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Does Crop Rotation Enhance Groundwater Health? A Review of the Winter Wheat Fallow Policy in the North China Plain

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Abstract: Agricultural water management is a vital component of realizing the United Nation's Sustainable Development Goals because of water shortages worldwide leading to a severe threat to ecological environments and global food security. As an agro-intensified irrigation area, the North China Plain (NCP) is the most important grain basket in China, which produces 30%–40% of the maize and 60%–80% of the wheat for China. However, this area has already been one of the largest groundwater funnels in the world due to long-term over-exploitation of groundwater. Due to the low precipitation during the growing period, winter wheat requires a large amount of groundwater to be pumped for irrigation, which consumes 70% of the groundwater irrigation. To alleviate the overexploitation of groundwater, the Chinese government implemented the Winter Wheat Fallow Policy (WWFP) in 2014. The evaluation and summarization of the WWFP will be beneficial for improving the groundwater overexploitation areas under high-intensity irrigation over all the world. So far, there have been few attempts at estimating the effectiveness of this policy. To fill this gap, we assessed the planting area of field crops and calculated the evapotranspiration of crops based on remote-sensed and meteorological data in the key area—Hengshui. We compared the agricultural water consumption before and after the implementation of this policy, and we analyzed the relationship between changes in crop planting structure and groundwater variations based on geographically weighted regression. Our results showed the overall classification accuracies for 2013 and 2015 were 85.56% and 82.22%, respectively. The planting area of winter wheat, as the most reduced crop, decreased from 35.71% (314,053 ha) in 2013 to 32.98% (289,986 ha) in 2015. The actual reduction in area of winter wheat reached 84% of the target (26 thousand ha) of the WWFP. The water consumption of major crops decreased from 2.98 billion m^3 of water in 2013 to 2.83 billion m^3 in 2015, a total reduction of 146 million m^3, and 88.43% of reduced target of the WWFP (166 million m^3). The planting changes of winter wheat did not directly affect the change of shallow groundwater level, but ET was positively related to shallow groundwater level and precipitation was negatively related to shallow groundwater levels. This study can provide a basis for the WWFP's improvement and the development of sustainable agriculture in high-intensity irrigation areas.

Keywords: Hengshui; winter wheat; evapotranspiration; Winter Wheat Fallow Policy; geographically weighted regression

1. Introduction

Water management is a vital component of realizing the United Nation's Sustainable Development Goals (SDGs). Several SDGs (e.g., no poverty, no hunger, food security, clean water and sanitation, and life below water and on land) will not be achieved unless water resources are smartly managed, given the current status of the worldwide water shortage [1,2]. The North China Plain (NCP) is the most important granary of China, which produces 30%–40% of the maize and 60%–80% of the wheat in China's annual production of those two crops [3,4]. However, the NCP is one of the world's largest underground water funnel areas, where the groundwater has been being depleted at a mean rate of 0.46 ± 0.37 m/year for the shallow aquifer and 1.14 ± 0.58 m/year for the deep aquifer since 1980 [5]. The rapid decline in groundwater level has caused land subsidence at the rate of 2 mm/year. This has been seriously threatening sustainable ecosystem services' provision in terms of fresh water and secure food [6,7].

In the NCP, agriculture generally accounts for approximately 70% of all water consumption, compared with 20% for industry and 10% for domestic use. Many studies show that large amount of agricultural water in this area was pumped from the groundwater [8–11]. The long-term groundwater over-pumping caused rapid and continuous drops in groundwater levels, and as a result, water shortage has been a central issue on the agricultural development in the NCP [12,13]. Traditional farming systems in the NCP have summer maize and winter wheat rotation so that lands can yield the maximum amount of crops within a year. However, this intensive use of land has severe impacts on groundwater due to the unequal and seasonal rainfalls. With a summer monsoon climate, most rainfall in the NCP is concentrated between June and September. The seasonal rainfall is the primary source of water in crop growth. When there is not sufficient rainfall, irrigation is widely applied to maintain crop growth and high yields. For example, the winter wheat relies heavily on irrigations—using 70% of total irrigation water [9,14]. Continuous extraction of groundwater to irrigate winter wheat is one of the main reasons for the decline in groundwater level. Therefore, it is an urgent requirement to reduce groundwater exploitation by controlling winter wheat planting.

In order to alleviate the overexploitation of the groundwater, the Chinese government implemented a Winter Wheat Fallow Policy (WWFP) in 2014. The WWFP aims to improve the imbalance of groundwater use by making appropriate reductions to the amount of farmland devoted to winter wheat, involving about 50 thousand hectares (ha) of farmland that covers the largest underground funnel area in the NCP. Although this policy has been implemented for five years, there have been few attempts at estimating the effectiveness of this policy [15–17]. Specifically, the change in winter wheat planting area and the impact on groundwater resources have yet to be evaluated prior to and after WWFP's implementation. As an agro-intensified irrigation area, the NCP represents a large number of irrigated agricultural regions in the world. High-intensity irrigated agriculture often causes serious over-exploitation of groundwater, and an evaluation and summarization of the WWFP will be a good example of improving a groundwater over-exploitation area under high-intensity irrigation. In this study, we assessed the planting area of field crops and calculated the evapotranspiration of crops based on remote sensed and meteorological data. We compared the agricultural water consumption of this policy, and analyzed the relationship between changes in crop planting structure and groundwater level. The results provide valuable information for water management and the development of sustainable agriculture in high-intensity irrigation areas.

2. Study Area

Hengshui, a prefecture-level city in Hebei Province, is located in the southeastern part of the NCP, between 115°10′–116°34′ E and 37°03′–38°23′ N (Figure 1). Hengshui is located in the alluvial plain of Hebei Province. The terrain is gently inclined from southwest to northeast, with an altitude of 12 to 30 m. It belongs to the continental monsoon climate zone and is warm and semi-arid; the highest temperature reaches 42.7 °C, and the lowest temperature is −23 °C. In the study area, the average annual precipitation is 438.7 mm, with 70%–80% in July, August and September. The average annual evaporation is >2000 mm. The local agriculture focuses on a yearly wheat–maize double cropping system. Due to the continuous over-exploitation of groundwater for agricultural irrigation and industrial water for many years, Hengshui has become a deep groundwater funnel.

