

Application of the InVEST model for assessing water yield and its response to precipitation and land use in the Weihe River Basin, China (Post-print)

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Abstract

Abstract: With realizing the importance of ecosystem services to society, the efforts to evaluate the ecosystem services have increased. As the largest tributary of the Yellow River, the Weihe River has been endowed with many ecological service functions. Among which, water yield can be a measure of local availability of water and an index for evaluating the conservation function of the region. This study aimed to explore the temporal and spatial variation of water yield and its influencing factors in the Weihe River Basin (WRB), and provide basis for formulating reasonable water resources utilization schemes. Based on the InVEST (integrated valuation of ecosystem services and tradeoffs) model, this study simulated the water yield in the WRB from 1985 to 2019, and discussed the impacts of climatic factors and land use change on water yield by spatial autocorrelation analysis and scenario analysis methods. The results showed that there was a slight increasing trend in water yield in the WRB over the study period with the increasing rate of 4.84 mm/10a and an average depth of 83.14 mm. The main water-producing areas were concentrated along the mainstream of the Weihe River and in the southern basin. Changes in water yield were comprehensively affected by climate and underlying surface factors. Precipitation was the main factor affecting water yield, which was consistent with water yield in time. And there existed significant spatial agglomeration between water yield and precipitation. Land use had little impact on the amount of water yield, but had an impact on its spatial distribution. Water yield was higher in areas with wide distribution of construction land and grassland. Water yield of different land use types were different. Unused land showed the largest water yield capacity, whereas grassland and farmland contributed most to the total water yield. The increasing water yield in the basin indicates an enhanced water

supply service function of the ecosystem. These results are of great significance to the water resources management of the WRB.

Full Text

Preamble

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Abstract

As awareness of the importance of ecosystem services to society has grown, efforts to evaluate these services have intensified. The Weihe River, as the largest tributary of the Yellow River, provides numerous ecological service functions, among which water yield serves as both a measure of local water availability and an index for evaluating regional conservation capacity. This study aimed to explore the temporal and spatial variation of water yield and its influencing factors in the Weihe River Basin (WRB) to provide a basis for formulating rational water resource utilization schemes. Using the InVEST (Integrated Valuation of Ecosystem Services and Tradeoffs) model, we simulated water yield in the WRB from 1985 to 2019 and examined the impacts of climatic factors and land use change through spatial autocorrelation analysis and scenario analysis. The results revealed a slight increasing trend in water yield over the study period, with a rate of 4.84 mm/10a and an average depth of 83.14 mm. Primary water-producing areas were concentrated along the Weihe River mainstream and in the southern basin. Water yield changes were comprehensively affected by both climate and underlying surface factors. Precipitation was the dominant factor affecting water yield, showing temporal consistency and significant spatial agglomeration with water yield. Land use had minimal impact on the total amount of water yield but influenced its spatial distribution, with higher water yield observed in areas with extensive construction land and grassland. Water yield varied among different land use types, with unused land exhibiting the highest yield capacity, while grassland and farmland contributed most to total water yield. The increasing water yield in the basin indicates enhanced water supply service functions of the ecosystem. These findings hold great significance for water resources management in the WRB.

Keywords: water yield; InVEST model; Weihe River Basin; Geoda model; scenario analysis

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1 Introduction

Ecosystems directly or indirectly provide various services to human beings (Symank et al., 2020), which have been defined as “the benefits that humans derive from nature” (Hassan and Scholes, 2005). As an attribute of ecosystems and a key component of ecological processes, water yield can produce water-related ecosystem services (Costanza et al., 1998). For example, it regulates surface runoff during dry and flood seasons, reduces potential drought and flood risks, and ensures drinking water sources (Zhang et al., 2010). In summary, water yield is a resource supporting human life and development, including agriculture, industry, human consumption, hydropower, fisheries, and recreational activities (Natalia et al., 2015).

Over the last few decades, growth in the global human population, improvements in living standards, changes in consumption patterns, and expansion of irrigated agriculture have resulted in gradually increasing demand for water resources (Ercin and Hoekstra, 2014; Gómez et al., 2014; Vorosmarty et al., 2000). Consequently, many countries face escalating water scarcity challenges (Qiu, 2010; Liu and Wu, 2012; Mekonnen and Hoekstra, 2016). In China, high food demand and regional economic development imbalances have led to increased water resource utilization and uneven distribution (Mekonnen and Hoekstra, 2016).

