doi:10.5194/piahs-368-331-2015

Forecast of irrigation water demand considering multiple factors

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Abstract Many factors influence irrigation water requirement on the basin scale, which make it difficult to obtain comprehensive data. Despite the advantage of less needing historical data, the prediction precision of traditional trend prediction methods is hard to guarantee. For water scarce basins, the artificial influence on irrigation requirement should be thought of as important impact factors. In this paper, the PCA (principal component analysis) method is used to identify the main influencing factors, such as precipitation, irrigation area, water saving technology and so on. Based on that, an irrigation water demand prediction model considering multiple factors is developed for water shortage regions. The method is applied in the Haihe River basin as an example. The study results show that the irrigation water demand forecasting method considering multiple factors in this paper can achieve higher modelling accuracy, compared with the traditional trend prediction method and the method that does not consider the human influence. In view of the small average relative error, 1.32%, it has good values for application.

Key words irrigation water demand; PCA; water saving coefficient; forecast

1 INTRODUCTION

Irrigation water is the main component of off-stream water uses. It is important to reasonably estimate irrigation water demand. At present, the forecast methods at home and abroad are mainly of three types: The Judgment method, based on the individual and collective experience and knowledge to make predictions, has a low requirement for data and is highly subjective. The Trend prediction method, which is associated with the past, mainly considers time change but ignores the other factors. The Simulation model prediction method, which considers many factors, but is limited in data scarce regions.

A time series method combining the grey GM(1,1) model with cycle analysis of variance and the ARMA model was established to describe the change rules of irrigation water (Shao Dongguo *et al*., 1998). The historical data were divided into three kinds: the tendency item, the periodic item and the random item. The three factors were simulated. Chi Daocai (2009) combined the neural network prediction method with the grey model to establish a parallel grey neural network prediction model. Bai Cunyou (2004) developed the equal-dimension and new-info model GM(1,1) according to the grey system theory and the model can refresh data in time. Leenhardt (2004) set up a simulation platform called ADEAUMIS, which includes a bio-decision model and a specialized input database necessary to run it. It considered factors such as irrigation area, climate and irrigation techniques. Domestic research mostly focuses on improving the algorithm. Abroad, studies have developed many multivariable driver models, which can guarantee the precision but are difficult to use in watershed research because of the dependence on large amounts of data.

In recent years human activity (technology progress, policy mechanism, production inputs, etc.) has become the leading factor influencing irrigation water demand and food production (Wu Pute *et al*., 2010). In water-short regions, which have a large intensity of water-saving irrigation, only considering climate factors is obviously inadequate. This has barely been considered in the above studies. To solve the above problems, we explored an irrigation water demand prediction method having an "artificial–natural" binary feature at the watershed scale. The method in this paper is based on principal component analysis (PCA) and regression analysis methods, and also considers the influence of water saving.

2 FORECASTING METHOD

Farmland irrigation water is influenced by climate and human factors, therefore five factors including rainfall, irrigation area, food production, planting structure and agricultural water saving level were selected as the impact factors to be analysed. The first three can be expressed by quantitative numerals, while the planting structure and water saving level are difficult to present quantitatively.

Irrigation water-saving methods at the watershed scale mainly include improving the utilization coefficient of irrigation water and adjustment of planting structure, both of which have the same change trend over time, namely to develop in the direction of reducing irrigation water. In this paper, planting structure, and the influence of water saving technology are generalized as the agricultural water-saving coefficient α. The meaning of α is: due to the adjustment of planting structure and the increasing popularization of water-saving irrigation technology, irrigation water can be different in different years. Under the same conditions of rainfall and irrigation area, irrigation water will decrease year by year.

To simplify the calculation and reduce the requirements for data, PCA was used to extract the main impact factor first. The target of PCA is to lower the dimension of high variant space and eliminate the relativity of sample data under the principal of minimum information loss. Namely, a few variables are used to replace the original multi-dimensional variables, through linear transformation and giving up a small part of the information. The PCA method could achieve a high precision of prediction supported by a few data. The highly correlation between the factors reducing the precision of regression analysis could also be avoided. Using the regression analysis method, an irrigation water consumption function including the extracted main components and water-saving coefficient α was established. We call this the α model:

$$W = \frac{f(P,F,\dots)}{\alpha^{(t-t_0)}} \tag{1}$$

where W is the forecasted irrigation water demand, $f(P,F,\dots)$ is a linear regression equation based on the principal component, P is the predicted rainfall, F is the predicted irrigation area, α is the annual average coefficient of water saving progress, t is the forecasting year, and t_0 is the start year of the data series.

