Assessment of the impact of short-term land use/land cover changes on water resources in the Yanghe reservoir basin, China

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ABSTRACT

Land Use/Land Cover (LULC) is a main factor that affects the hydrological process of catchments. A better understanding of its influence is of great significance to future land use planning and water resources management. Since 2011, the local government has implemented a land remediation plan, and the LULC in the Yanghe Reservoir Basin has undergone major changes. This paper uses The Soil and Water Assessment Tool (SWAT) model to study blue water (BW) and green water (GW) resources in three typical years (a wet year, dry year, and normal year) under two LULC scenarios in the basin in 2010 and 2017. The results show that from 2010 to 2017, the area of cultivated land and residential construction land increased by 227.28% and 269.23%, respectively; the area of unused land, woodland, and grassland decreased by 98.84%, 35.90% and 39.52%, respectively. Compared with the results of the 2010 LULC scenario, the average BW of the three typical years under the 2017 LULC scenario decreased by 11.66%, 52.32%, and 21.95%, respectively, and the average GW flow increased by 6.72%, 2.90%, and 6.83%, respectively, and the average GW reserves decreased by 14.80%, 11.39%, and 7.67%, respectively. Therefore, this study believes that changes of LULC have led to a significant decrease in runoff and an increase in evapotranspiration in the basin.

Key words: blue water, green water, land use/land cover, SWAT, typical years, water resources

HIGHLIGHTS

• A SWAT model was used to study the blue water and green water resources in three typical years under two LULC scenarios in 2010 and 2017 for the Yanghe Reservoir basin.
• The increase in the area of arable land in the Yanghe Reservoir basin has led to an increase in the green water coefficient.

1. INTRODUCTION

Water resources are essential for maintaining ecological balance and the sustainable development of human activities (Liang et al. 2020). In the past few decades, due to the impact of climate change and rapid population growth, water shortage has become more and more serious in many parts of the world and has become a major challenge worldwide. With the development of social economy, human beings need more water (such as for agricultural irrigation, industrial development, power generation, etc.), which leads to the contradiction between water supply and demand (Du et al. 2018). In addition to climate change, Land Use/Land Cover (LULC) change is also one of the important interventions for humans to change the quality and quantity of surface and groundwater. Due to the complex interrelationships among hydrological components such as precipitation, evaporation, transpiration, infiltration, and runoff, the study of hydrological cycles and hydrological responses has become very complicated in the basin. Changes in climate and LULC have adverse effects on the runoff, evapotranspiration, underground runoff, and infiltration of the natural hydrological system (Moriasi et al. 2007). The main factors leading to LULC changes include population change, climate change, national resource protection policies, and socio-economic factors (Elfert & Bormann 2010). The planning and management of LULC are closely related to the sustainability of water resources because changes in LULC are related to hydrological processes and water volume (Schulze 2000). The integrated management of...
land and water resources requires the ability to assess the impact of land use changes on water resources. Therefore, in many cases, the need for basin managers seems to be not only the correct assessment of the scale of change but also the correct assessment of the direction of change (Calder 2003). In the long run, understanding the impact of LULC changes on freshwater resources is of great significance for improving water resources management.

Falkenmark (1995) first proposed the concept of Blue Water (BW) and Green Water (GW) resources, which can help water resources management and evaluation (Yuan et al. 2019). Falkenmark reclassified water resources into two types, GW and BW. The water in aquifers, lakes, wetlands and reservoirs is considered BW resources, and the water in the soil is a GW resource. The liquid BW flows through a river, and the GW in an aquifer flows back to the atmosphere through evaporation. BW and GW can be converted to each other (Johansson et al. 2016). GW flow is composed of two parts: transpiration and evaporation (Falkenmark & Rockström 2006). Water resources managers often use hydrological models to rationally allocate BW and GW resources (Veettil & Mishra 2016). The Soil and Water Assessment Tool (SWAT) can effectively simulate the impact of land use and climate change on hydrological changes (Zhou et al. 2013). For instance, Matjaž et al. (2013) used SWAT to investigate the influence of land use situations in 200 years on the hydrological processes and provision of BW and GW flow and storage in two Slovenian Mediterranean catchments. Du et al. (2018) quantified the relative effects of land use and climate changes on BW and GW dynamics over 80 years (1935–2014).