Since 1980, the deep groundwater levels there have dropped at an annual rate of 2 m [5]. In order to alleviate the continuous decline of groundwater levels in the NCP, the government implemented the WWFP pilot policy in 2014 to reduce over-exploitation of groundwater and restore groundwater by reducing winter wheat planting. In 2015, it is necessary to decrease 46 thousand ha of winter wheat in the NCP. Hengshui needed to adjust 26 thousand ha of winter wheat, accounting for 56% of the WWFP in the NCP. Therefore, Hengshui is a vital research area for winter wheat fallow.

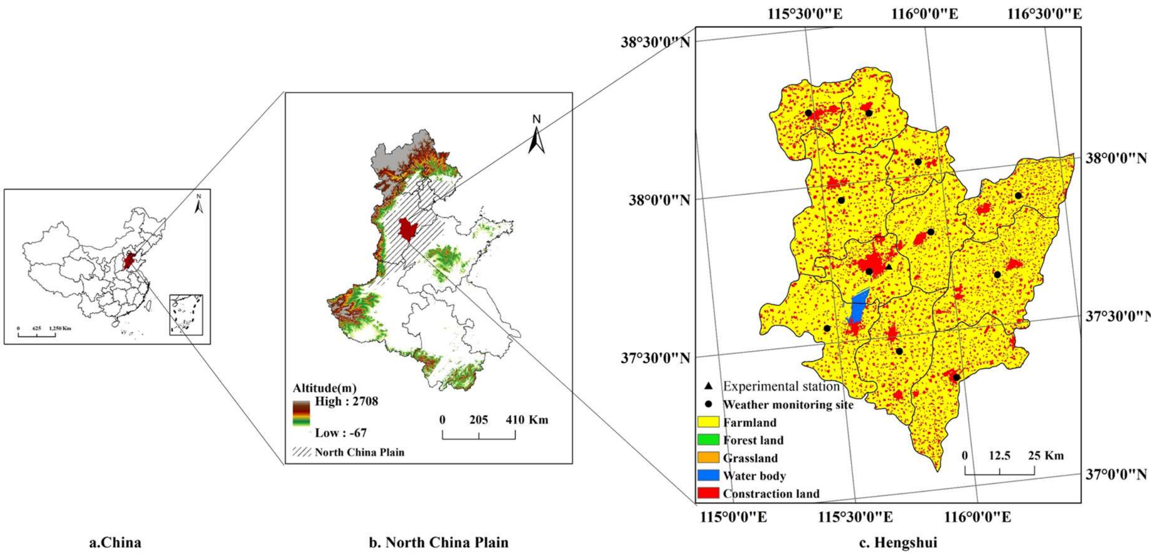

Figure 1. (**a**) Map of China (**b**) Topographic map of North China Plain (**c**) Land use of Hengshui in 2015.

3. Materials and Methods

3.1. Data

We collected remote sending data, meteorological data, experimental station data and groundwater monitoring data for 2013 and 2015, because the WWFP pilot policy began in 2015. The facility project was completed the end of 2014, and the actual policy took place in 2015, so we choose the data before (2013) and after (2015) the implementation. (1) For remote sensing data, we used Landsat 8 (LC_8) from the United States Geological Survey for the years 2013 and 2015. Based on the phenology of the crops of interest (i.e., winter wheat, spring maize and cotton) in the study area, we chose early-May images for both years. 12 May 2013 and 12 May 2015 data were available and considered good matches, and were, thus, used in this study. (2) The meteorological data for 2013 and 2015 were obtained from the China Meteorological Data Sharing Service System (http://data.cma.cn) for 11 weather stations located within Hengshui (Figure 1). The meteorological data were mainly used to calculate crop evapotranspiration (ET). (3) The field observation data came from the Institute of Agricultural Sciences in Hengshui (http://www.hbhzs.com/), for verifying ET calculations. (4) We collected the groundwater monitoring data for the study area from the Geo-Cloud of China Geological Survey (http://www.groundwater.cn/).

3.2. Land-Cover Classification

Based on Google Earth (Google Earth Pro V7.3) and our research interest—policy impacts on agricultural land cover change—we classified the land cover into five categories: winter wheat and summer maize (WW_SM), cotton (CT), spring maize (SM), other crops (OC) and non-cultivated land (NOL). Here WW_SM represents farmed areas in early May and September with green surface cover. OC includes soybeans, peanuts and greenhouses. NCL includes water and construction land. Water represents water bodies such as lake, river and pond, and construction land refers to all residential and industrial areas and roads. Other insignificant amounts of land or unclassified land (such as fruit trees or small gardens) were included in the category of others (OT), and were not involved in the calculations or analyses of this study.

To differentiate spring maize (SC) and cotton (CT), we relied on both Google Earth and Environment for Visualizing Images 5.3 (ENVI 64-bit) to inspect the different Normalized Difference Vegetation Index (NDVI) and spectral reflectance values of these two crops. In May, the NDVIs for spring maize and cotton were slightly different, as with the threshold of 0.3, the spring maize NDVI was above 0.3, while the cotton's was just below 0.3 [18].

To create a training data set, each of the land cover classes were assigned with at least 10 polygons. Each of the polygons had more than seven pixels so that multiple spectral bands could be used to perform the classification. The training data were developed in Google Earth because they were only accessible 'ground truth' data obtained from both 2013 and 2015. Some adjustments were made in ENVI 5.3 based on the satellite images with apparent mismatches. A supervised classification (maximum likelihood classification, MLC) was used to classify the two-year multispectral images, respectively. The probability threshold was set at 0.2 so that pixels with a probability of less than 20% for being in any of the classes would not be classified. The data scale factor was set at 16,000 for both classifications.