3 APPLICATION EXAMPLE

3.1 Current water consumption in Haihe River basin

Haihe River basin belongs to the temperate semi-humid, semi-arid continental monsoon climate zone, and has four distinctive seasons. Haihe River basin occupies the minimal rainfall areas along the east coasts of our country, where drought occurs nine years out of ten. From 2001 to 2012, the basin experienced successive years of drought, having an average annual precipitation 502.5 mm, 5% lower than the average of 526.8 mm from 1956 to 2010.

In the recent 12 years, great changes have taken place in Haihe River basin water utilization structure. The water use rivalry between different industries was also exacerbated. Because of the population growth, rapid urbanization and our rising living standards, urban life and industrial demand for water resource is growing rapidly. Irrigation water is the main water consumption in Haihe River basin, but its proportion of total water consumption of the watershed fell from 67% in 2001 to about 59% in 2012.

3.2 The main factors that influence the Haihe River basin irrigation water

According to comprehensive planning and water resources reports for Haihe River basin, four factors were selected as objects of the research: the irrigation area, food production, per capita occupancy of grain and precipitation. Data from 1980 to 1998 were used to extract the principal components (Table 1).

Table 2 shows the contribution rate and the cumulative contribution rate of each component. The total cumulative contribution rate of rainfall and irrigation area is 98.88%, which exceeds the standard rate 85% for extracting principal factors. So these two factors can be used to conduct regression analysis.

Table 1 Agricultural indicators of Haihe River basin in 1980–1998.

Year	Irrigation area (million Ha)	Grain output (million ton)	Per capita occupancy of grain (kg)	Precipitation (mm)	Irrigation water (billion m^3)
1980	6.3	27.7	283	441	30.5
1981	6.3	29.1	294	422	30.0
1982	6.3	30.5	305	514	29.5
1983	6.3	32.0	314	480	28.9
1984	6.4	33.3	324	466	28.4
1985	6.4	33.7	324	544	26.2
1986	6.4	34.0	324	434	30.0
1987	6.4	34.4	321	545	28.6
1988	6.4	36.3	333	555	29.9
1989	6.5	38.2	347	434	32.2
1990	6.5	40.1	354	648	27.2
1991	6.7	41.9	365	541	28.3
1992	6.7	42.8	369	442	29.5
1993	6.8	47.4	405	479	28.5
1994	6.9	49.0	416	578	27.5
1995	7.0	53.0	442	610	26.8
1996	7.1	51.2	423	598	27.3
1997	7.2	49.9	412	368	29.9
1998	7.3	53.9	442	551	29.3

Note: The data are from the Haihe River basin integrated water resources planning.

Table 2 The characteristic value and contribution of the compositions.

Composition	The initial eigenvalue		
	Total	Variance %	Cumulative %
Rainfall	3.050	76.262	76.262
Irrigation area	0.903	22.581	98.843
Food production	0.044	1.0920	99.936
Food per capita	0.003	0.0640	100.00

When these main factors were combined into the model mentioned above, the irrigation water demand prediction function of Haihe River basin is as followed:

$$W = \frac{a+b*P+c*F}{\alpha^{(t-t_0)}} \tag{2}$$

3.3 Parameters and validation

To verify the simplified water-saving coefficient, trend analysis was carried out on the planting structure and water-saving level. Haihe River basin irrigation area can be divided into paddy fields, irrigated land and vegetable plantation.

We take the main agricultural province, Hebei, as an example. The dry land (except irrigated) has a single downward trend, while the irrigated area is increasing (Fig. 1). Paddy field area nearly remains unchanged and only accounts for a very small proportion of the total area, 1–1.8%. Therefore, the planting structure trend of Haihe River basin can be thought of as a kind of single change over time.

