

ENSEMBLE PROJECTION OF RUNOFF FOR THE NEXT 30-50 YEARS IN THE YELLOW RIVER BASIN WITH BMA APPROACH

ZIQI YAN

State Key Laboratory of Simulation and Regulation of a Water Cycle in a River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China, Corresponding author, yanzq@aliyun.com

ZUHAO ZHOU

State Key Laboratory of Simulation and Regulation of a Water Cycle in a River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China, zzh@iwahr.com

JIAJIA LIU

State Key Laboratory of Simulation and Regulation of a Water Cycle in a River Basin, China Institute of Water Resources and Hydropower Research, Beijing 100038, China, wereworld@163.com

ABSTRACT

With the optimization and selection of climate models, hydrological model, as well as an uncertainty analysis via the bayesian model averaging approach, an ensemble projection framework was established to significantly improve the reliability of runoff in the future. Runoff in 2050 and 2070 was projected with data from the Yellow River Basin, China. The runoff and its 90% confidence intervals at the six main stations of the Yellow River Basin were obtained. The runoff in 2050 and 2070 in the upper and middle reaches of the Yellow River is found to decrease by 4.1 billion m³ and 2.7 billion m³, respectively, compared with the reference period. The water supply–demand situation in the whole Yellow River Basin is not optimistic. The ensemble projection method in this study is a general calculation process, which can be used widely in hydrometeorological ensemble forecasting, and provides a basis for water resource management planning.

Key Words: Yellow River Basin, Bayesian model averaging, Ensemble projection, WEP-L model, Runoff

1. INTRODUCTION

Runoff projections under climate change and human activities are crucial for the future management of water supplies; undertaking these assessments on a large-scale basin is a challenge for water resources engineers and planners. The current suite of global climate models (GCMs) greatly assist the process. Projecting the runoff in future mainly relies on scenario analyses based on results generated by hydrological model driven by various climate models (Arnell, 1992; Arnell and Reynard, 1996; Ragab and Prudhomme, 2002; Thomson et al. 2005; Abbaspour et al., 2009; Abouabdillah et al., 2010; Montenegro and Ragab, 2010; Piao et al. 2010; Zhang et al., 2012). However, the projected impacts of climate change on runoff are associated with large uncertainties: the results of runoff under different scenarios are quite different (Jonas and Ken, 2015). This will be further confusion in river basin management and planning. How to reduce the uncertainties of climate models to generate relatively reliable projections that meet the requirements of government planning has always been a difficult scientific problem.

In view of the uncertainties associated with projections generated by multiple models, numerous methods for uncertainty analysis have been developed. In recent years, Bayesian model averaging (BMA) has been applied in comprehensive hydrological projections (Duan et al., 2007; Zhang et al., 2009; Dong et al., 2013a). BMA can not only be used to obtain the uncertainties of a combination of multiple models (Dong et al., 2013b).

To project the runoff of a large-scale basin under climate change and human activity, this study aimed to establish an ensemble projection method, which consists of climate and hydrological models; uncertainty analysis is also a focal point. BMA approach was applied for large-scale basins. The method is demonstrated using the Yellow River Basin, which is a typical large basin in China. This paper is structured as follows. Section 2 describes the study area and the data. Section 3 proposes the ensemble projection method. Section 4 discusses the results. Lastly, Section 5 concludes the paper.

2. STUDY AREA AND DATA

The Yellow River is the world's fifth longest river. Its main stream is 5,464 km long in total, with a drainage area of 795,000 km² (Figure 1). The upper and middle reaches of the Yellow River Basin account for 97% of the total drainage area, whereas the lower reach, which is several hundreds of kilometers long and has a riverbed

above the level of the riverbanks, has a drainage area that only comprises 3% of the total basin. The Yellow River Basin is the most sensitive region of global climate change in China. In the past two decades, as a result of climate change and human activity, there has been a sharp decrease in the runoff and sediment discharge of the Yellow River Basin (Xiao et al., 2009). Projecting the runoff of the Yellow River Basin under climate change and human activity is a scientific issue that urgently needs to be addressed. Based on GCMs, it is generally believed that the runoff of the Yellow River Basin will decrease significantly in the future (Xu et al., 2007; Xu et al., 2009; Hao et al., 2006; Li et al., 2011; Zhang et al., 2012). However, these studies are still based on a variety of scenarios and do not give the exact range of runoff change, and there is a lack of in-depth analysis of the uncertainty.