Because we were only interested in the policy's impacts on farmers' farming choices and the interchange among wheat, spring maize and cotton, we stratified 90 random samples of those three classes with at least 25 sample plots per class. There could have been bias of sample selection based on the mapper's subjectivity and image availability [19]. The accuracy of ENVI classification against sample data points from Google Earth was represented in a confusion matrix. The overall classification accuracy and kappa coefficient were used to estimate the overall classification results. User's (commission error) and producer's (omission error) accuracies were shown to represent each land-cover classification outcome [19]. A post-classification comparison approach was used to analyze the land-cover changes between 2013 and 2015. A land-cover change map was produced (Figure 2), and detailed information is summarized in Table 1.

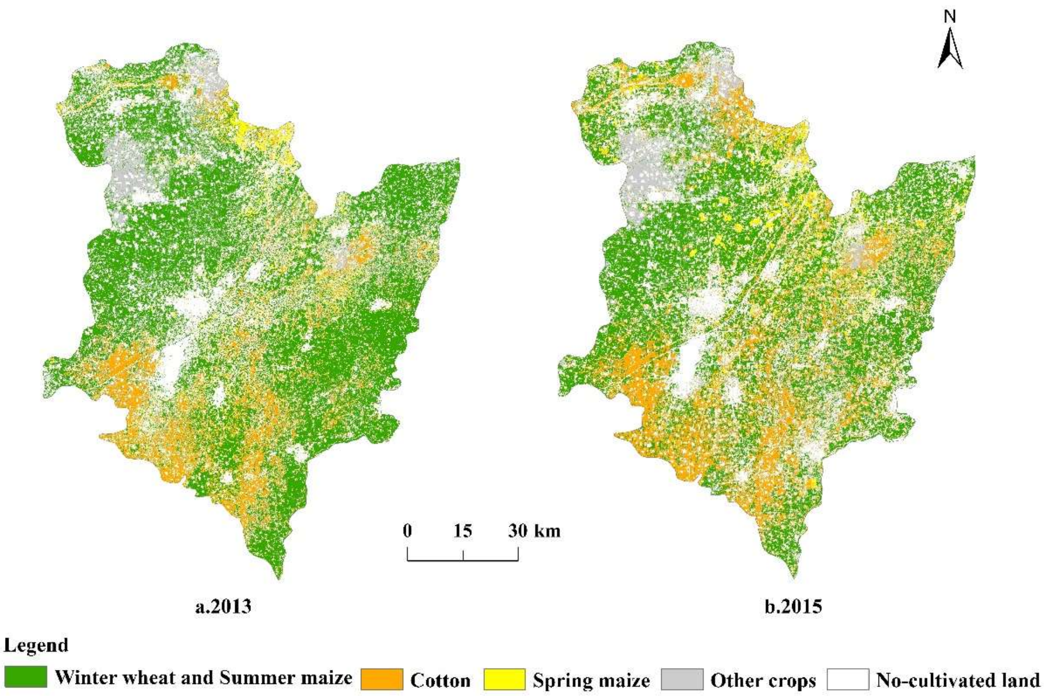

Figure 2. Land-cover in 2013 (**a**) and land cover in 2015 (**b**).

Table 1. The crop coefficient (K_c) values of different crops.

Kc/Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Winter wheat	0.43	0.38	0.57	1.23	1.42	0.72				0.6	0.82	0.86
Summer maize						0.65	0.84	0.94	1.34			
Spring maize					0.45	0.70	1.40	1.15	0.65	0.35		
cotton				0.38	0.38	0.53	1.00	1.07	1.28	0.78		

3.3. Evapotranspiration Calculation

The crop evapotranspiration (ET_0) was calculated with the Food and Agriculture Organization (FAO) version of the Penman–Monteith equation, which uses standard values for a hypothetical reference surface with an assumed height of 0.12 m, a fixed surface resistance of 70 s/m and an albedo of 0.23 [20]. The only factors considered to be affecting ET_0 are climatic parameters. Consequently, ET_0 is a climate-based parameter and can be computed with climatic data. The Penman–Monteith equation is described below:

$$ET_0 = \frac{0.408\Delta(R_n - G) + \gamma\frac{900}{T+273}u_2(e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)}$$

where ET_0 reference evapotranspiration (ET) (mm/day); R_n is net radiation at the crop surface (MJ/m^2/day); G is soil heat flux density (MJ/m^2/day); T is the mean of daily air temperature at 2 m height (°C); u_2 is wind speed at 2 m height (m/s); e_s is the saturation vapor pressure (kPa); e_a is the actual vapor pressure (kPa); $e_s - e_a$ is the saturation vapor pressure deficit; Δ is slope vapor pressure curve (kPa/°C); and γ is psychometric constant (kPa/°C).

Crop ET is affected by soil water and salinity stress, crop density, pests and diseases, weed infestation or low fertility. Therefore the actual crop evapotranspiration (ET_c) is adjusted with reference crop evapotranspiration ET_0, using a crop coefficient approach. The effects of the various weather conditions are incorporated into ET_0 and the crop characteristics into the K_c coefficient as:

$$ET_c = K_c ET_0$$

where ET_c is the actual crop ET; ET_0 is the reference crop ET; and K_c is the crop coefficient. These are important calculation procedures of the actual crop ET. The actual crop ET_c varies during the different growth stages and lengths of crop, by selecting the corresponding K_c coefficient. The crop coefficients K_c of winter wheat, summer maize and cotton were obtained from the study of Liu et al. [21] from the Luancheng Station site in 1995–2000 and the crop coefficient K_c of spring maize was accessed using the result of Gao et al. [22] from the Xinxiang station site in 2003–2005 (Table 1).

3.4. Geographically Weighted Regression

In order to understand whether the implementation of the WWFP alleviated the downward trend of the groundwater level, the study attempted to construct a virtual variable of land use change; analyzed the relationship between winter wheat area changes and groundwater level changes before and after the policy; and considered the impact of ET and precipitation on groundwater level changes. Due to the slow recharge of deep groundwater aquifers (i.e., confined aquifer) in a short period of time [23], the change of shallow groundwater level was the main research object. In order to analyze the spatial relationship between variables, in view of the heterogeneity of the variable space, we used the following calculation method. Geographically weighted regression (GWR), an extension of ordinary least squares regression (OLS), analyses the local relationships between the independent and dependent variables [24]. GWR also takes non-stationary variables into consideration (e.g., climate; environmental factors) and allows for the interpolation of values that are not included in the data set [25]. GWR has many utilities in environmental science, particularly for land cover change research and the evaluation of environmental policies [26]. A GWR model can be defined as:

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i$$

where y_i is the estimated value of the dependent variable for observation i, (u_i, v_i) denotes the coordinates of the location of the observation i; $\beta_0(u_i, v_i)$ is the intercept; $\beta_k(u_i, v_i)$ is the regression coefficient for variable k at regression i; x_{ik} is the value for the k variable for observation i; and ε_i is the error term [24].