However, these studies have certain shortcomings. Most studies mainly focus on the long-term comprehensive effects of climate and LULC. But there is no relevant exploration of the impact of relatively drastic changes in LULC caused by short-term human activities on BW and GW resources. Also, the records of meteorological data used are already the result of comprehensive change in climate and LULC in these studies, so the use of observed meteorological data to simulate BW and GW changes may not accurately reflect the actual variation (Zhao et al. 2016). Therefore, the purposes of this study are: (1) to use a land transfer matrix to analyze the results of rapid changes of LULC in the Yanghe Reservoir basin from 2010 to 2017, (2) to use the SWAT model to investigate the different typical years of 2010 and 2017, and BW and GW resources in two periods in 2017, (3) to analyze the difference between BW and GW resources under the two land use scenarios in 2010 and 2017, and provide suggestions for improving future regional land use planning and water resources management.

2. MATERIALS AND METHODS

2.1. Study area

Yanghe Reservoir basin is located in the northern part of Qinhuangdao City, Hebei Province, China. As shown in Figure 1, the total watershed area is 726 km². Here, four rivers were researched across the study area. These are the Dongyang River, Miwu River, Maguying River, and Xiyang River. The Yanghe Reservoir basin has a warm temperate semi-humid continental monsoon climate. The average precipitation for many years is 750 mm. About 80% of the annual precipitation is concentrated in the flood season from June to September. The runoff of the basin is mainly recharged by rainfall. The average annual runoff depth is 224 mm and the annual runoff is 169 million m³. The annual average temperature in the basin is 10.2 °C, the highest monthly average temperature is 24.6 °C, the lowest monthly average temperature is –6.8 °C, and the average annual temperature difference is 31.4 °C. The water surface evaporation is about 1,200 mm per year. The annual average wind speed is 2.7 m/s. From April to early August, the wind is mostly southeast, and after mid-August, the wind is mainly northwest. The Yanghe Reservoir basin is an agricultural area where corn, peanuts and sweet potatoes are mainly grown.

2.2. Data collection

This study collected basin topography elevation data, hydrological data, land use, soil data, and weather data. These data are the fundamental inputs for the SWAT model and served as the driving force for other simulation processes in the model. The digital elevation model (DEM) data, with a spatial resolution of 50 m, was collected from the Geospatial Data Cloud (http://www.gscloud.cn). The hydrological data and social-economic data were obtained from the Water Resources Department and Statistical Yearbook of Local Government, respectively. The land use data were derived from the land cover of 1:50,000 space vector data in Qinhuangdao City, Hebei Province, and the Tsinghua University Finer Resolution Observation and Monitoring Global Land Cover (FROM-GLC) database (http://data.ess.tsinghua.edu.cn) (2010 and 2017). It was classified into five types: grassland, woodland, rural residential area, cultivated land, and water area by the ArcGIS analysis module. The dominant types of land use are farmland, woodland, and grassland, which collectively account for 91% of the study region. The soil data is based on the Harmonized World Soil Database (HWSD) which was constructed by the Food and Agriculture Organization of the United Nations (FAO) and the Vienna International Institute for Applied Systems (IIASA). The data source is a
1:1,000,000 China soil map in the second national land survey provided by the Nanjing Soil Research Institute. The soil classification system used is mainly FAO-90 (FAO 2019) (Figure 2). The weather data included precipitation, air temperature, wind speed relative humidity, and solar radiation. The air temperature, wind speed relative humidity, and solar radiation data came from the China Meteorological Data Service Center (http://data.cma.cn). The rainfall data (1972–2017) was provided by the Yanghe Reservoir Watershed Management Bureau.

Figure 1 | Study area and distribution of weather stations.

