Analysis on natural influencing factors of groundwater depth in Dengkou County and forecast of its variation trend

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Abstract. To reveal the main natural factors that influences groundwater depth of Dengkou county and predict the variation trend of groundwater depth, this thesis, based on the principal component analysis (PCA), conducts analysis on natural factors that are likely to affect the groundwater depth, and establishes a multiple linear regression model to show the quantitative relationship between the main natural factors and the groundwater depth. Then grey prediction method is adopted to predict possible change of main natural influence factors in the coming five years with employment of multivariate regression equation for further fitting. Results: Among the selected natural influencing factors, the most influential one is evaporation, followed by air temperature and sunshine hours, which are negatively correlated with groundwater depth, and the reason for this is related to the flood season of Yellow River. Relative humidity and precipitation have little influence on groundwater depth. According to the grey prediction results, the temperature, evaporation and sunshine duration will all be on the rise in the coming five years, and the average groundwater level will also increase slowly. The average depth of groundwater in summer is about 2.5m. Due to local dry climate and vigorous evaporation, secondary salinization of the land is likely to occur. Especially, the water level in the irrigation area of the Yellow River is generally high, deserving enhanced vigilance. This paper has reference significance for the ecological construction & planning of Dengkou County in the next five years.

1. Introduction

In arid and semi-arid regions with little precipitation, vigorous evaporation and little surface runoff, groundwater resources are of great significance for maintaining local ecological sustainable development and are also the primary factor that restricts social and economic development in desert and desert regions [1, 2]. Dynamic change of groundwater depth is one of the important contents reflecting groundwater dynamics, which is affected by both man-made and natural factors at the same time. It is a complex hydrological change process [3]. Climate change is one of the most important natural factors affecting the change of groundwater level. Factors like precipitation, temperature, and evaporation etc. may all affect the change of groundwater level [4, 5]. Excessive exploitation of groundwater will result in low groundwater level and difficult survival or even degradation of surface vegetation. For the ecologically sensitive arid and semi-arid areas, land desertification in large area is
unavoidable. However, large area irrigation will lead to high groundwater level and poor water quality, which will easily cause secondary salinization of land, making it difficult for plants to grow [6-8].

At present, there have been a large number of studies on groundwater resources in arid areas in China, mainly focusing on dynamic monitoring, pollution control, water quality assessment and prediction model etc., especially in the oasis areas such as Minqin oasis and Hetian oasis. Dynamic analysis and prediction of groundwater resources have always been a hot topic. In recent years, more and more researches have been conducted on groundwater prediction by using neural network and MODFLOW model with good results obtained. However, considering that Dengkou County, the study area, has the transit of Yellow River and is in a unique geographical position in the arid area, finding out the natural factors that have a greater impact on the study area is of great help for the prediction.

This paper firstly adopts the principal component analysis to find out the factors that have the biggest influence on groundwater depth of Dengkou County and then establishes the multiple linear regression model to represent the relationship between the groundwater depth and impact factors. Then grey prediction GM (1, 1) model is employed to predict change of the influence factors in the coming five years. Finally the multiple linear regression model is used to obtain predictive value of groundwater depth so that reference can be provided for ecological construction & planning of Dengkou county in the coming five years.

2. Materials and method

2.1. Profile of the research area and data source

Dengkou County, which belongs to Bayannur City of Inner Mongolia Autonomous Region, is located at the junction where the northeast edge of Wulanbuhe desert connects with Hetao Plain, which is the boundary line between the desert and the grassland in northern China. Its geographical location is E106°9’ to 107°10’ and N40°9’ to 40°55’. With a length of 92 kilometers from the east to the west and a width of 65 kilometers from north to south, the county covers an area of 4176km2. In the northwest, it is connected with Wulate houqi by Wolf Mountain, and its central and southern part is penetrated by Ulanbuhe desert. In the northeast, the terrain is flat and belongs to Houtao Plain. The overall terrain is high in the southeast and low in the northwest, and the terrain gradually slopes from the southeast to the northwest. The county enjoys a dry climate with less precipitation and exuberant evaporation, belonging to a temperate dry continental monsoon climate [9-12].