The daily observed data from 1956 to 2017 at six control stations on the main stream of the Yellow River, namely, from the upper to the lower reaches, Tangnaihai, Lanzhou, Toudaoguai, Longman, Tongguan, and Sanmenxia (Figure 1). The Sanmenxia station control the upper and middle reaches of the Yellow River, where the runoff accounts for 90% of the total runoff of the entire basin. The region upstream of the Lanzhou hydrological station is the source region of the Yellow River, where the runoff accounts for 64% of the total runoff of the basin. The daily meteorological observation data from 1956 to 2017 were supplied by the National Climate Center of China.

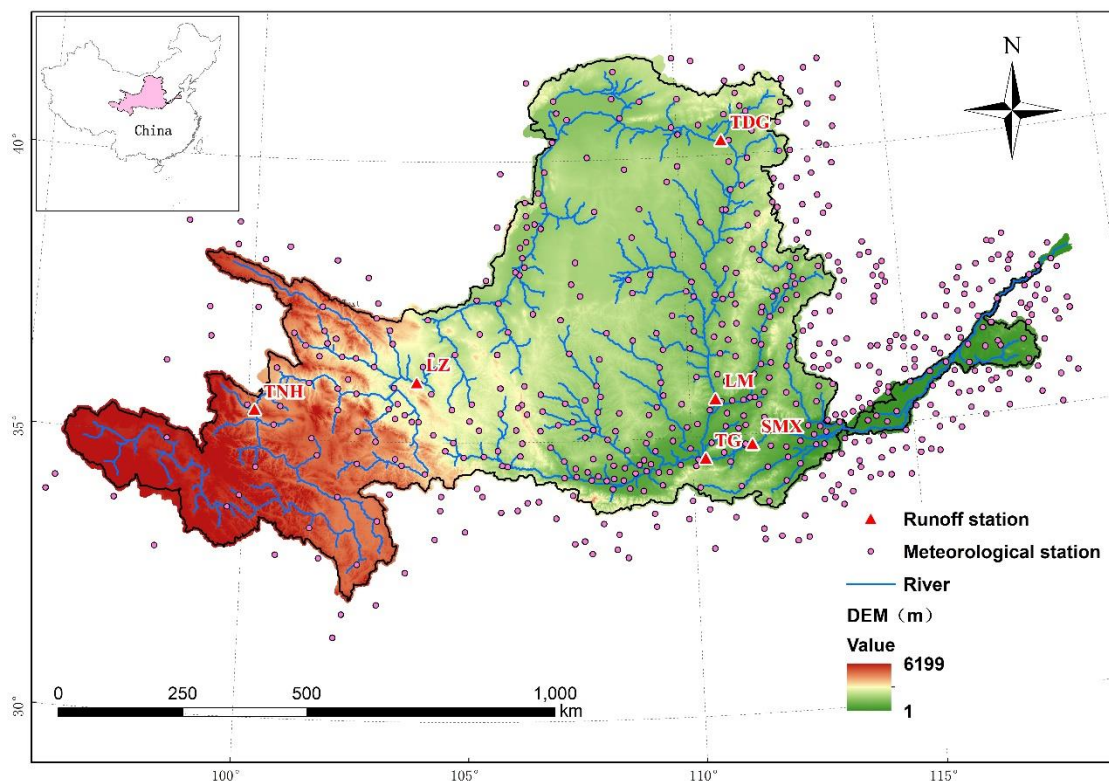


Figure 1. The Yellow River Basin (TNH-Tangnaihai, LZ-Lanzhou, TDG-Toudaoguai, LM-Longmen, TG-Tongguan, SMX-Sanmenxia station)

GCMs have been extensively used to simulate future climate scenarios and evaluate the hydrological, agricultural, and environmental effects of climate change. Zhou and Han (2018) evaluated the simulation capacity of 18 GCMs for temperature and precipitation in the Yellow River Basin, and six climate sequences for each of the two future periods were obtained based on the quantile mapping method (Cannon et al., 2015) and RegCM4(Gao et al., 2016; Gao et al., 2017).