Figure 2 | Basic data of study area. (a) Soil classification. (b) Slope classification.
2.3. Method

2.3.1. The SWAT model

SWAT is a distributed, physically-based, watershed-scale model developed by the United States Department of Agriculture (USDA)-Research-Service and Texas A&M University. So far, it has been widely used in many countries (Naramngam & Tong 2013; Sun & Ren 2013). The SWAT model divided the study catchment into many sub-catchments, which were further partitioned into hydrologic response units (HRUs). Every HRU includes a unique combination of land cover, soil and management combinations. The water balance in the model is expressed as follows:

\[ SW_t = SW_o + \sum_{i=1}^{t} (R_{\text{day}} - Q_{\text{surf}} - E_a - W_{\text{seep}} - Q_{\text{gw}}) \]  

where \( SW_t \) is the final soil water content (mm); \( SW_o \) is the previous soil water (mm); \( t \) is the time step (d); \( R_{\text{day}} \), \( Q_{\text{surf}} \) and \( E_a \) are the amount of precipitation, surface runoff, and evaporation on day \( i \) (mm), respectively; \( W_{\text{seep}} \) is the amount of water entering the vadose zone from the soil profile on day \( i \) (mm) and \( Q_{\text{gw}} \) is the amount of the groundwater return flows on day \( i \) (mm).

The DEM was applied to delineate the boundaries, river networks and HRUs in the Yanghe Reservoir basin. In this study, thresholds for defining HRUs in the SWAT model were set at 10% for soil, 20% for land use, and 20% for slope. The overlay of soil and land-use maps generated 27 sub-basins and 504 HRUs.

2.3.2. Calculation of blue water and green water resources

The SWAT model calculates the BW and GW in the basin based on the hydrological cycle principle of the model. The calculation of BW resources is expressed as:

\[ BW = WYLD + DA_{\text{RCHG}} \]  

where \( WYLD \) indicates the amount of water entering the main river from the HRU within the time step (mm); \( DA_{\text{RCHG}} \) indicates the recharge of deep aquifers.

In the SWAT model, \( WYLD \) is defined as water production, which is expressed as:

\[ WYLD = SURQ + LATQ + GW_Q - TLOSS \]  

where \( WYLD \) represents the water production volume (mm); \( SURQ \) represents the surface runoff generated in the HRU within the time step (mm); \( LATQ \) represents the lateral flow entering the main river channel during the time step (mm); \( GW_Q \) represents the groundwater flow into the river (mm); \( TLOSS \) represents the amount of transmission loss (mm).

\( DA_{\text{RCHG}} \) is defined as the recharge of the deep aquifer, and the relationship between it and the recharge of the shallow aquifer (\( SA_{\text{RCHG}} \)) is:

\[ SA_{\text{RCHG}} = GW_{\text{RCHG}} - DA_{\text{RCHG}} \]  

where \( GW_{\text{RCHG}} \) represents the recharge amount of the aquifer within the time step (mm).

In the GW flow calculation model, the GW resource is the sum of actual evapotranspiration (\( ET \)) and soil water content (\( SW \)). Its expression is:

\[ GW = ET + SW \]  

where \( ET \) means GW flow (mm); \( SW \) means GW storage (mm).

In this paper, the GW coefficient (\( GWC \)) is used to evaluate the proportion of river basin GW resources in the total water resources. The GW coefficient is given by the following:

\[ GWC = \frac{GW}{BW + GW} \times 100\% \]
2.3.3. Simulation experiments

In order to explore the impact of short-term LULC changes on water resources in the Yanghe Reservoir basin, three typical year scenarios were set for simulation analysis to study the changes in BW, GW flow and GW storage under different LULC methods from 2010 to 2017. In this study, two indicators, the percentage of precipitation anomaly (Pa) and the Standardized Precipitation Index (SPI) (Seiler et al. 2002) were used to determine the typical years. The percentage Pa reflects the degree of deviation of precipitation in a certain period from the average state of the same period. Different regions and different periods have different average precipitation. Therefore, it is a relative index with temporal and spatial contrast. The SPI has the characteristics of multiple time scale applications, which makes it possible to use the same drought indicator to reflect the water resources status of different time scales and different aspects. The use of two indicators at the same time can avoid errors in the calculation of a single indicator. Based on these two indicators, this study finally selected 2012 as a wet year (1,175 mm), 1992 as a dry year (384 mm), and 1983 as a normal year (632 mm).

3. RESULTS

3.1. Land use and land cover change in the Yanghe Reservoir basin

The SWAT model reclassified cultivated land, woodland, grassland, rural residential land, water area, and unused land. The woodland was divided into virgin forest and artificially planted shrubs. The SWAT land-use codes are AGRL (cultivated land), FRST (forest), RNGB (artificial shrub), PAST (grassland), URLD (residential land), WATR (waters), and BARR (unused land). Figure 3 showed the distribution of land use in the Yanghe Reservoir basin during the three periods of 2010, 2015, and 2017. The dominant land use types were cultivated land, woodland, and grassland, which took up about 80% of the whole area in 2010 (79.15%) and 2017 (94.64%). Two main trends of land use change existed from 2010 to 2017: increase of cultivated land and the decrease of unused land, woodland, and grassland.