Dengkou County is located in the upper reaches of Hetao irrigated area. The Yellow River flows through the county, covering about 52 kilometers. Three main channels draw 400 million cubic meters of water, which is the main source of groundwater recharge. The river bed in the county is 1.5-4km wide, the flood period starts from July and ends in September, and the dry period lasts from December to January. The maximum flow rate is 4600m3/s, and the average flow rate is 1000-2000m3/s. There are 31 natural lakes (total area of 36,400 mu) in the county territory. The main aquifer in Dengkou County is divided into two layers, namely the water-table aquifer and the artesian aquifer. The buried depth of the water-table aquifer is only 2-3m, which is easy to be used. Therefore, it is the main research object of this paper.

2.2. Data source

The data are the monthly observed values of groundwater depth of 40 observation wells that are evenly distributed in Dengkou County from 2006 to 2015 and the monthly meteorological monitoring data from meteorological stations, including temperature, relative humidity, precipitation, evaporation and sunshine duration. Due to lack of groundwater depth value in November and December, this paper only studies the change of groundwater depth value from January to October and make prediction based the study.
2.3. **Principal component analysis**

Principal component analysis (PCA), based on multiple original indicators, is to construct a few unrelated comprehensive indicators through linear combination to replace the original indicators, and these comprehensive indicators can reflect enough original information. This method is often used to simplify complex problems in various fields [13, 14]. Main calculation step [15] is as the follows.

Firstly, to standardize the original data. Indicator samples (N) are designed with $X_{ij}$ as the $j^\text{th}$ index value of the $i^\text{th}$ sample, $\bar{X}_j$ and $S_j$ are the mean value and standard deviation of the $j^\text{th}$ index respectively, and the standardized formula is:

$$Z_{ij} = \frac{X_{ij} - \bar{X}_j}{S_j} \quad (1)$$

Calculate the eigenvalue $\lambda_j$ of the correlation matrix R and the eigenvector matrix. Calculate variance contribution rate ($w_j$) of each principal component and cumulative variance contribution rate $\sum w_j$. The variance contribution rate is the weight of the principal component, and the cumulative variance contribution rate represents the proportion of the extracted principal component information in the total information.

Principal component weight is extracted and principal component scores and comprehensive scores are calculated. The higher the comprehensive score is, the higher the level will be. The positive comprehensive score means the evaluation result is above the average level, and the negative comprehensive score means the evaluation result is below the average level.

2.4. **Multiple linear regression model**

In most real-world problems, changes in one variable are often influenced by other variables. Multiple linear regression model is to describe the linear relationship between a dependent variable and multiple independent variables by establishing multiple linear regression equation [16]. Suppose a dependent variable $Y$ is dependent on several (n) independent variables $X_1, X_2, ..., X_n$, the regression equation is [17-19]:

$$\hat{Y} = b_0 + b_1x_1 + b_2x_2 + \cdots + b_nx_n \quad (2)$$

In the equation, $b_0$ is a constant term, $b_1, b_2, \ldots b_n$ are partial regression coefficients, which can be calculated by the least square method.

$F$ test can be used to test the significance of regression equation, and the statistic $F$:

$$F = \frac{u/k}{Q/(n-k-1)} \quad (3)$$

In the equation, $U = \sum_{a=1}^{n} (\hat{Y}_a - \bar{Y})^2$, $K$ is the degree of freedom of the regression sum of squares (U). $Q = \sum_{a=1}^{n} (Y_a - \hat{Y}_a)^2$, $(n-k-1)$ is the degree of freedom of the remaining sum of squares (Q). With the significant level $\alpha$, if $F > F_{(k,(n-k-1))}$, the linear relationship between dependent variable $Y$ and independent variables $X_1, X_2...X_n$ is significant, and the regression model has a good fitting effect.