3. METHODOLOGY

An ensemble projection framework was designed to project the future runoff of large basins (Figure 2). The first step is to calculate six future runoff series with a distributed hydrological model based on climate boundaries consisting of six climate sequences (Table 1) while considering future land surface and water usage. The second step is to use a global BMA approach to produce a weighted average ensemble projection based on multiple runoff results.

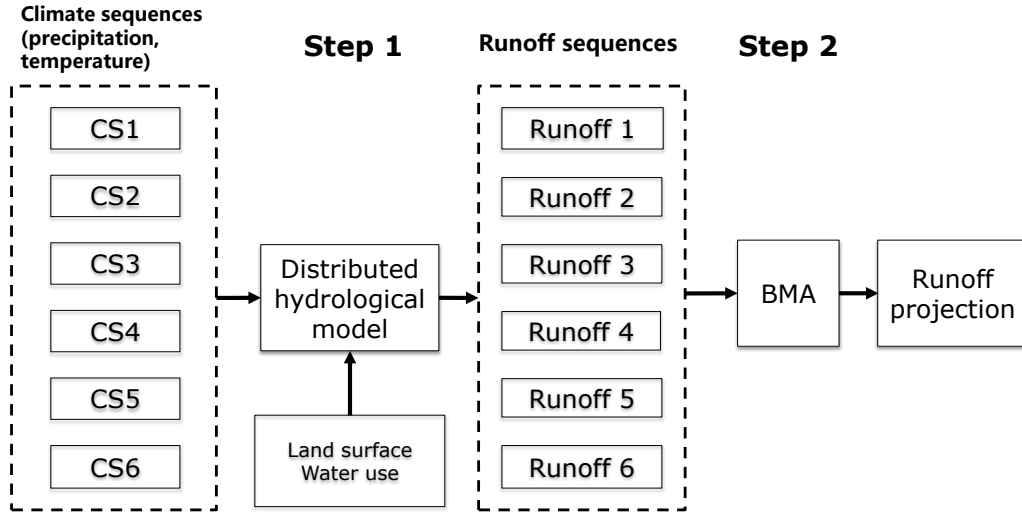


Figure 2 Ensemble projection process.

For the second step, the BMA ensemble projection requires the division of the period into calibration, validation, and projection periods. The weights of each runoff sequence are determined in the calibration period. Then, the ensemble simulation accuracy is evaluated in the validation period. On this basis, the BMA parameters (w_k and σ_k^2) are used to project runoff in the projection period (Figure 3). The relative errors are used for the accuracy analysis by comparing the ensemble simulation with the observed data.

BMA is a statistical approach designed to infer a prediction by weighted averaging over many different competing models (Ajami et al., 2006). This approach can combine different models and be used to reduce the uncertainties of models. Let Q be the projected value, $D = [X, Y]$ be the input data (X and Y are the simulated runoff data and observed runoff data, respectively), and $f = [f_1, f_2, \dots, f_k]$ be projected runoff values generated by a K number of models. Thus, the BMA probability project can be expressed as follows:

$$p(Q|D) = \sum_{k=1}^K p(f_k|D) \cdot p_k(Q|f_k, D) \quad (1)$$

In Eq (1), $p(f_k|D)$ is the posterior probability of the projection f_k provided by the k th model for the given input data D . $p(f_k|D)$ reflects the degree of match between f_k and the observed runoff Y . In fact, $p(f_k|D)$ is the weight w_k of model k in BMA. The higher the projection accuracy of a model is, the greater the weight assigned to it is. All the weights are positive values with a total sum of 1. Additionally, in Equation (1), $p(Q|f_k, D)$ is the conditional probability density function of the projected Q under the given model project f_k and data D conditions.

The average projected value obtained by BMA is a weighted average of projected values generated by multiple models. If the projected values generated by individual models and the observed runoff follow a normal distribution, then the BMA average projected value is as follows:

$$E[Q|D] = \sum_{k=1}^K p(f_k|D) \cdot E[g(Q|f_k, \sigma_k^2)] = \sum_{k=1}^K w_k f_k \quad (2)$$

The expectation maximization (EM) algorithm is further used to calculate the weight w_k of each model and its project error σ_k^2 .