In the matrix (Table 1), rows A1–An represent the land use type at time T1, while columns A1–An represent land use at time T2. Diagonal Pii is the area of the land use type that has not changed during the period. Pij (Pji) is the area where Ai (Aj) converted to Aj (Ai). Rows P1–Pn represent the total area of corresponding types at time T1, while columns P1–Pn represent the area at time T2.

According to the land improvement policy of Qinhuangdao City, the wasteland that has not been cultivated for many years is to be restored to maximize the productivity of cultivated land, increasing the utilization rate of land, and increasing land income. From 2010 to 2017, using figures from Table 2 it can be calculated that 88.39% of unused land was converted to farmland, and can be used for rehabilitation, which is mainly due to a significant increase in the cultivated area. Similarly, 58.86% of grassland and 32.13% of woodland were converted to cultivated land. Compared to 2010, cultivated land and rural residential construction land increased by 280.78 km² and 15.4 km², while unused land, woodland, and grassland decreased by 123.75 km², 110.82 km², and 56.49 km² in 2017, respectively. The water area in the study area remains basically unchanged.
3.2. Calibration and validation of the SWAT model

This study used the SUFI-2 algorithm of SWAT-CUP software. The SUFI-2 algorithm is expected to seek to include most of the measured data with the smallest possible uncertainty band. After 1,000 iterations, the parameters of the model were determined. The main parameters of the SWAT model runoff and their physical meanings are shown in Table 2. The sensitivity analysis of SWAT-CUP parameters adopts the Latin hypercube sampling method. The sensitivity of the parameters depends on the following multiple regression system calculations:

\[ g = \alpha + \sum_{i=1}^{m} \beta_i b_i \]  

(7)

where \( g \) is the predicted value; \( \alpha \) is the uncertainty random residual; \( m \) is the number of iterations; \( \beta_i \) is the regression coefficient; \( b_i \) is the parameter variable. The t-stat value gives the degree of sensitivity, the larger the absolute value, the more sensitive it is; the P-value determines the significance of the sensitivity, the closer the value is to 0, the more significant it is.

In this study, Nash-Sutcliffe efficiency coefficient (NSE the) and determination coefficient (\( R^2 \)) were selected to evaluate the fit of the model simulation.

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>t-stat</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>R__CN2.mgt</td>
<td>Runoff curve coefficient</td>
<td>5.295</td>
<td>0.009</td>
</tr>
<tr>
<td>V__ALPHA_BF.gw</td>
<td>Base flow division factor</td>
<td>2.052</td>
<td>0.048</td>
</tr>
<tr>
<td>V__GW_REVAP.gw</td>
<td>Groundwater evaporation coefficient</td>
<td>-1.791</td>
<td>0.082</td>
</tr>
<tr>
<td>V__SLSUBBSN.hru</td>
<td>Average slope length</td>
<td>-1.643</td>
<td>0.109</td>
</tr>
<tr>
<td>V__RCHRG_DP.gw</td>
<td>Permeability ratio of deep aquifer</td>
<td>1.625</td>
<td>0.113</td>
</tr>
<tr>
<td>V__BIOMIX.mgt</td>
<td>Biological mixing efficiency</td>
<td>-1.309</td>
<td>0.199</td>
</tr>
<tr>
<td>V__CANMX.hru</td>
<td>Canopy maximum water holding capacity</td>
<td>-1.081</td>
<td>0.287</td>
</tr>
<tr>
<td>V__CH_K2.rte</td>
<td>Hydraulic conductivity of main river</td>
<td>-0.767</td>
<td>0.448</td>
</tr>
<tr>
<td>R__SOL_Z.sol</td>
<td>Soil layer thickness</td>
<td>-0.464</td>
<td>0.646</td>
</tr>
<tr>
<td>V__ESCO.bsn</td>
<td>Soil evaporation compensation coefficient</td>
<td>0.443</td>
<td>0.661</td>
</tr>
<tr>
<td>V__CH_N2.rte</td>
<td>River Manning coefficient</td>
<td>-0.267</td>
<td>0.791</td>
</tr>
<tr>
<td>V__EPCO.bsn</td>
<td>Vegetation water absorption compensation coefficient</td>
<td>0.152</td>
<td>0.880</td>
</tr>
<tr>
<td>R__SOL_K.sol</td>
<td>Soil saturated hydraulic conductivity</td>
<td>0.094</td>
<td>0.926</td>
</tr>
</tbody>
</table>