Relevant studies have shown sharp decreases in measured runoff in major Chinese river basins in recent decades (Xu et al., 2010). Changes to water resources in the Yellow River have attracted particular attention due to this river’s importance in China (Qiang et al., 2009). In the late 1990s, the average runoff entering the Yellow River was only $35.99 \times 10^8 \text{ m}^3$, a decrease of $62.06 \times 10^8 \text{ m}^3$ compared with the 1950s (Xia et al., 2007). This runoff further decreased in the 21st century (Zhao et al., 2018).

The Weihe River is the largest tributary of the Yellow River and provides irrigation water for nearly $1 \times 10^4 \text{ km}^2$ of farmland in the Guanzhong Plain, supporting nearly 61% of the population, 56% of cultivated land, and 81% of gross domestic product (GDP) in Shaanxi Province, China (Liu and Hu, 2008). However, the imbalance between water supply and demand in the Weihe River Basin (WRB) has intensified due to rapid human development, water conservancy construction, soil conservation projects, and other engineering measures

(Ma et al., 2008; Cheng et al., 2019; Xu et al., 2021). According to the Shanxi Water Resources Bulletin (2019), agriculture is the sector consuming the most water in the basin ($55.13 \times 10^8 \text{ m}^3$), including forestry, animal husbandry, fishery, and livestock farming, accounting for 60% of total water consumption. Industrial and municipal water consumption were $14.85 \times 10^8 \text{ m}^3$ and $14.28 \times 10^8 \text{ m}^3$, accounting for 16.05% and 14.12% of total water consumption, respectively. Water consumption in the basin will increase further with economic development, imposing additional pressure on available water resources (Zhang et al., 2016).

The WRB belongs to a typical transitional climate zone in the arid and semi-arid area of northwestern China, where water resources are sensitive to climate change (Chen et al., 2013). Global climate variability over the last few centuries has been characterized by temperature rise and precipitation changes, which have had destructive impacts on natural ecosystems and human economic and social development (Milliman et al., 2008). Water yield has gradually become an important factor restricting sustainable societal development. Therefore, evaluating water yield in the WRB is of great significance.

Models serve as useful tools for evaluating water-related ecosystem service functions and quantitatively estimating water yield under various conditions. Available models include the Soil and Water Assessment Tool (SWAT) (Baker and Miller, 2013; Gassman et al., 2017), Social Values for Ecosystem Services (SolVES) (Greg et al., 2012; Sherrouse et al., 2011), Multi-scale Integrated Models of Ecosystem Services (MIMES) (Boumans and Costanza, 2008), and Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) (Sharp et al., 2020). Among these, the InVEST model has been most widely applied due to its lower data requirements and ability to visualize simulation results (Huang et al., 2013; Scordo et al., 2018; Cara et al., 2020). The InVEST model integrates a series of ecosystem processes and can simulate the quality and value of ecosystem services regulated by land use, physical environmental factors, and socio-economic factors (Jiang et al., 2021). Numerous studies have applied it to various regions worldwide, achieving good results in North Korea (Kim and Jung, 2020), the Wildcat Creek Watershed in Indiana and Upper Upatoi Creek Watershed in Georgia, United States (Dennedy-Frank et al., 2016), and several regions of China (Yang et al., 2019; Yin et al., 2020; Li et al., 2021). However, few attempts have applied the InVEST model to the WRB, and those that did were unable to identify temporal and spatial variation characteristics in water yield due to short study periods. Most of these studies also only analyzed quantitative relationships between water yield and driving factors (Yang et al., 2019) without examining their spatial correlations.

The present study used the InVEST model to: (1) simulate water yield in the WRB from 1980 to 2019 and analyze its spatiotemporal variation; (2) identify the main factors regulating water yield under different climate conditions and land use types; and (3) discuss the mechanisms regulating water yield.