2.5. **Grey prediction model**

Grey model (GM) is a model construction method based on the concept of grey generating function and with differential fitting as the core. The modeling process is to process the data changing according to time series within a certain range, reduce its randomness and enhance its regularity, and then generate new data series with regularity through differential fitting. Among all GM models, the most commonly used one is GM (1,1), which is used for prediction. This model is called the single-sequence first-order linear dynamic model. It can predict unknown systems by constructing the first-order difference equation of a single variable, and the effect is comparatively satisfactory when it is used in the environment prediction with insufficient historical data [20]. During the prediction process, the original data sequence is firstly treated by accumulated generation to obtain the 1-AGO sequence, and then the new sequence is used to construct the corresponding discrete prediction model. Finally, the least square method is used to calculate and obtain the gray parameters A and B which will be further used to construct the gray prediction model [21, 22].
\[ x^{(1)}(k + 1) = \left[ x^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \]  

where: \( a \) is the development coefficient, \( b \) is the grey action quantity.

Gray prediction has a high modeling accuracy for smooth discrete data sequence, but in practical problems, most of the data sequence has a low smoothness, which limits the application scope of grey prediction model.

3. Analysis of influencing factors and linear regression

3.1. Principal component linear regression analysis
Firstly, analysis on correlation of the influencing factors and the groundwater depth is carried out (Table 1) with air temperature, evaporation, sunshine duration showing higher negative correlation with groundwater depth, and correlation among some natural influencing factors is relatively high, requiring principal component analysis. After data standardization of five natural influencing factors, principal component regression analysis is carried out according to time series. By analyzing the eigenvalue and the cumulative contribution rate of variance (Table 2, Fig. 1), the first three principal components are finally selected, and the cumulative contribution rate of variance reaches 92.968%. It is generally believed that only when the variance contribution rate reaches 85% can the information of the original variable be well reflected.

### Table 1. Correlation matrix between influence factors and groundwater depth

| Impact factor       | Groundwater depth | Air temperature | Relative humidity | Precipitation | Evaporation | Sunshine duration |
|---------------------|-------------------|-----------------|------------------|---------------|-------------|-------------------|
| Groundwater depth   | 1.000             |                 |                  |               |             |                   |
| Air temperature     | -0.712            | 1.000           |                  |               |             |                   |
| Relative humidity   | 0.016             | -0.023          | 1.000            |               |             |                   |
| Precipitation       | -0.266            | 0.434           | 0.339            | 1.000         |             |                   |
| Evaporation         | -0.714            | 0.848           | -0.222           | 0.339         | 1.000       |                   |
| Sunshine duration   | -0.449            | 0.520           | -0.617           | -0.021        | 0.631       | 1.000             |

### Table 2. Explanation of the total variance

| Principal component | Characteristic root | Variance /% | Variance accumulation /% |
|---------------------|---------------------|-------------|--------------------------|
| 1                   | 2.570               | 51.402      | 51.402                   |
| 2                   | 1.610               | 32.190      | 83.593                   |
| 3                   | 0.469               | 9.376       | 92.968                   |
| 4                   | 0.223               | 4.453       | 97.421                   |
| 5                   | 0.129               | 2.579       | 100.000                  |
Figure 1. The scree plot.