Note: the t-stat value gives the degree of sensitivity, the larger the absolute value, the more sensitive it is; the P-value determines the significance of the sensitivity, the closer the value is to 0, the more significant it is.
The calculation formula of the Nash-Sutcliffe efficiency coefficient is as follows:

\[
NSE = 1 - \frac{\sum_{i=1}^{n} (Q_{mi} - Q_{si})^2}{\sum_{i=1}^{n} (Q_{mi} - \overline{Q}_m)^2}
\]  

(8)

\[R^2 = \frac{\left(\sum_{i=1}^{n} (Q_{si} - \overline{Q}_s)(Q_{mi} - \overline{Q}_m)\right)^2}{\sum_{i=1}^{n} (Q_{si} - \overline{Q}_s)^2 \sum_{i=1}^{n} (Q_{mi} - \overline{Q}_m)^2}
\]  

(9)

where \(Q_m\) is the measured value; \(\overline{Q}_m\) is the mean of the measured data; \(Q_s\) is the model simulation data; \(\overline{Q}_s\) is the mean of the model simulation data. The closer the \(NSE\) value is to 1, the better applicability the model has. The closer \(R^2\) is to 1, the better the consistency of the simulation (Moriasi et al. 2007). The simulated and observed streamflow for the calibration period (January 2008–December 2013) and the validation period (January 2014–December 2017) are compared in Figure 4.

![Figure 4](http://iwaponline.com/ws/article-pdf/22/1/833/990995/ws022010833.pdf)

**Figure 4** | Observed and simulated monthly streamflow for (a) calibration and (b) validation periods.
Figure 5 | Distribution of BW resources in Yanghe Reservoir basin.
The $R^2$ of flow were all greater than 0.9 and the NSE values were all greater than 0.7 during the calibration and validation periods in Figure 4. The calibration and validation results could be accepted with $R^2$ values and NSE values of flow larger than 0.6. The SWAT model had satisfactory applicability in the Yanghe Reservoir basin.

### 3.3. Impact of LULC changes on water resources changes in Yanghe Reservoir basin

#### 3.3.1. Impacts of LULC changes on blue water

Figure 5 and Table 3 are the results of the BW simulation. It can be seen from Figure 5 that the BW volume is the largest in the surrounding area of the reservoir (sub-basin No. 25), and it is decreasing from the reservoir to the upstream. From the perspective of LULC, the amount of BW in the water area is the largest, followed by the amount of BW in grassland, then in farmland and forest. Under the same rainfall weather conditions in the typical year selected, the effects of two LULC patterns in 2010 and 2017 on the average BW volume of the basin were compared. The analysis showed that under the 2017 LULC scenario, the average BW volume of the wet year, dry year, and normal year decreased by 44.70 mm, 15.10 mm, 24.18 mm, and the average BW reduction rates were 11.66%, 52.32%, and 21.95%, respectively. Therefore, the LULC type in 2017 is more unfavorable for BW production in the basin, and LULC changes have a more significant impact on BW in the dry year. Under the same LULC scenario, this study compared the dry year BW with the wet year and normal year BW. Under the 2010 LULC scenario, BW in the dry year was reduced by 354.56 mm and 81.30 mm, respectively, compared with the wet year and normal year, with a reduced rate of 92.47% and 73.80%, respectively. Under the 2017 LULC scenario, the BW in the dry year was reduced by 324.95 mm and 72.21 mm, respectively, compared with the wet year and normal year, with a reduced rate of 95.94% and 83.99%, respectively. It can be concluded that the amount of BW in the basin under the LULC type scenario in 2017 is affected by the typical annual rainfall and the reduction is greater.