4. Results and Discussion

4.1. Land-Cover Classification

The overall classification accuracies for 2013 and 2015 were 85.56% and 82.22%, respectively (Table 2). The major errors were between spring maize and cotton, because the training data set may have had some mixed or close spectral band variations of both classes, or because of an entanglement of mixed pixels. The numbers in first three columns of the reference data section are the counts of sample data ('ground truth') against the same type of training data. Column total is the sum of numbers in the first three columns by row (number of commission pixels). Row total is the sum of numbers in each row by column (number of omission pixels). User's accuracy (UA) is each count divided by the row total; producer's accuracy (PA) is each count divided by the column total.

Table 2. Accuracy assessment of land-cover classification results in 2013 and 2015.

Year	Type	Reference Data					Overall Accuracy			
		Wheat	Spring Maize	Cotton	Column Total	Row Total	UA	PA		
2013	Wheat	41	8	2	42	51	80.39%	97.62%		
	Spring Maize	1	15	0	25	16	93.75%	60.00%	OA=	85.56%
	Cotton	0	2	21	23	23	91.30%	91.30%	KC=	0.77
2015	Wheat	36	0	1	39	37	97.30%	92.31%		
	Spring Maize	1	18	5	25	24	75.00%	72.00%	OA=	82.22%
	Cotton	2	7	20	26	29	68.97%	76.92%	KC=	0.73

Note: UA denotes user's accuracy, PA denotes producer's accuracy, OA denotes overall classification accuracy and KC denotes the kappa coefficient.

The land-cover change results from 2013 to 2015 show the interchange among wheat, spring maize, cotton, other crops and no-cultivated land in the Hengshui area (Figure 2). Overall, wheat and cotton decreased from 2013 to 2015, while spring maize, other crops and non-cultivated land increased. For major crops, total wheat was the most reduced crop, as it decreased from 35.71% in 2013 to 32.98% in 2015, and cotton decreased from 13.45% to 12.83%. Spring maize's area remained stable, with an increase of 1.58% (Table 3).

Table 3. The area and percentage of each land cover in 2013 and 2015.

Land Type	2013		2015	
	Area (ha) and Percentage of Each Land Cover			
Winter Wheat/Summer maize	314,053.86	35.71%	289,986.06	32.98%
Cotton	118,291.71	13.45%	112,804.76	12.83%
Spring maize	23,717.80	2.70%	37,595.17	4.28%
Other crops	250,475.49	28.48%	260,080.90	29.58%
No-cultivated land	172,837.52	19.65%	178,909.49	20.35%

Note: both years of land cover excluded unclassified pixels.

From the land cover transfer chord diagram (Figure 3), the WW_SM area was lost due to the conversion to spring maize and cotton: although 91% of the WW_SM remained, 4.92% (15,467 ha) of the WW_SM was converted to spring maize and 2.48% (6877 ha) of the WW_SM to cotton. There was some interchange of spring maize (897 ha) and cotton (527 ha) to WW_SM, but that was still less than the lost area of WW_SM. For the cotton, it reduced from 118,291 ha to 112,804 ha, which was caused by the total amount (12,159 ha) of cotton transferred to other crops and non-cultivated land greater than the amount of wheat transferred to cotton (6877 ha). The increase in spring maize area was caused by the intensive, annual wheat–maize double cropping system.

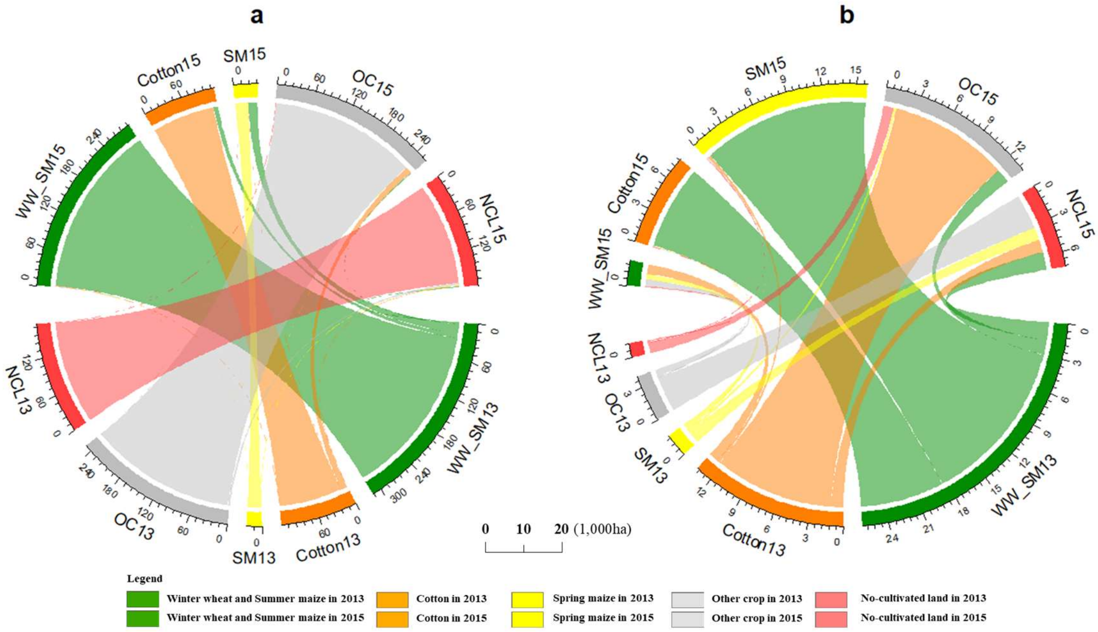

Figure 3. Land cover transfer chord diagram from 2013 to 2015 (**a**), and a land cover mutual transfer chord diagram after the same land cover transfer was excluded from 2013 to 2015 (**b**).