Actual irrigation water data of Haihe River basin from 1986 to 2005 were used to calibrate the parameters and data from 2006 to 2012 were used for verification. SPSS data analysis software was used to seek the optimal parameters; result are shown in Table 3. The parameters show that the coefficient of rainfall is negative, which explains the negative relationship between irrigation water and climate. Where rainfall is larger, the artificial irrigation water is less. The coefficient of irrigation area is positive, indicating that when the irrigation area increases, the need of irrigation

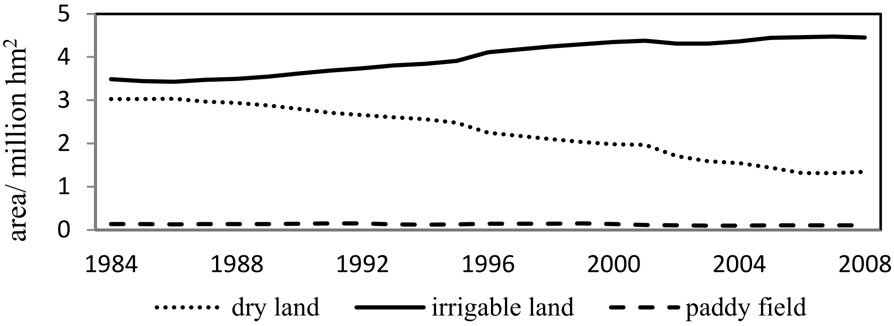

Fig. 1 Cultivated land area of Heibe province over the years.

Table 3 Parameters of the equation.

Parameter	Estimator	Std Error	95% confidence interval lower limit	upper limit
a	272.5	55.09	155.7	389.3
b	–0.135	0.033	–0.205	–0.064
c	0.010	0.005	–0.001	0.022
α	1.011	0.002	1.008	1.015

R-squared = 0.920.

water is larger. The water-saving coefficient α is greater than 1, indicating that even under the same conditions of rainfall and irrigation area, irrigation water will be reduced year by year because of the improvement of water saving technology.

For comparison, the GM(1,1) forecasting method and a simple linear regression method were also used. The same data for calibration These three models have the same data for verification. The ratio of predicted and actual values is shown in Fig. 2. Results show that the α model set up in this paper is more stable than the simple linear regression method, which does not consider the coefficient α. According to data from 2006 to 2012 which are used to verify the simulation, the average error of GM(1,1) model is 3.38%, and the mean error of linear regression prediction method is 12.64%, while the α model established based on the "artificial- natural" just has a mean error of 1.32%.

Table 4 The comparison of actual values and the predicted values.

Year	Actual value (billion m^3)	GM(1,1) (billion m^3)	Relative error %	Linear regression (billion m^3)	Relative error %	α model (billion m^3)	Relative error %
2006	25.6	25.0	–2.49	28.0	9.43	25.3	1.19
2007	25.1	24.7	–1.42	28.0	8.2	24.7	1.37
2008	23.9	24.5	2.63	27.1	10.15	23.9	0.24
2009	23.6	24.2	2.86	26.3	15.52	24.0	1.86
2010	23.0	24.0	4.27	27.2	14.6	23.5	1.92
2011	22.9	23.8	3.73	26.4	15.51	23.4	2.29
2012	22.1	23.5	6.22	26.5	15.05	22.2	0.37

As can be seen from the trend, the GM(1,1) model cannot reflect changes in the single factors due to its characteristic of only considering the change of time series. Although the linear regression result fluctuates up and down with rainfall, the predicted values are significantly larger because they do not consider the change of water-saving level year by year.

It is also shown that the impact of climate change on irrigation water requirement has been reduced but the influence of human factors enhanced. The regression equation considering the irrigation water-saving technology changes can not only reflect the influence of different years, but also reflect the effects of water saving technology progress, so the simulation result is better.

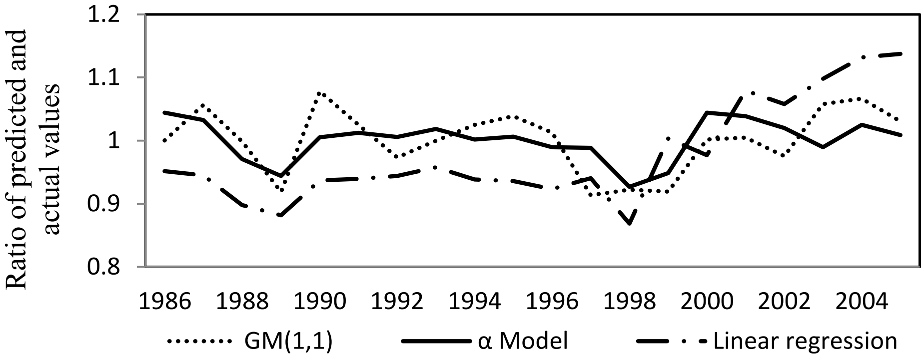

Fig. 2 Ratio of predicted and actual values.