#### 3.3.2. Impacts of LULC change on green water flow

In different typical years, the 2010 and 2017 LULC layers were loaded respectively, and the distribution of GW flow in the basin was simulated by SWAT. The results are shown in Figure 6 and Table 4. From the perspective of LULC, the GW flow in the forest and grassland coverage area is greater than that of the cultivated land. There are some differences in the distribution of GW flow in the three typical years. For the wet year, under the 2010 LULC scenario, the sub-basins 1, 2, 3, 4, 6, 11, 12, and 13 have the larger GW flow, because the main land types in these sub-basins are grassland and forest, and plant evapotranspiration is relatively strong. Under the 2017 LULC scenario, the larger value of GW flow is only distributed in sub-basins 11, 12, and 13. For the dry year, the distribution of GW flow is relatively consistent under the two LULC scenarios, and the sub-basins with larger GW flow are mainly concentrated in grassland and forest coverage areas. In the normal year, compared with the GW flow under the LULC scenario in 2010, the GW flow in the western part of the basin increased under the LULC scenario in 2017. Based on the same typical annual rainfall conditions, this study compared the effects of two LULC patterns on the average GW flow in the basin in 2010 and 2017. The study found that under the 2017 LULC scenario, the average GW flow in a wet year, dry year, and normal year increased by 35.58 mm, 11.99 mm, and 31.53 mm, respectively, and the average GW flow growth rates were 6.72%, 2.90%, and 6.83%, respectively. It can be concluded that GW flow has increased, but the increase was limited. Under the same LULC scenario, the average GW flow in dry years is compared with the average GW flow in wet and normal years to analyze the significance of its changes. The analysis showed that under the LULC scenario in 2010, the average GW flow in a dry year was reduced by 116.08 mm and 48.08 mm, compared with the wet year and normal year, with reduced rates of 21.92% and 10.41%, respectively; Under the LULC scenario in 2017, the average dry year GW flow was reduced by 139.66 mm and 67.61 mm, and the reduction rates were 24.70% and 13.71%, respectively. This situation revealed that under the 2017 LULC scenario, the GW flow change was more prominent, and the GW flow increased in the basin. It meant that evapotranspiration was major under the 2017 LULC scenario.

<table>
<thead>
<tr>
<th>Typical year</th>
<th>2010 LULC</th>
<th>2017 LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet year</td>
<td>383.43</td>
<td>338.71</td>
</tr>
<tr>
<td>Dry year</td>
<td>28.86</td>
<td>13.76</td>
</tr>
<tr>
<td>Normal year</td>
<td>110.16</td>
<td>85.97</td>
</tr>
</tbody>
</table>

Table 3 | Average amount of BW in different situations unit: (mm)
Figure 6 | Distribution of GW flow in Yanghe Reservoir basin.
3.3.3. Impacts of LULC change on green water storage

Figure 7 and Table 5 show the results of GW storage by loading the two types of LULC in 2010 and 2017 in the SWAT model under three typical annual rainfall weather conditions. Under the same typical annual rainfall and meteorological conditions, the sub-basins with the largest GW reserves simulated under the two LULC scenarios in 2010 and 2017 are mainly concentrated in the area around the reservoir, decreasing upstream along the reservoir. This study compared the simulation results of GW storage under LULC scenarios in 2010 and 2017, respectively. The analysis indicated that the average GW storage in the wet year, dry year, and normal year decreased by 12.71 mm, 7.04 mm, and 4.94 mm, and the average GW storage reduction rates were 14.80%, 11.39%, and 7.67% respectively, under the 2017 LULC scenario. Under the same LULC scenarios, the GW storage in the dry year was compared with the wet year and normal year. Under the 2010 LULC scenario, the average GW reserves in the dry year were reduced by 24.31 mm and 2.63 mm, compared with the wet year and normal year, and the reduction rates were 28.24% and 4.08%, respectively. Under the 2017 LULC scenario, the average GW storage in the dry year was reduced by 18.61 mm and 4.73 mm, compared with the wet year and normal year, and reduced rates were 95.94% and 83.99%, respectively. In general, under the same typical year's climatic conditions, this study compared the GW storage of the basin under the two LULC scenarios in 2010 and 2017, and the latter was smaller. Comparing the change in the GW storage under different typical year climatic conditions, the change of GW storage under the LULC scenario in 2017 was more significant.

