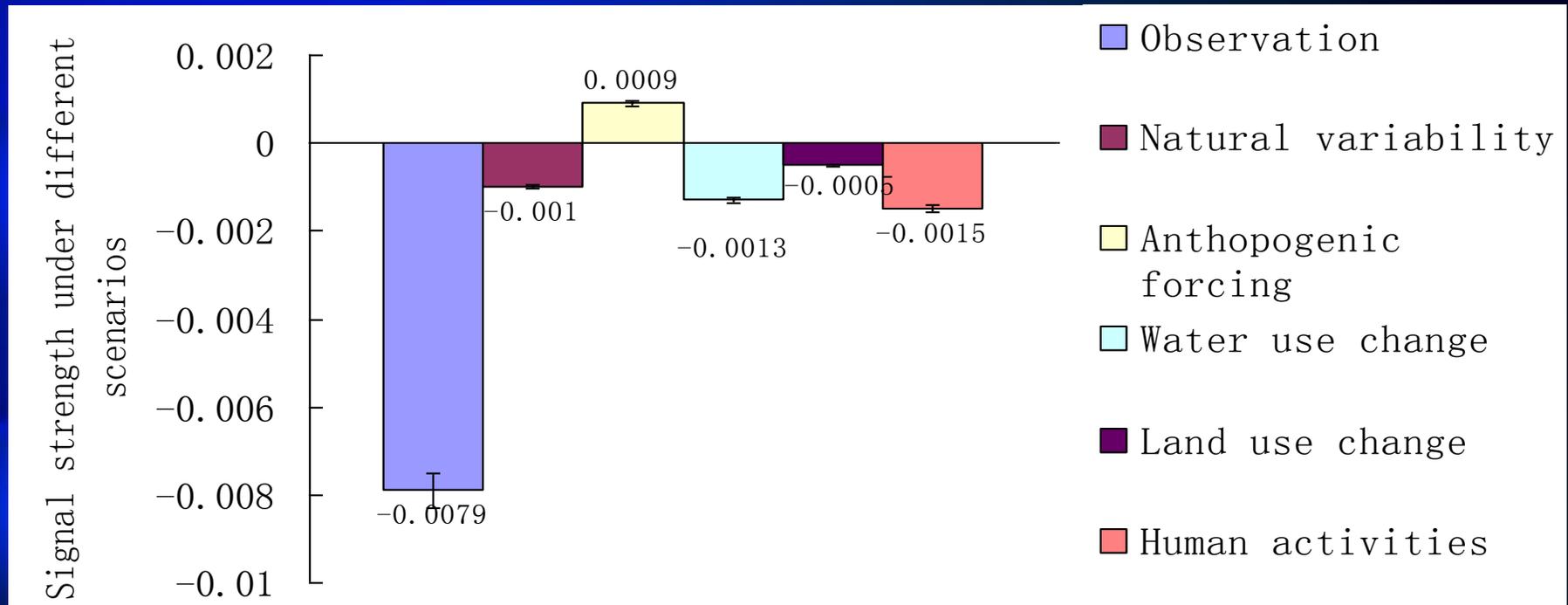
## Water resources amount



The decrease trend is significant at 95% confidence level



## 3.5 Attribution analysis



- S under anthropogenic forcing (global warming) is not consistent with actual signal strength
- S under natural variability, water use, land use change are consistent with actual signal strength, and account for 36%, 46% and 18% of water resources amount changes (human activity accounts for 60%)
- Natural variability and human activity may be the reasons, and human activity are the main reasons resulting in the water resources amount changes in past 40 years in the basin



## 4. Conclusion



## 4 Conclusion

- In large river basins that are greatly affected by climate change and human activities like the Haihe River Basin, it is of great importance to distinguish impacts of climate change and human activities on water resources.
- Human activities are the main reasons resulting in the water resources amount changes in past 40 years in the basin (it accounts for 60% , while natural variation 40%).
- It is urgent to protect water resources in the basin for a sustainable development while developing economy. More great efforts should be made to realize sustainable management and effective use of water resources.



**Thanks for your attention!**