2.1 Study Area

The Weihe River originates from Niaoshu Mountain in Weiyuan County, Gansu Province, and flows through the Ningxia Hui Autonomous Region and Shaanxi Province from west to east, covering 10 regions and 84 counties. The Weihe River merges into the Yellow River at Tongguan County, Shaanxi Province, China. As the largest tributary of the Yellow River, the Weihe River has a total length of 818 km and drains an area of $13.5 \times 10^4 \text{ km}^2$. The WRB is located in the southeastern Loess Plateau, China ($33^\circ 42' - 37^\circ 20' \text{ N}$, $106^\circ 18' - 110^\circ 37' \text{ E}$). The terrain of the WRB gradually decreases from west to east, with an elevation difference of over 3000 m a.s.l. (Fig. 1). The climate of the WRB is cold and dry in winter and hot and rainy in summer, with an annual average temperature of $7.8^\circ\text{C} - 13.5^\circ\text{C}$ and average annual precipitation of 572 mm.

Fig. 1. Elevation, and hydrological and meteorological stations in the Weihe River Basin, China

2.2 Data Sources

The model requires meteorological, soil, and land use/land cover (LULC) data. Raster input data were derived directly or indirectly from these sources. Table 1 summarizes the relevant basic data used in the present study.

Table 1. Relevant basic data sources and description

Data description	Data source
Climate data	
Daily precipitation	China Meteorological Science Data Sharing Service Network (http://www.cma.gov.cn/)
Daily maximum temperature	
Daily minimum temperature	
Daily mean temperature	
Soil data	
Soil texture (clay, sand, and silt)	Harmonized World Soil Database (HWSD)
Soil organic carbon	
Soil depth	
Land use/land cover	
Land use/land cover during 1980–2020 at 1 km spatial resolution	Resource and Environmental Science Data Center, Chinese Academy of Sciences (http://www.resdc.cn)
Digital elevation model (DEM)	

Data description	Data source
Elevation of the Weihe River Basin at 30 m spatial resolution	Geospatial Data Cloud Platform of Chinese Academy of Sciences (https://www.gscloud.cn/)
Streamflow data	
Runoff data	
Measured runoff of Huaxian and Zhuangtou hydrological stations from 1980 to 2019	Yellow River Hydrological Yearbook
Restored runoff of Huaxian and Zhuangtou hydrological stations from 1980 to 1984	Runoff data of the Yellow River Basin

2.3.1 Introduction of the InVEST Model

The InVEST model calculates water yield using the Budyko curve (Budyko, 1974) and annual average precipitation (P). Water yield simulated by the model represents water outflow from the landscape, including surface flow, underground flow, and base flow (Sharp et al., 2020). The model assumes that water yield from a pixel reaches the specified outlet through one of several paths mentioned above (Zhang et al., 2004; Donohue et al., 2012). The formula is expressed as:

$$Y(x) = P(x) \times \left(1 - \frac{AET(x)}{P(x)}\right)$$

where $AET(x)$ is the annual actual evapotranspiration (mm) and $P(x)$ is the precipitation for a pixel (mm).

For vegetation-covered land, $AET(x)$ was calculated (Fu, 1981; Zhang et al., 2004):

$$\frac{AET(x)}{P(x)} = \left[1 + \frac{PET(x)}{P(x)} - \left(1 + \left(\frac{PET(x)}{P(x)}\right)^{\omega(x)}\right)^{1/\omega(x)}\right]$$

where $PET(x)$ is the potential evapotranspiration (mm) and $\omega(x)$ is a nonphysical parameter characterizing regional climate and soil conditions, ranging from 1.25 to 5.00 (Yang et al., 2008; Donohue et al., 2012). The minimum value can be selected when the root depth is 0 cm (bare soil), and $\omega(x)$ is calculated as:

$$\omega(x) = Z \times \frac{AWC(x)}{P(x)} + 1.25$$

where Z is a local parameter related to precipitation and other hydrogeological features, with possible values of 1 to 30, and $AWC(x)$ is the plant available water capacity (mm), calculated as:

$$AWC(x) = \min(\text{rest layer depth}, \text{root depth}) \times PAWC$$

where $PAWC$ is the plant available water capacity (Fig. 2a) and rest layer depth is the depth of the root restricting layer, often expressed as the depth at which 95% of root biomass of the plant occurs (Fig. 2b).