3.3.4. Green water coefficient

Figure 8 depicts the distribution of the GW coefficient of each sub-basin calculated according to Equation (6). It can be seen from the figure that the GW coefficient of the No. 25 sub-basin is the smallest, and the GW coefficient in the eastern and western parts of the basin is greater than that in the middle of the basin. The eastern part of the basin is mainly covered by forest and grassland, and the western part of the basin is mainly arable land. Table 6 shows the average GW coefficient of the basin. It can be seen that in the wet year, dry year, and normal year, the average GW coefficient under the 2017 LULC scenario is higher than that under the 2010 LULC scenario. For the same LULC types, the GW coefficient of the whole basin is also significantly different in different typical years. The GW coefficient of a typical dry year is significantly greater than that of a typical wet year, indicating that the proportion of dry year evapotranspiration to water resources is higher than that of the wet year. In general, compared with the LULC types in 2010, the GW coefficient of the LULC types in 2017 was higher, and the watershed evapotranspiration consumed more water resources.

4. DISCUSSION

This paper selected two time periods of LULC types in 2010 and 2017, and analyzed the change characteristics of LULC types in the two periods. A SWAT model was used to simulate the BW and GW resources of the basin under different scenarios. Here, the change rates of the BW and GW resources were used to reflect the impact of short-term LULC changes on the water resources of the basin. According to Table 2, the quantitative changes in LULC from 2010 to 2017 were: cultivated land and residential building land increased by 280.78 km² and 15.4 km² (increased by 227.28% and 269.23%), and unused land, woodland and grassland decreased by 123.75 km², 110.82 km², and 56.49 km² (reduction of 98.84%, 35.90% and 39.52%), respectively. From the perspective of land transfer, the conversion area of unused land to cultivated land is the largest, the conversion areas of unused land accounting for 39.56% of the total cultivated land conversion areas, followed by forest land, which accounts for 35.45%. The main reason for the existence of a large amount of unused land is that a large number of laborers in rural areas have moved to cities, and the shortage of rural labor forces has made a large amount of cultivated land idle all the year round (Yan & Klein 2010), which also contributed to the decrease of cultivated land. In recent years, the government has made great efforts curbing the reduction of cultivated land loss through initiating a set
Figure 7 | Distribution of GW storage in Yanghe Reservoir basin.
of farmland protection policies. Recultivation of land that has been idle for many years is the main measure to restore cultivated land and reduce the loss of cultivated land.

It can be seen from the simulation results of BW variation in the wet year, dry year and normal year that the impact of LULC change on runoff is not a simple linear relationship. With the gradual increase of arable land, the planting area of crops also increased substantially. The main crop in the Yanghe Reservoir basin is maize, and studies have shown that crops can intercept rainfall during the growth period (Nazari et al. 2019), and the stubble left after harvesting of crops such as maize will also affect the evaporation of soil water and reduce surface water runoff. Even a small amount of surface stubble can effectively reduce runoff (Scopel et al. 2004). It can be seen that, without considering other influencing factors, the increase in crop area planted affects soil infiltration and land water conservation capacity. The more rainfall intercepts and penetrates into the soil, the more soil water is consumed by plants, which is relatively unfavorable for the horizontal and vertical movement of water flow. Then, the less surface and underground runoff that can be generated, the more likely precipitation is to be converted into GW resources, and BW resources are reduced accordingly (Hunikj et al. 2012). The change trend of the influence of LULC changes on BW is consistent with the research results of Awotwi et al. (2015). The reduction of BW resources means that the amount of water in rivers and reservoirs is reduced. The Yanghe Reservoir is an important water supply reservoir for downstream cities and towns, and a small amount of water in the reservoir will cause water shortages.