4. Result

4.1 Hydrological model calibration and validation

The WEP-L model (Jia et al., 2006) was used to simulate runoff in the ensemble projection process. Based on DEM, soil, and land-use distribution data, the Yellow River Basin was divided into 8,485 subbasins and 38,720 computational units. Model calibration and validation were performed with the 6 main stations in Figure 5. For both the calibration and validation periods, the relative error and Nash–Sutcliffe efficiency coefficient of the model were found to be within 5% and greater than 0.6, respectively (Table 1). Thus, the distributed hydrological model established based on the WEP-L model for the Yellow River Basin is capable of depicting the water cycle process in this typical region and provides a basis for analyzing runoff evolution and the effects of climate change on runoff in this region.

Table 1 Runoff calibration and validation

Station	Calibration period (1956–2000)		Validation period (2001–2017)	
	NSE	Relative error (%)	NSE	Relative error (%)
Tangnaihai	0.787	-4.7	0.756	-4.1
Lanzhou	0.787	0	0.745	-2.1
Toudaoguai	0.646	7.1	0.598	6.9
Longmen	0.603	7.3	0.672	7.9
Tongguan	0.653	8.6	0.621	8.5
Sanmenxia	0.643	8.1	0.612	9.3

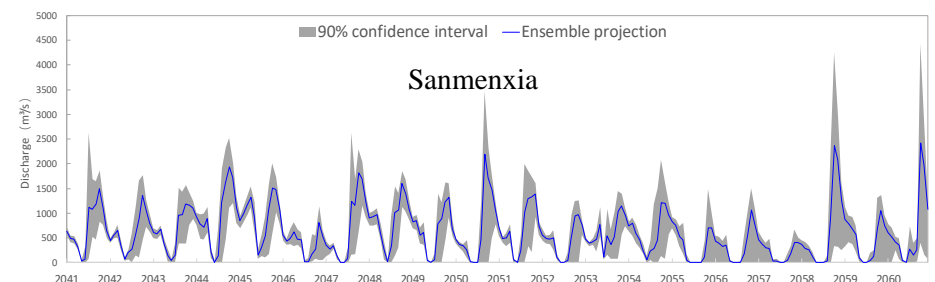
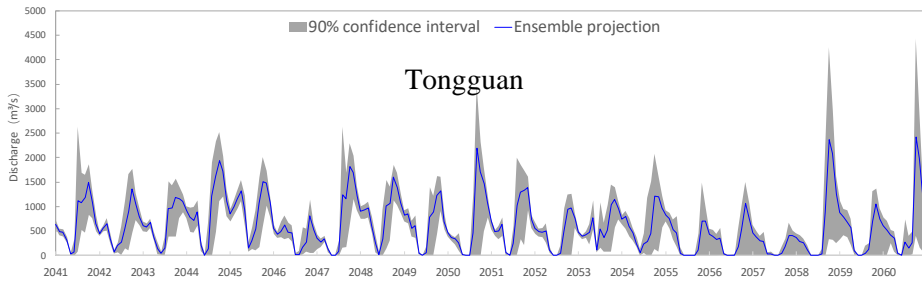
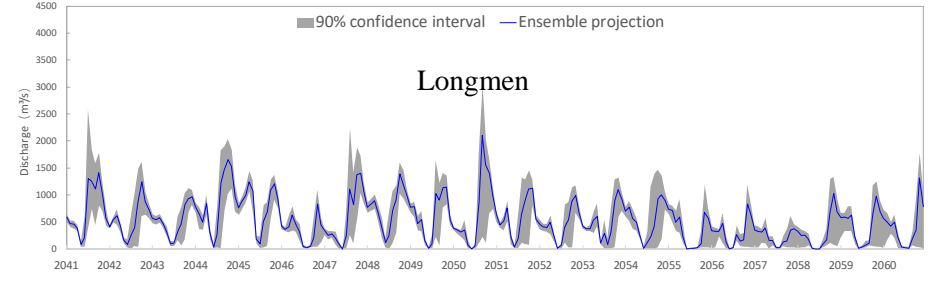
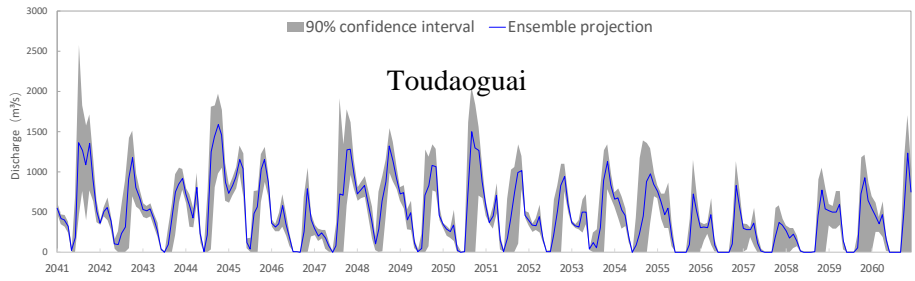
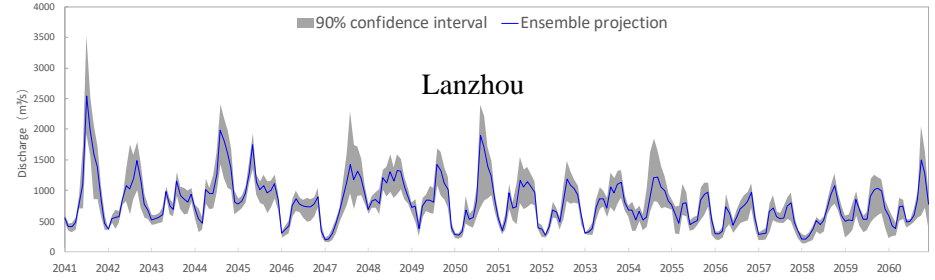
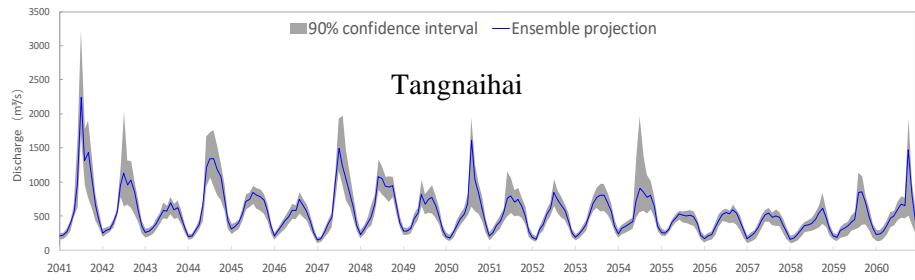
4.2 Ensemble projection of future runoff