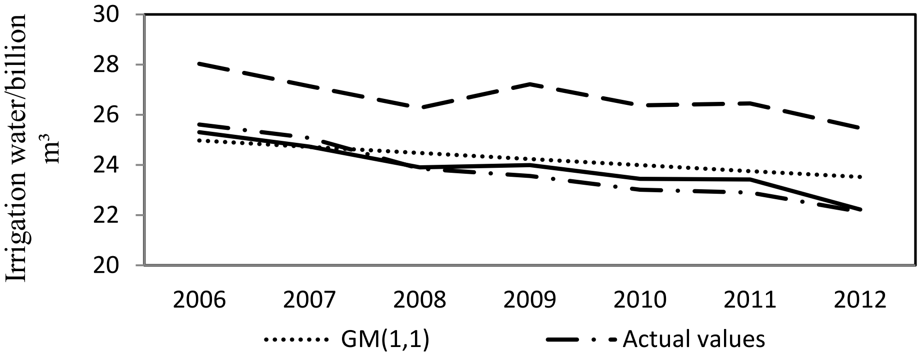

Fig. 3 Validation of predicted values of each method.

3.4 Forecast of irrigation water demand of Haihe River basin in 2030

Thus it can be proved by the above validation that the method proposed in this paper can reflect the change of irrigation water in Haihe River basin well. But an important problem should be noted. The potential of agricultural water-saving will be decline, and therefore the rate of water-saving technology change may be slower and slower over time. Domestic and foreign water growth statistics show that the water demand growth rate changes in different phases. The trend generally experiences three stages: rapid growth phase, the slow growth phase and stationary phase.

For coefficient α, the benchmark year t_0 changes in different periods. So we are better to choose data of recent years to calibrate the parameters. Setting 2000 as the start year, and 2000 to 2012 as the calibration period, we get the parameters shown in Table 5. The value of α in this table is lower than that for the series 1986–2005, which indicates that the speed of water-saving technology change is slowing. Parameters in Table 5 are used to predict the irrigation water demand in 2030.

Rainfalls in different level years are predicted by the P-III curve based on data from 1980 to 2012. The P-III curve is generally adopted in hydrological frequency analysis. The values under water frequency of 25%, 50% and 75% are respectively 545.4, 490 and 438.2 mm. The irrigation area is predicted to be 120 billion mu. Plugging the above parameters in the equation, we find the

Table 5 Parameters used in prediction.

Parameter	Estimator	Std Error	95% confidence intervals	
			Lower limit	Upper limit
a	315.3	35.16	235.7	394.8
b	−0.128	0.027	−0.189	−0.068
c	0.004	0.003	−0.002	0.011
α	1.010	0.001	1.006	1.013

forecasted irrigation water data are 25.8 billion m^3, 26.7 billion m^3 and 27.2 billion m^3 under the three types of water frequency years.

4 CONCLUSIONS

Irrigation water requirement is mainly affected by climate change and human factors. Rainfall is the main climate factor and human factors include irrigation area, irrigation technology level, etc. With the development of water-saving irrigation technology, the influence of human factors is more and more notable.

The concept of the water-saving improvement coefficient is introduced into the water demand forecasting model based on the dual characteristic of "artificial–natural". The model set up in this paper can reflect the influence of water-saving technology and planting structure adjustment on irrigation water better, and has a better simulation effect than time series analysis and the traditional regression.

The irrigation water requirements of Haihe River basin in 2030 are predicted to be 25.8 billion m^3, 26.7 billion m^3 and 27.2 billion m^3, respectively, in high flow years, normal years and low flow years. These are values are lower than the present situation.

It is worth exploring how the coefficient α representing water-saving technology and planting structure adjustment is changing. Our next work is to quantitatively describe the relationship between its change rule and the various impact factors.

Acknowledgements This paper was jointly supported by funds from Hydrological Simulation & Regulation of Watersheds (No. 51021066) of the Funds for Creative Research Groups of China, Ministry of Water Resources' Special Funds for Scientific Research on Public Causes (201001024, 201101026 and 201101024).

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