4.2. Evaluation of Water Consumption under Land Cover Change

The main crops ET of Hengshui in 2013 and 2015 were estimated based on the proposed functions. Compared with the field-observed ET in Hengshui agricultural experimental station, the relative error of each sample between the mean values of estimated and field-observed ET varied from 0.39% to 8.31% (Figure 4). The root mean square error (RMSE) is the standard deviation of the residuals (prediction errors), which is a measure of how spread out these residuals are. The root-mean-square error (RMSE) of the estimated ET of the main crops was 18.62 mm. A regression analysis between estimated and observed ET was performed, and the coefficient of determination R^2 was 0.90. The estimate's result had matched well with the field-observed ET.

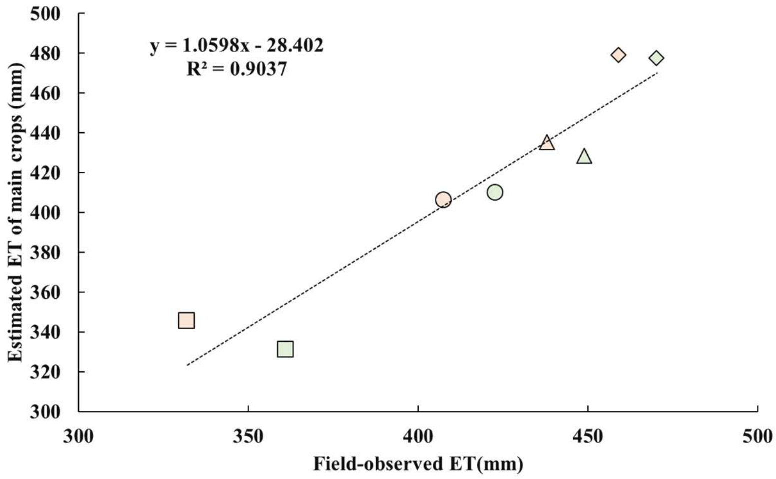

Figure 4. A comparison of estimated and field-observed evapotranspiration (ET) of the main crops in Hengshui.

With the combination of the land cover and meteorological data, the spatial distributions of the ETs of major crops in 2013 and 2015 were identified (Figure 5). The ET of wheat was between 396 mm and 421 mm, with an apparent spatial difference. In 2013, the areas with ET below 400 mm were mainly distributed in the east–west direction, while in 2015, the areas with ET below 400 mm were dispersed in the north–south direction. The ET of summer maize did not exceed 360 mm, and the high part of it was mainly concentrated in the middle area. Spring maize had a higher ET than summer corn due to the former's longer growth period. The ET of spring corn varied mostly from 400 mm to 450 mm. The ET of cotton was the highest in major crops; both in 2013 and 2015, it was above 460 mm.

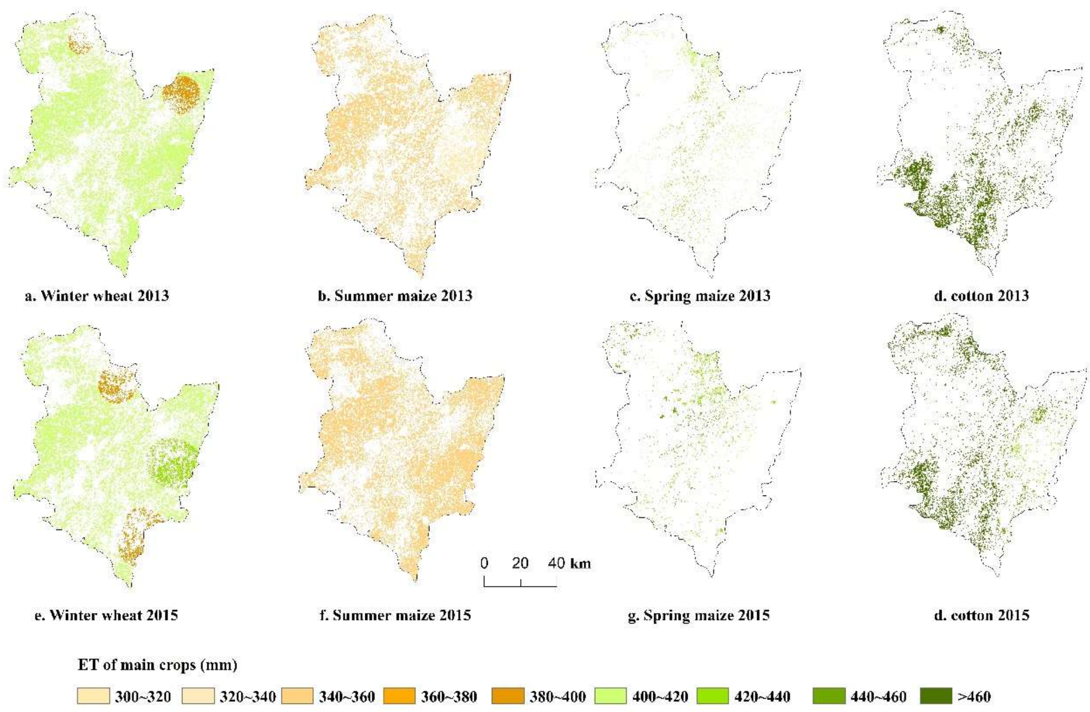

Figure 5. Spatial distribution of the ETs of main crops in Hengshui.

The comparison between the precipitation during the growth period of crops and the actual ET indicates the water shortage conditions and these conditions changed for different crops over time (Figure 6). In order to compensate for the lack of precipitation during the growing period, the average wheat crop in 2013 received 319 mm from irrigation, accounting for 78.63% of its ET. In 2015, wheat was irrigated by an average of 193 mm, accounting for 47.14% of the groundwater consumption. The precipitation during the growth period in 2013 was greater than 2015, and the precipitation in 2013 was more than the ETs of summer maize, spring maize and cotton put together; hence, giving birth to a water surplus. In 2013, summer maize, spring maize and cotton had surpluses of 172, 113 and 84 mm, respectively. In 2015, the average precipitation during the growth period was lower than the ETs of those crops. Therefore, summer maize, spring maize and cotton were irrigated by 38, 43 and 33 mm, respectively.