Based on the BMA parameters, runoff at each main station (i.e., Tangnaihai, Lanzhou, Toudaoguai, Longmen, Tongguan, and Sanmenxia) was projected for the 2050 and 2070 periods (Figure 3). For the two future periods, the ensemble projection method was capable of providing monthly discharge for each section and the 90% confidence interval of the monthly discharge. In the two future periods, the 90% confidence intervals of the monthly runoff at the hydrological stations in the upper reaches of the Yellow River Basin were significantly narrower than those at other hydrological stations. This suggests that under the ensemble projection framework, the hydrological model produces better simulations for the upper reaches of the Yellow River Basin. Additionally, it suggests that it is more difficult to simulate the middle and lower reaches of the Yellow River Basin as a result of land surface conditions and human activity, and there are greater uncertainties in the simulation results for the middle and lower reaches of the Yellow River Basin.

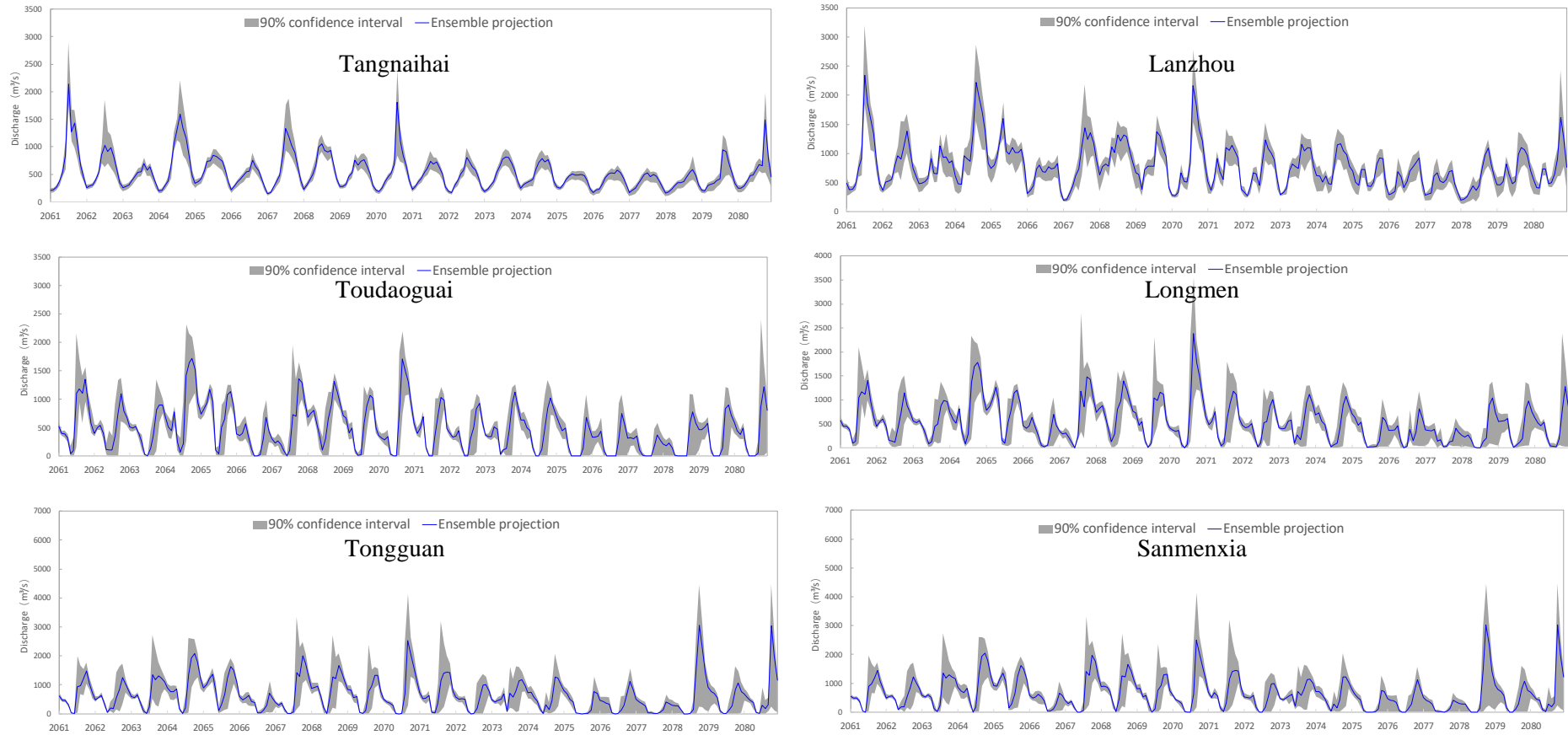
Table 2 summarizes the annual average runoff at the main stations and their 90% confidence intervals. In the 2050 period, the annual average runoff values for the six main sections (i.e., Tangnaihai, Lanzhou, Toudaoguai, Longmen, Tongguan, and Sanmenxia) are 17.7, 28.5, 27.9, 31.1, 37.9, and 38.2 billion m³, respectively. In the 2070 period, the annual average runoff values for the six main sections are 17.2, 27.8, 27.3, 31.2, 39.2, and 39.5 billion m³. The 90% confidence interval of the annual average runoff at the Tangnaihai station in the source region of the Yellow River is the narrowest. The 90% confidence interval of the station close to the lower reaches is the widest, reflecting the greater uncertainty in the projected results.

Table 2 Ensemble projection of annual average runoff (Billion m³)

Section	Reference period	2050 (2041–2060)		2070 (2061–2080)	
		Runoff	90% confidence interval	Runoff	90% confidence interval
Tangnaihai	20.1	17.7	[13.3, 20.8]	17.2	[12.9, 21.2]
Lanzhou	31.7	28.5	[22.3, 33.1]	27.8	[21.7, 33.4]
Toudaoguai	30.4	27.9	[21.5, 32.4]	27.3	[21.2, 32.7]
Longmen	34.1	31.1	[23.6, 35.8]	31.2	[23.8, 38.2]
Tongguan	41.9	37.9	[27.5, 45.5]	39.2	[26.7, 48.9]
Sanmenxia	42.2	38.2	[27.7, 45.9]	39.5	[26.8, 49.3]



a Ensemble projection of discharge (m^3/s) in the 2050 period.



b Ensemble projection of discharge (m³/s) in the 2070 period.
 Figure 3 Ensemble projection of discharge in 2050 (a) and 2070 (b) periods (m³/s).