Although the area of forest and grassland in the basin has decreased, which has reduced the intercepted evaporation, the large area of cultivated land and crops has increased at the same time, which has strengthened evaporation and transpiration (Zhao et al. 2016). From the simulation results of three typical years, the interception and transpiration of crops are more obvious, so the GW flow has increased relatively, but the relative growth rate lies within a narrow range. GW storage decreased during the LULC change from 2010 to 2017, mainly due to the expansion of arable land and the increase in soil water consumption by vegetation. From the simulation results, it can be concluded that the impact of land cover changes on BW is greater than that on GW. This conclusion is consistent with the research results of Li et al. (2012). Actually, this work cannot completely explain the transformation processes between BW and GW by using the SWAT model because the hydrological processes are very complex, and the model only represents one-direction transformation processes with no feedback to the atmosphere. There are some shortcomings in the research of this paper. First, this paper studies the comparison of the impact of LULC change on BW and GW resources, rather than the actual degree of impact. Secondly, for the BW and GW resources in the study basin, the use of watershed evapotranspiration data and soil moisture data may be more credible than a SWAT model calibrated by river flow data (Faramarzi et al. 2009). However, this work lacks watershed evapotranspiration and soil moisture data. Finally, the paper only uses two LULC maps, and there is no instantaneous change map of LULC. More maps will be added in future research.

5. CONCLUSIONS

This paper analyzed the short-term LULC changes in the Yanghe Reservoir basin and evaluated the impact of short-term LULC changes on the BW and GW volume of the basin through a SWAT model. (1) From 2010 to 2017, the changes in cultivated land, forest, grassland, wasteland, urban residential construction land, and waters in the Yanghe Reservoir basin was complicated. Cultivated land increased from 16.92% in 2010 to 55.47% in 2017, wasteland decreased from 17.52% to 0.2%, forest decreased from 42.53% to 27.26%, and grassland decreased from 19.69% to 11.19%. Urban residential construction land increased from 0.78% to 2.91%, and the water area remained unchanged. (2) This paper has compared the simulation results of BW and GW resources under two different LULC scenarios in three typical years: a wet year, dry year, and normal year. It can be concluded that the amount of BW in the basin under the LULC type scenario in 2017 was significantly

<table>
<thead>
<tr>
<th>Typical year</th>
<th>2010 LULC</th>
<th>2017 LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet year</td>
<td>86.09</td>
<td>73.35</td>
</tr>
<tr>
<td>Dry year</td>
<td>61.78</td>
<td>54.75</td>
</tr>
<tr>
<td>Normal year</td>
<td>64.42</td>
<td>59.47</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Average amount of GW storage in different situations unit: (mm)</th>
<th>2010 LULC</th>
<th>2017 LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet year</td>
<td>86.09</td>
<td>73.35</td>
</tr>
<tr>
<td>Dry year</td>
<td>61.78</td>
<td>54.75</td>
</tr>
<tr>
<td>Normal year</td>
<td>64.42</td>
<td>59.47</td>
</tr>
</tbody>
</table>
Figure 8 | GW coefficient distribution.
reduced, that is, land cover change has a more significant impact on runoff. The GW flow has increased, the GW storage has decreased, and the GW coefficient has increased, meaning that the proportion of total water resources consumed by evapotranspiration in the basin has increased. It symbolizes that the LULC change from 2010 to 2017 had an important impact on the water resources of the Yanghe Reservoir. This research will provide a scientific reference for the rational planning of LULC and the rational allocation of water resources in the Yanghe Reservoir basin. (3) The novelty of this paper is that it establishes typical years to evaluate the impact of LULC changes on water resources, which can reduce the impact of comprehensive changes in climate and LULC on the results. The method in this paper can be used for reference when carrying out water resources evaluation in a basin with less measured data. However, this method can only be used for qualitative research. Quantitative research still requires a long sequence of measured data and as many LULC change maps as possible.

**AUTHORS’ CONTRIBUTIONS**

Daming Li: Writing – review, Conceptualization, Methodology. Shilong Bu: Writing – original draft, Data collection Software. Shuo Chen: Writing – review and editing, Software. Qicheng Li: Data analysis. Yanqing Li: Data curation and support. All authors contributed to the manuscript.

**CONFLICT OF INTEREST**

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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**DATA AVAILABILITY STATEMENT**

All relevant data are included in the paper or its Supplementary Information.

**REFERENCES**


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**Table 6** | Average of GW coefficient in different situations

<table>
<thead>
<tr>
<th>Typical year</th>
<th>2010 LULC</th>
<th>2017 LULC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wet year</td>
<td>62.41%</td>
<td>66.04%</td>
</tr>
<tr>
<td>Dry year</td>
<td>94.23%</td>
<td>97.39%</td>
</tr>
<tr>
<td>Normal year</td>
<td>83.46%</td>
<td>87.34%</td>
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</tbody>
</table>