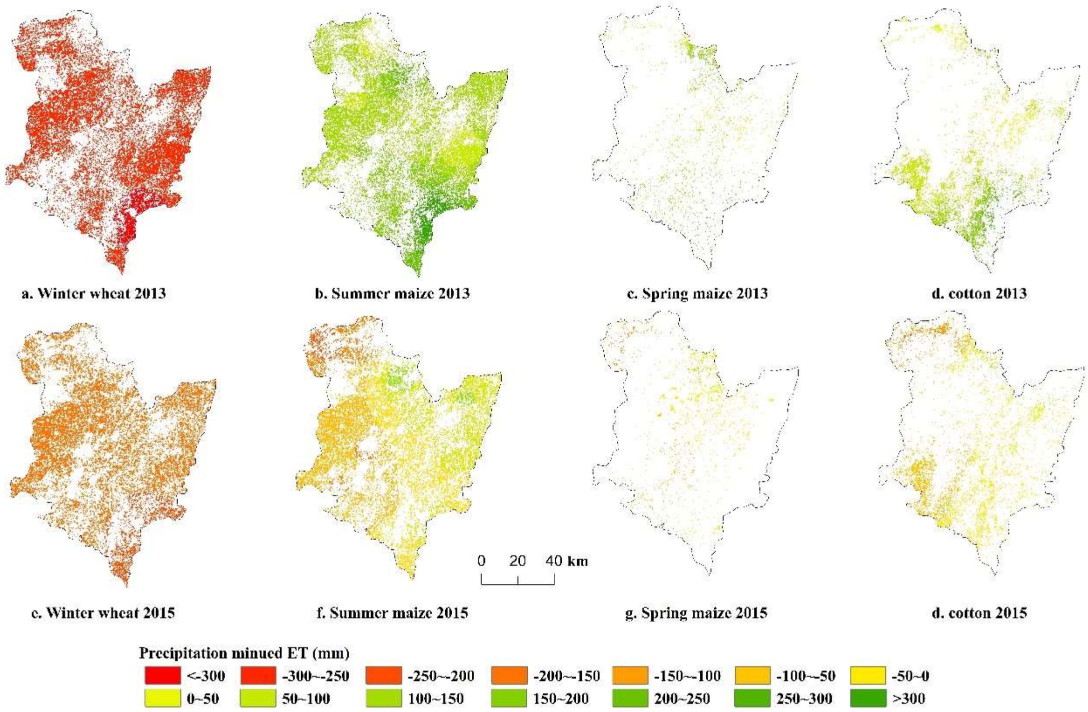

Figure 6. Net irrigation water of main crops in Hengshui. There is a gap between precipitation and ET, which can be considered to be the amount of irrigation required for crops. Since the precipitation for some crops was greater than ET (positive value in the figure), it can be assumed that no groundwater was consumed, and groundwater was replenished; if the precipitation during the crop growth period was less than ET (negative value in the figure), the gap needed to be extracted by groundwater.

In terms of the overall water consumption of crops, the total amount of water used in the four main crops showed a decreasing trend (Figure 7). The water consumption of winter wheat decreased from 1.27 billion m^3 in 2013 to 1.18 billion m^3 in 2015. Secondly, summer maize also reduced water consumption by 38.05 million m^3. The main reason for the decrease in total water consumption of winter wheat and summer maize was that the policy altered the wheat–maize double cropping system to annual spring maize. A large number of winter wheat crops lacking sustainable water sources in winter were converted to other crops, and that was an important step in groundwater recovery. At the same time, the total water consumption of spring maize increased by 1.65 million and that of cotton decreased by 24.28 million. In general, the water consumption of major crops decreased from 2.98 billion m^3 in 2013 to 2.83 billion m^3 in 2015, a total reduction of 146 million m^3, and 88.43% of the target reduction of the Winter Wheat Fallow Policy (166 million m^3).

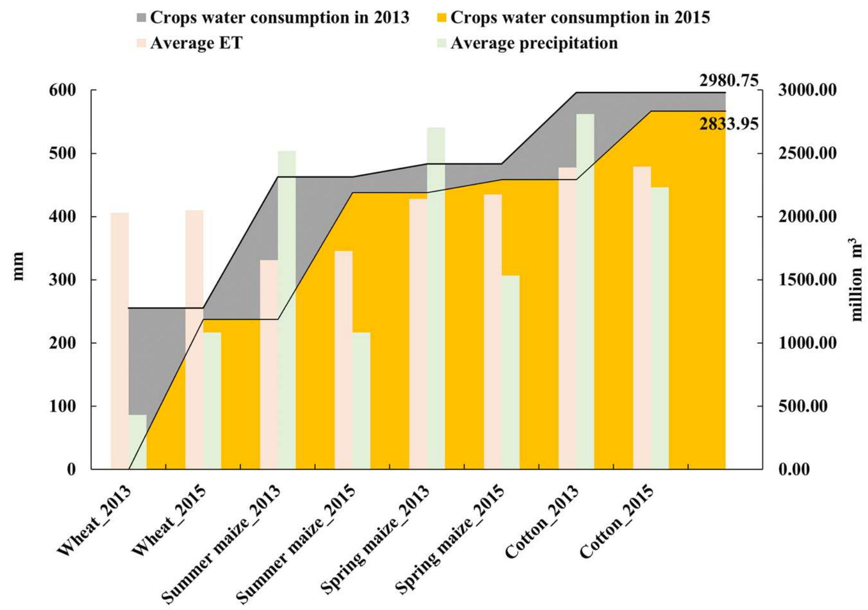

Figure 7. A comparison of average ETs, average amounts of precipitation and crops' water consumptions in Hengshui. The histogram shows the average ET and average precipitation during the growth period for every crop. The gap between the two is the demand for crop irrigation. The area chart accumulates the total water consumption of the main crops in 2013 and 2015 in turn.