The initial factor load matrix is obtained by calculation through statistical software (see Table 3). The corresponding eigenvector is obtained by dividing the arithmetic square root of the characteristic root of the corresponding principal component by the factor loading value (Table 4).

| Impact factor    | Principal component |
|------------------|---------------------|
|                  | 1       | 2       | 3       |
| Air temperature  | 0.874   | 0.330   | 0.244   |
| Relative humidity| -0.391  | 0.823   | 0.333   |
| Precipitation    | 0.347   | 0.782   | -0.518  |
| Evaporation      | 0.932   | 0.131   | 0.162   |
| Sunshine duration| 0.815   | -0.442  | -0.066  |

| Impact factor    | Principal component |
|------------------|---------------------|
|                  | 1       | 2       | 3       |
| Air temperature  | 0.545   | 0.260   | 0.356   |
| Relative humidity| -0.244  | 0.648   | 0.486   |
| Precipitation    | 0.217   | 0.616   | -0.756  |
| Evaporation      | 0.581   | 0.103   | 0.237   |
| Sunshine duration| 0.508   | -0.349  | -0.097  |

The principal component expression can be obtained according to Table 4:
\[ F_1 = 0.545X_1 - 0.244X_2 + 0.217X_3 + 0.581X_4 + 0.508X_5 \]  
(5)

\[ F_2 = 0.260X_1 + 0.648X_2 + 0.616X_3 + 0.103X_4 - 0.349X_5 \]  
(6)

\[ F_3 = 0.356X_1 + 0.486X_2 - 0.756X_3 + 0.237X_4 - 0.097X_5 \]  
(7)

In the equation, \( F_1, F_2 \) and \( F_3 \) represent three principal components respectively: \( X_1 \) for temperature, \( X_2 \) for relative humidity, \( X_3 \) for precipitation, \( X_4 \) for evaporation, and \( X_5 \) for sunshine duration.

According to the above analysis, among the first principal components, the variance contribution rate of \( X_1, X_4 \) and \( X_5 \) is up to 51.402\%, which is the highest among the three principal components and can represent the comprehensive influence of most of the natural influence factors on the groundwater depth. Therefore, air temperature, evaporation and sunshine duration are the three natural factors that have the greatest influence on local groundwater depth. With combination to the correlation matrix and principal component expression, it can be concluded that the influence order of these natural factors on burial depth is: evaporation > air temperature > sunshine hours > precipitation > relative humidity. Temperature, evaporation and sunshine duration show negative correlation with the groundwater depth. The higher the value of these factors, the shallower the groundwater depth is. This is the difference between the variation of groundwater depth of Dengkou County and that of most other areas. Dengkou County is water seepage of Yellow river for which the flood season is from July to September, the hottest time during the summer. This leads to the negative correlation of temperature, evaporation, and sunshine duration with the groundwater depth. And this further illustrates that the water seepage of the Yellow River has far greater influence on the underground water level of Dengkou County than any other natural factors. Precipitation and relative humidity have relatively little correlation with groundwater depth. The reason is that the local climate is arid with rare and unevenly distributed precipitation but evaporation is very vigorous. Consequently, precipitation is far less than evaporation, and relative humidity is very low, making it difficult for these factors to influence groundwater depth.

3.2. Multivariate regression liner model

According to the results of principal component analysis, air temperature, evaporation and sunshine duration are the main components of the principal components. Besides, the extracted three principal components are not collinear with each other, which satisfy the conditions for the construction of multivariate linear regression model. The extracted principal components \( F_1, F_2, F_3 \) and the groundwater depth were subjected to multivariate linear regression, and the regression equation is as follows:

\[ Y = 2.866 - 0.062X_1 - 0.169X_4 - 0.051X_5 \]  
(8)

where \( Y \) is the fitting value of groundwater depth.

\( T \) test is carried out for each coefficient. The \( t \) value of constant is 171.467, corresponding to \( P = 0.000 < 0.01 \). The \( T \) value of \( F_1 \) is -10.085, corresponding to \( P = 0.000 < 0.01 \); \( T \) value of \( F_2 \) is -3.020, corresponding \( P = 0.003 < 0.01 \); The \( T \) value of \( F_3 \) is -3.699, corresponding to \( P = 0.000 < 0.01 \).