5. CONCLUSIONS

Based on GCMs, the BMA algorithm, and the WEP-L distributed hydrological model, an ensemble hydrological projection method was established. Additionally, the main conclusions derived from this study are summarized as follows:

(1) By combining multiple GCMs and uncertainty analysis, a general ensemble projection framework for future hydrological conditions was established. With several technical steps, such as the optimization and selection of climate models, as well as an uncertainty analysis using the BMA approach, the framework was found to significantly improve the reliability of ensemble projections.

(2) The runoff at the six main stations (i.e., Tangnaihai, Lanzhou, Toudaoguai, Longmen, Tongguan, and Sanmenxia) of the Yellow River Basin is expected to be 17.7, 28.5, 27.9, 31.1, 37.9, and 38.2 billion m³ in the 2050 period and 17.2, 27.8, 27.3, 31.2, 39.2, and 39.5 billion m³ in the 2070 period, respectively, in the 2070 period. Table 4 summarizes the corresponding 90% confidence intervals. The runoff in the 2050 and 2070 periods in the upper and middle reaches of the Yellow River Basin decreases by 4.0 billion m³ and 2.7 billion m³, respectively, compared with the reference period.

(3) The 90% confidence intervals of the monthly runoff at the stations in the upper reaches of the Yellow River Basin in the two future periods are significantly narrower than those at the other hydrological stations (Figure 3). This result suggests that under the ensemble projection framework, the hydrological model provides better simulations for the upper reaches of the Yellow River Basin. As a result of land surface conditions and human activity, it is more difficult to simulate the middle and lower reaches of the Yellow River Basin, and the results have more uncertainty. It is critical to improve the hydrological model in specific areas to increase its projection reliability.

ACKNOWLEDGMENTS

This study was supported by the National Key Research and Development Program of China (No. 2016YFC0402405), National Natural Science Foundation of China (No. 51779270, 51309248), Foundation of SKL-WAC (SKL2018TS04), Jiangxi Project (KT201501, KT201508, KT201411) and Yunnan Project (YSZD-2014-001, YNWRM-.2012-01).

REFERENCES

- Abbaspour, K.C., Faramarzi, M., Ghasemi, S.S., Yang, H., 2009. Assessing the impact of climate change on water resources in Iran. *Water Resour. Res.* 45, W10434. doi:10.1029/2008WR007615.
- Abouabdillah, A., Oueslati, O., De Girolamo, A.M., Lo Porto, A., 2010. Modeling the impact of climate change in a Mediterranean catchment (Merguellil, Tunisia). *Fresenius Environ. Bull.* 19 (10A), 2334–2347.
- Ajami, N. K., Duan, Q., Gao, X. & Sorooshian, S., 2006. Multimodel combination techniques for hydrological forecasting: application to distributed model intercomparison project results. *Journal of Hydrometeorology*, 7, 755–768.
- Arnell, N.W., 1992. Factors controlling the effects of climate change on river flow regimes in a humid temperature environment. *J. Hydrol.* 132 (1–4), 321–342.
- Arnell, N.W., Reynard, N.S., 1996. The effects of climate change due to global warming on river flows in Great Britain. *J. Hydrol.* 183 (3–4), 397–424.
- Cannon, A.J., Sobie, S.R. and Murdock, T.Q. (2015) Bias correction of GCM precipitation by quantile mapping: How well do methods preserve changes in quantiles and extremes? *J. Climate*, 28, 6938–6959.
- Dong, L.H., Xiong, L.H., Zheng, Y.F., 2013a. Uncertainty analysis of coupling multiple hydrologic models and multiple objective functions in Han River, China. *Water Science & Technology*, 68(3): 506–513
- Dong, L.H., Xiong, L.H., Yu, K.X., 2013b. Uncertainty Analysis of Multiple Hydrologic Models Using the Bayesian Model Averaging Method. *Journal of Applied Mathematics*, Article ID 346045
- Duan, Q., Ajami, N.K., Gao, X., Sorooshian, S., 2007. Multi-model ensemble hydrologic prediction using Bayesian model averaging. *Advances in Water Resources*, 30(5): 1371–1386.
- Gao, X., Y. Shi, F. Giorgi, 2016. Comparison of convective parameterizations in RegCM4 experiments over China with CLM as the land surface model. *Atmospheric and Oceanic Science Letters*, 9, 246–254.
- Gao, X., Y. Shi, Z. Han, M. Wang, J. Wu, D. Zhang, Y. Xu, and F. Giorgi, 2017. Performance of RegCM4 over major river basins in China. *Adv. Atmos. Sci.*, 34, 441–455.
- Hao, Z.C., Wang, J.H., Li, L., Wang, Z.H., Wang, L., 2006. Impact of Climate Change on Runoff in Source Region of Yellow River. *Journal of Glaciology and Geocryology*, 28(1): 1–7. (in Chinese)
- Jia, Y.W., Wang, H., Zhou, Z.H., Qiu, Y.Q., Luo, X.Y., Wang, J.H., Yan, D.H., Qin, D.Y., 2006. Development of the WEP-L distributed hydrological model and dynamic assessment of water resources in the Yellow River basin. *Journal of Hydrology*, 331, 606–629