4.3. Land Cover Change, ET and Precipitation Impacts on Groundwater Depth

Based on the comparison of shallow groundwater depth monitoring data between 2013 and 2015, the variation of the two years was between 1.04 m and −4.64 m (Figure 8c), given the depth of shallow groundwater in 2013 ranging between 5.21–20.86 m (Figure 8a) and 2.53–21.91 m (Figure 8b) in 2015. The groundwater depth reduction area was mainly concentrated in the southeast, while the depth-rising area was located in the northwest.

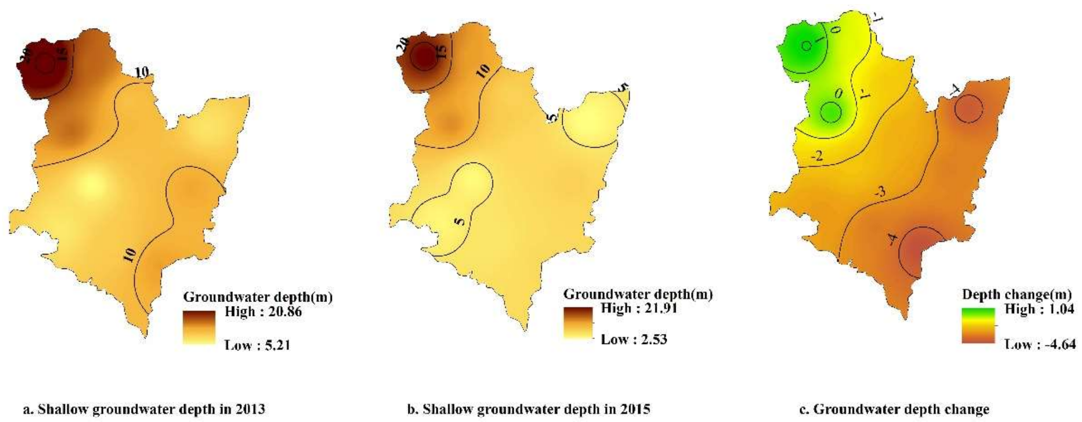

Figure 8. The groundwater depth and the groundwater depth change.

To analyze whether the change of winter wheat acreage was caused by the WWFP, which directly impacted the groundwater depth, we used dummy variables to represent the process of the change for winter wheat. The transformations from winter wheat to other crops between 2013 and 2015 (e.g., from winter wheat to cotton or from winter wheat to spring maize) were represented and calculated with dummy variables from 1 to 3. For example, the change of winter wheat to cotton was assigned a value of 1; the change of winter wheat to spring maize was 2. The change of winter wheat and groundwater depth had spatial heterogeneity. To deal with this issue, geographically weighted regression (GWR) was utilized in this study, as an extension of ordinary least squares regression, doing well in the local relationships between the independent and dependent variables. From the result (Figure 9a), the model was not significant ($p > 0.1$), and the mean local coefficient of determination after GWR was low (local $\overline{R^2} = 0.006$), the change of winter wheat was not a good explanatory variable. Therefore, the planting changes of winter wheat could not directly affect the variation of groundwater depth.

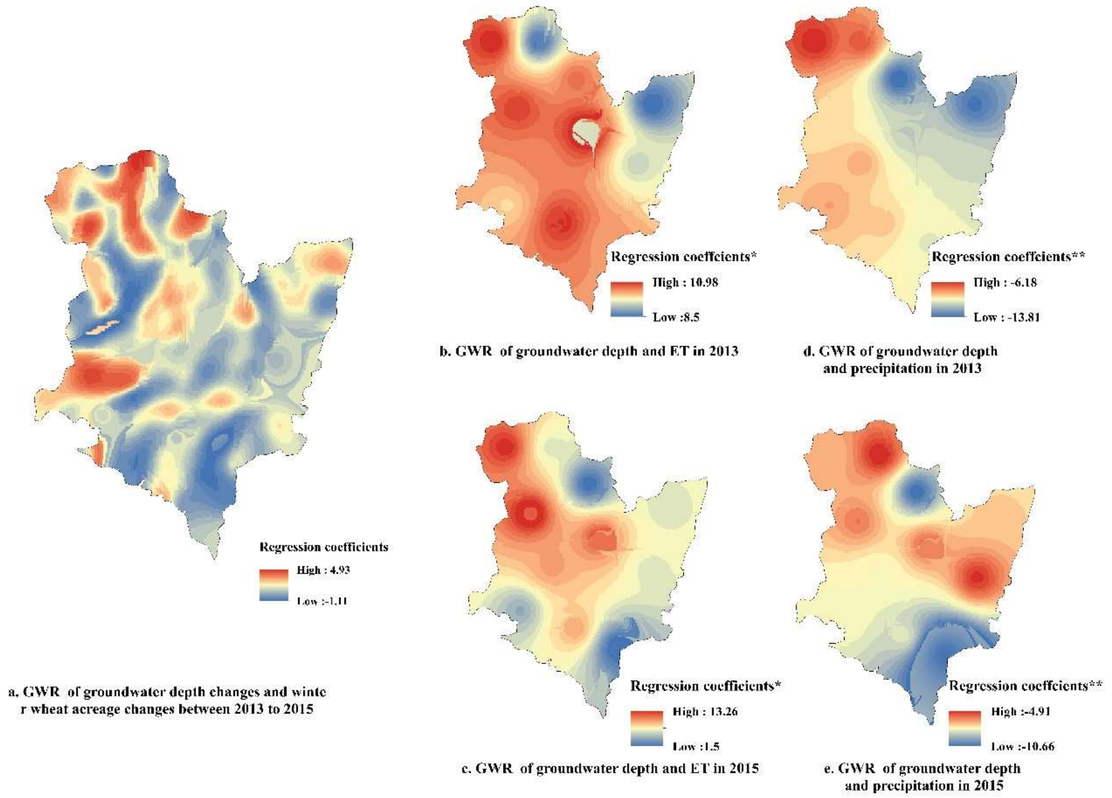

Figure 9. GWR analysis of shallow groundwater depth and influencing factors between 2013 and 2015. Local $\overline{R^2}$ is mean local coefficient of determination after GWR. *** indicates values significant at $p < 0.01$; ** indicates values significant at $p < 0.05$; * indicates values significant at $p < 0.1$.