\( F \) test is carried out on the whole, and the value of \( F \) was 41.483, corresponding to \( P = 0.000 < 0.01 \). Therefore, the overall height of the regression equation is significant and the influence of individual variables on the changes of dependent variables is also extremely significant. Histogram of regression normalized residuals and P-P chart in Fig. 2 and Fig. 3 showed good overall linear fitting accuracy.
The standardized meteorological data from 2006 to 2015 are substituted into the regression equation to obtain the fitting value for comparison with the measured value (Fig. 4).
4. Prediction and analysis of groundwater depth

Prediction and accuracy test for 2011-2015 is carried out according to the data of monthly temperature, Monthly evaporation and monthly sunshine hours in 2001-2010. The grey forecast GM (1,1) model is used to predict the temperature, evaporation and sunshine duration from 2016 to 2020, and then the predicted natural influencing factor data are substituted into the multiple regression model for fitting to obtain the predicted groundwater depth in the next five years.

4.1. Prediction of temperature change

Relative error of the forecast values of 2014 and 2015 (Table 5) are all within the acceptable range except for the relatively large errors of certain months (0.1429 and 0.1324 respectively), and the average annual relative errors are 0.0287 and 0.0318 respectively, which meet the prediction accuracy requirements. The average annual relative errors of other years are also less than 0.04. It can be seen from Fig. 5 that the local average annual temperature in the past 15 years shows a slight upward trend in general and the upward trend will continue to be evident in the coming 5 years.

![Figure 4. Fitting diagram of regression model.](image)

**Table 5. Calculation and check to air temperature in 2014 and 2015**

| Year | Month | Measured | Simulated | Relative error | Year | Month | Measured | Simulated | Relative error |
|------|-------|----------|-----------|---------------|------|-------|----------|-----------|---------------|
| 2014 | 1     | -10.80   | -11.20    | 0.0370        | 2015 | 1     | -11.57   | -11.98    | 0.0355        |
| 2014 | 2     | -6.60    | -6.74     | 0.0212        | 2015 | 2     | -7.65    | -7.95     | 0.0393        |
| 2014 | 3     | 5.50     | 5.43      | 0.0127        | 2015 | 3     | 6.12     | 6.93      | 0.1324        |
| 2014 | 4     | 12.40    | 11.89     | 0.0411        | 2015 | 4     | 12.69    | 12.35     | 0.0265        |
| 2014 | 5     | 17.50    | 17.69     | 0.0109        | 2015 | 5     | 17.70    | 17.50     | 0.0113        |
| 2014 | 6     | 22.10    | 22.13     | 0.0014        | 2015 | 6     | 22.10    | 22.11     | 0.0005        |
| 2014 | 7     | 26.10    | 26.86     | 0.0291        | 2015 | 7     | 27.89    | 27.88     | 0.0004        |
| 2014 | 8     | 24.40    | 24.47     | 0.0029        | 2015 | 8     | 25.20    | 25.56     | 0.0143        |
| 2014 | 9     | 22.52    | 22.14     | 0.0169        | 2015 | 9     | 20.20    | 20.01     | 0.0094        |
| 2014 | 10    | 8.60     | 8.78      | 0.0209        | 2015 | 10    | 9.40     | 8.80      | 0.0638        |
| 2014 | 11    | -0.28    | -0.24     | 0.1429        | 2015 | 11    | -0.20   | -0.21     | 0.0500        |
| 2014 | 12    | -7.70    | -7.64     | 0.0078        | 2015 | 12    | -7.60   | -7.59     | -0.0013       |

Mean: 0.0287, Mean: 0.0318
4.2. Prediction of evaporation change

Relative error of the forecast values of 2014 and 2015 (Table 6) are all within the acceptable range except for the relatively large errors of certain months (up to 0.1562), and the average annual relative errors are 0.0287 and 0.0321 respectively, which meet the prediction accuracy requirements. The average annual relative errors of other years are also less than 0.04. It can be seen from Fig. 6 that the local average monthly evaporation in the past 15 years shows an upward trend in general and the upward trend will continue to exist in the coming 5 years.