- Jonas Roberts & Ken Snelgrove (2015): Uncertainty in Regional Climate Model Mean Runoff Projections under Climate Change: Case Study of Labrador's Churchill River Basin, *Atmosphere-Ocean*, DOI: 10.1080/07055900.2015.1026872
- Li, L., Shen, H.Y., Dai, S., et al., 2011. Response to climate change and prediction of runoff in the source region of Yellow River. *Acta Geographica Sinica*, 66(9): 1261-1269. (in Chinese)
- Montenegro, A., Ragab, R., 2010. Hydrological response of a Brazilian semi-arid catchment to different land use and climate change scenarios: a modelling study. *Hydrol. Process.* 24 (19), 2705–2723. doi:10.1002/hyp.7825.
- Piao, S.L., Ciais, P., Huang, Y., Shen, Z.H., Peng, S.S., Li, J.S., Zhou, L.P., Liu, H.Y., Ma, Y.C., Ding, Y.H., Friedlingstein, P., Liu, C.Z., Tan, K., Yu, Y.Q., Zhang, T.Y., Fang, J.Y., 2010. The impacts of climate change on water resources and agriculture in China. *Nature* 467 (7311), 43–51.
- Ragab, R., Prudhomme, C., 2002. Climate change and water resources management in arid and semi-arid regions: prospective and challenges for the 21st century. *Biosyst. Eng.* 81 (1), 3–34. doi:10.1006/bioe.2001.0013.
- Thomson, A.M., Brown, R.A., Rosenberg, N.J., Srinivasan, R., Izaurralde, R.C., 2005. In: Rosenberg, N.J., Edmonds, J. (Eds.), *Climate Change Impacts for the Conterminous USA: An Integrated Assessment*. Part 4. Water Resources. Springer, Netherlands, pp. 67–88.
- Xiao, T., Liu, J.Y., Shao, Q.Q., 2009. A simulation on changes in vegetation productivity in "Three River Sources" Nature Reserve, Qinghai Province over past 20 years. *Journal of Geo-information Science*, 11(5): 557-565.
- Xu, Y.L., Zhang, Y.X., Lin, W.T., 2007. Analyses on the climate change scenarios over the Three Rivers'Headstream Region in China. *Climatic and Environmental Research*, 12(5): 667-675.
- Xu, Z.X., Zhao, F.F., Li, J.Y., 2009. Response of streamflow to climate change in the headwater catchment of the Yellow River basin. *Quaternary International*, 208: 62-75.
- Zhang, Y.Y., Zhang, S.F., Zhai, X.Y., Xia, J., 2012. Runoff variation and its response to climate change in the Three Rivers Source Region. *Journal of Geographical Sciences*, 22(5): 781-794
- Zhou, W.C., Han, Z.Y., 2018. Assessing CMIP5 climate simulations and objective selection of models over the Yellow River basin. *Journal of Meteorology and Environment*, 2018, 34(6): 42- 55.