Since the changes of land-cover-affected the ETs of crops, and ET and precipitation were the primary impact factors for groundwater replenishment based on the water balance function, we considered ET and precipitation to be important explanatory variables in the regression of groundwater change. The regression results (Figure 9b,c) between ET and groundwater depth in 2013 and 2015 were significant ($p < 0.1$). The mean of the local R^2 of ET and groundwater depth regression model was 0.433 in 2013 and 0.501 in 2015. These showed that the groundwater depth change could be explained by ET. Both regression coefficients between ET and groundwater depth in 2013 and 2015 were positive, meaning a greater ET would drive a larger groundwater depth. In terms of spatial distribution of the regression coefficients between ET and groundwater depth in 2013 and 2015, the regression coefficient in the western region was higher than the rest of area in 2013, and the regression coefficient in the northwest was higher than the rest of area in 2015.

In Figure 9d,e, the GWR indicated precipitation is a more significant variable affecting groundwater depth than the change of winter wheat and ET ($p < 0.05$). The means of local R^2 for the 2013 and 2015 models were 0.677 and 0.625, respectively, which showed precipitation could explain most changes in groundwater depth. Both regression coefficients between precipitation and groundwater depth in 2013 and 2015 were negative, indicating that more precipitation resulted in a lower groundwater depth. Spatially, the regression coefficient in the western region was higher in 2013, and the regression coefficient in the northwest was higher in 2015.

In general, despite the implementation of the WWFP, the groundwater depth in 2015 increased compared with that in 2013. The planting changes of winter wheat did not directly affect the change of groundwater depth, but ET was positively correlated to the groundwater depth. The increased ET led to an increase in the groundwater depth. Besides, the precipitation had a close relationship with the groundwater depth and the increase in precipitation resulted in a decrease in the groundwater. Despite the implementation of the WWFP and the reduction of ET of agricultural crops, the groundwater depth in 2015 lowered because of less precipitation.

5. Conclusions and Discussion

We obtained the crops' spatial distributions for both 2013 and 2015 through remote sensed data, and then analyzed the crop cover transitions; secondly, we calculated ETs of the main crops and the net irrigation water. Finally, we discussed the relationships between crop pattern change, ET, precipitation and groundwater variation by using a spatial regression analysis method.

(1) The overall classification accuracies for 2013 and 2015 were 85.56% and 82.22%, respectively. The winter wheat shrank the most among all crops, decreasing from 35.71% in 2013 to 32.98% in 2015, while the cotton decreased from 13.45% to 12.83% and the spring maize increased by 1.58%. The reduction of winter wheat was replaced with 6877 ha of cotton and 15,467 ha of spring corn. The actual reduction in wheat area achieved 84% of the target (26,000 ha) of the Winter Wheat Fallow Policy (WWFP). (2) The water consumption of major crops decreased from 2.98 billion m^3 of water, in 2013 to 2.83 billion m^3 of water in 2015, a total reduction of 146 million m^3. This realized 88.43% of the reduction goal in the WWFP (166 million m^3). The water consumption of winter wheat decreased from 1.27 billion m^3 to 1.18 billion m^3. (3) The reduced winter wheat area did not directly affect the groundwater depth, but ET was positively related to the groundwater depth. As a result, the increase of ET led to an increase in groundwater depth and the decrease in precipitation caused a decrease in groundwater depth.

According to the results, the winter wheat planting area of Hengshui from 2013 to 2015 decreased by 24,000 ha. The average output per hectare in Hengshui was 6.56 tons/ha; therefore, decreasing the total output by 157,879 tons, or 9.18%, of Hengshui's total winter wheat output of 1,718,641 tons in 2015. The WWFP was designed to reduce the winter wheat planting area of the NCP by about 50,000 ha in 2015; therefore, if the average winter wheat yield per hectare in the NCP was 6.19 tons/ha, there should have been a decrease of 346.640 tons, 2.43%, in the total winter wheat yield (14,300,721 tons) in the NCP in 2015. With the implementation of the policy, the wheat fallow area will increase, while the wheat yield will be on the decrease. Decision makers should be aware of the yield loss. In the future, how to optimize the spatial layout of wheat planting, supplement the partial production capacity with the international wheat market and assess reasonable fallow areas for wheat should be important questions in balancing environmental impact and food security in the WWFP practice.

With the implementation of the WWFP, this study has detected a large amount of winter wheat shifting to cotton or spring maize, while small amount of cotton, spring maize and other crops were converted to winter wheat. Besides variations of farmers' preferences and farming decisions due to the market, the WWFP may also have a spillover effect—driving farmers to switch from planting other crops to winter wheat. It is tricky, after planting winter wheat for a year, that farmers must then switch their farming decisions again by planting other crops rather than winter wheat. Farmers could receive economic benefits under the WWFP policy because of their 'reducing' winter wheat planting. This pitfall of the WWFP has caused an expected spillover effect regionally, which may scale up to the whole NCP. With high costs of management (administration, monitoring, communication and enforcement), decision makers should be aware of the spillover effect before it becomes a financial burden to the government and has significantly negative environmental and socioeconomic impacts.

The WWFP has cut down agricultural water usage by shifting farming decisions, which has an important impact on groundwater levels and helps with achieving the sustainable water management goal. To better manage the problem of groundwater overextraction, other strategies, such as south-to-north water transfer, increasing pond water collection and improving irrigation facilities, should also be incorporated. This integrated management of water resources would provide a smarter, more efficient and sustainable solution. Besides, this study assumed that the large-scale changes of crops in a short period of time (2013–2015) were mainly affected by the WWFP policy. Due to the fact that there are still other factors affecting crop planting (e.g., meteorological changes and farmers' decisions), we need to further confirm the scope and extent of the fallow policy in subsequent studies. In addition, compared with shallow groundwater, deep groundwater finds it more difficult and time-consuming to recharge. For the sustainable use of groundwater, this concern should also be addressed when making water restoration and management policies.

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