Table 6. Calculation and check of evaporation changes in 2014 and 2015.

| Year | Month | Measured | Simulated | Relative error | Year | Month | Measured | Simulated | Relative error |
|------|-------|----------|-----------|---------------|------|-------|----------|-----------|---------------|
| 2014 | 1     | 28.90    | 28.00     | 0.0311        | 2015 | 1     | 30.00    | 27.98     | 0.0673        |
| 2014 | 2     | 56.50    | 51.22     | 0.0935        | 2015 | 2     | 60.00    | 50.63     | 0.1562        |
| 2014 | 3     | 135.50   | 130.13    | 0.0396        | 2015 | 3     | 131.30   | 129.61    | 0.0129        |
| 2014 | 4     | 235.90   | 228.85    | 0.0299        | 2015 | 4     | 229.70   | 227.57    | 0.0093        |
| 2014 | 5     | 306.30   | 302.37    | 0.0128        | 2015 | 5     | 339.90   | 353.33    | 0.0395        |
| 2014 | 6     | 274.30   | 286.77    | 0.0455        | 2015 | 6     | 283.20   | 286.99    | 0.0134        |
| 2014 | 7     | 240.30   | 245.24    | 0.0206        | 2015 | 7     | 252.20   | 257.60    | 0.0214        |
| 2014 | 8     | 256.30   | 252.45    | 0.0150        | 2015 | 8     | 242.90   | 236.57    | 0.0261        |
| 2014 | 9     | 189.30   | 187.34    | 0.0104        | 2015 | 9     | 179.40   | 174.93    | 0.0249        |
| 2014 | 10    | 125.90   | 120.24    | 0.0450        | 2015 | 10    | 120.90   | 119.26    | 0.0136        |
| 2014 | 11    | 61.70    | 61.67     | 0.0005        | 2015 | 11    | 61.70    | 61.67     | 0.0005        |
| 2014 | 12    | 37.70    | 37.71     | 0.0003        | 2015 | 12    | 38.30    | 38.33     | 0.0008        |
| Mean |       | 0.0287   |           |               | Mean |       | 0.0321   |           |               |

Figure 5. Comparison in trends of air temperature
4.3. Prediction of sunshine duration change

Relative error of the forecast values of all months in 2014 and 2015 (Table 7) are all within the acceptable range and the average annual relative errors are 0.0124 and 0.0190 respectively, which meet the prediction accuracy requirements. The average annual relative errors of other years are also less than 0.03. It can be seen from Fig. 7 that the local average monthly sunshine duration in the past 15 years shows an upward trend in general and the upward trend will continue to exist in the coming 5 years.

Table 7. Calculation and check of sunshine duration variation in 2014 and 2015.

| Year | Month | Measured | Simulated | Relative error | Year | Month | Measured | Simulated | Relative error |
|------|-------|----------|-----------|----------------|------|-------|----------|-----------|----------------|
| 2014 | 1     | 237.40   | 236.80    | 0.0025         | 2015 | 1     | 239.20   | 238.57    | 0.0026         |
| 2014 | 2     | 217.40   | 220.10    | 0.0124         | 2015 | 2     | 238.80   | 247.81    | 0.0377         |
| 2014 | 3     | 302.80   | 298.51    | 0.0142         | 2015 | 3     | 280.30   | 269.97    | 0.0369         |
| 2014 | 4     | 297.40   | 293.02    | 0.0147         | 2015 | 4     | 309.80   | 329.48    | 0.0635         |
| 2014 | 5     | 333.90   | 335.86    | 0.0059         | 2015 | 5     | 337.80   | 338.43    | 0.0019         |
| 2014 | 6     | 330.20   | 329.67    | 0.0016         | 2015 | 6     | 325.40   | 322.54    | 0.0088         |
| 2014 | 7     | 323.40   | 314.74    | 0.0268         | 2015 | 7     | 321.30   | 316.58    | 0.0147         |
| 2014 | 8     | 308.80   | 297.43    | 0.0368         | 2015 | 8     | 308.50   | 303.36    | 0.0167         |
| 2014 | 9     | 268.20   | 265.60    | 0.0097         | 2015 | 9     | 247.80   | 251.26    | 0.0140         |
| 2014 | 10    | 252.80   | 246.67    | 0.0242         | 2015 | 10    | 273.10   | 281.68    | 0.0314         |
| 2014 | 11    | 234.50   | 234.47    | 0.0001         | 2015 | 11    | 233.80   | 233.87    | 0.0003         |
| 2014 | 12    | 232.60   | 232.59    | 0.0000         | 2015 | 12    | 235.30   | 235.27    | 0.0001         |

Mean 0.0124 Mean 0.0190

Figure 6. Comparison in trends of air evaporation
4.4. Prediction of groundwater depth

The standardized predicted data of temperature, evaporation and sunshine duration of 2016-2020 are substituted into the multiple regression equation to obtain the fitting value of the groundwater depth in 2016-2020. In the past decade, the average groundwater depth in Dengkou County has been slowly decreasing (Fig. 8), and this trend will continue in the next five years, that is, the average groundwater level is still slowly increasing, but at a much slower rate than that in the past decade. The average groundwater level in Dengkou County has increased by 0.13 m in the past decade, while in the five-year forecast the average groundwater level has increased by only 0.01 m. That is, over the next five years, groundwater consumption will be higher than that in the past without taking into account human factors, close to break-even overall.

5. Conclusion

Results show that the natural influencing factors that exert the maximum impact on groundwater depth change of Dengkou County are evaporation and temperature, followed by sunshine duration. All these
three factors show negative correlation with groundwater depth. Precipitation and relative humidity has little influence to groundwater change. This situation has a lot to do with the natural geographical environment where Dengkou County is located at. In a drought area with arid climate, less precipitation and exuberant evaporation, evaporation is far greater than precipitation; likewise, relative humidity in the semi-arid area is also difficult to affect the change of groundwater. The grey forecast GM (1,1) model is used to predict the trend of the next five years. It is concluded that the average annual temperature in the next five years is generally in the rising period, which is consistent with the overall rising trend of temperature in the past 15 years. Evaporation is still on the rising trend, which is consistent with the rising trend of the past 15 years. The sunshine duration is also on the rise, which is consistent with the overall trend of increasing sunshine duration in the past 15 years. Then the predicted natural factor data are substituted into the multiple regression equation to obtain the groundwater depth by fitting. In the next five years, average groundwater level in Dengkou County is still in a state of slow growth. Comparing the current projections, which consider only the effects of natural factors, with data from the past decade, the growth trend is increasingly flat, indicating that natural factors will have a very limited gain on groundwater in the next five years, and human factors are likely to have a relatively direct impact on groundwater. Generally the average groundwater level in Dengkou County is the highest in May every year, especially in the Yellow River irrigation area. In the whole summer, the average buried depth of groundwater is basically less than 2.5m, with a high water level. In addition, the local evaporation is in the rising period with strong phreatic evaporation. This is quite likely to cause secondary salinization of the land, which deserves more attention. In addition, the change of groundwater depth is the outcome of combined action of human factors and natural factors. Since it is difficult to obtain data relating to human factors, this paper does not take it into research. In terms of natural factors, it is relatively difficult to obtain data of vegetation evaporation and water seepage of the Yellow River etc. There are still some defects in the regression equation of groundwater change only from the aspect of natural factors. We hope this can be further improved in the future research.

Acknowledgement
This study was supported by the National Natural Science Foundation of China (Grant No. 71861147001) and Beijing Social Science Foundation (Grant No. 19GLA005).

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