Fig. 2. Spatial distributions of biophysical characteristics of the Weihe River Basin, China. (a) PAWC, plant available water capacity; (b) soil depth; (c) land use/land cover (LULC) in 2020.

2.3.2 Data Preparation

Model inputs included rasterized annual P, average annual ET_0 , LULC, depth of the root restricting layer, PAWC, watershed and sub-watershed layers, a biophysical table, and an appropriate Z parameter (Sharp et al., 2020). All raster data were unified into the Krasovsky_{1940}_{Albers} coordinate system before input. The processing methods are described below.

(1) P and ET_0

Annual P and ET_0 data were obtained by aggregating daily precipitation and monthly ET_0 data within each year, followed by Kriging interpolation of data from 22 meteorological stations around the WRB to provide values for each raster cell. ET_0 was calculated using the modified Hargreaves equation (Droogers and Allen, 2002):

$$ET_0 = 0.0013 \times 0.408 \times RA \times (T_{av} + 17) \times (TD - 0.0123)^{0.76}$$

where T_{av} is the average of mean T_{max} and T_{min} for each month ($^{\circ}\text{C}$), TD is the difference between mean T_{max} and T_{min} for each month ($^{\circ}\text{C}$), and RA is extraterrestrial radiation ($\text{MJ}/(\text{m}^2 \cdot \text{d})$). Radiation data were obtained from the United Nations Food and Agriculture Organization (FAO) Irrigation and Drainage Paper (Fao et al., 1982).

(2) PAWC

PAWC (Fig. 2a) is the field capacity minus wilting point, ranging from 0 to 1, calculated as (Zhou et al., 2005):

$$PAWC = 54.509 - 0.132 \times \text{sand} - 0.003 \times (\text{sand})^2 - 0.055 \times \text{silt} - 0.006 \times (\text{silt})^2 - 0.738 \times \text{clay} - 0.007 \times (\text{clay})^2 + 2.688 \times$$

where sand, silt, clay, and organic matter (OM) are expressed as percentages (%).

(3) LULC

ArcGIS 10.2 was used to reclassify 25 secondary land use types into 6 primary types (Fig. 2c): farmland, forestland, grassland, water body, construction land, and unused land.

(4) Watershed and sub-watershed

In ArcGIS 10.2, the hydrology tool was used to divide the WRB into 377 sub-watersheds by setting the threshold flow accumulation (TFA) to $4 \times 10^5 \text{ m}^3$.

(5) Biophysical table

The biophysical table (Table 2) contains information for each LULC grid required by the model (Sharp et al., 2020). The $LULC_{veg}$ parameter determines which AET calculation formula to use. LULC with vegetation cover is assigned as 1, and others as 0. K_c is the evapotranspiration coefficient of vegetation, based on alfalfa, used to adjust ET_0 to obtain PET, with a range from 0.0 to 1.5. Root depth (Fig. 2b) is the maximum depth that a plant root system can extend, often expressed as the depth at which 95% of root biomass occurs (Allen et al., 2006). Data in Table 2 were obtained from relevant literature (Yang et al., 2020) and values recommended by the FAO and InVEST model.

Table 2. Biophysical table for the InVEST model

Land use type	$LULC_{veg}$	Root depth (m)	K_c
Farmland	1	0.5	1.0
Forestland	1	3.0	1.0
Grassland	1	0.5	1.0
Water body	0	1.0	1.0
Construction land	0	0.1	0.2
Unused land	0	0.1	0.2

Note: $LULC_{veg}$, land use/land cover with vegetation cover; K_c , evapotranspiration coefficient.

2.3.3 Model Calibration

The InVEST model simulates natural runoff of a basin, with simulation accuracy largely dependent on parameter Z (Eq. 3). The present study validated parameter Z by comparing simulated water yield data with natural runoff data at Huaxian and Zhuangtou hydrological stations in the WRB from 1980 to 1984. Simulation accuracy was assessed using the correlation coefficient (R^2), Nash coefficient (NSE), and relative error (Re) (Rientjes et al., 2011). The study set

the Z value range for the study area to 3.6–9.0, consistent with relevant studies (Wu et al., 2018; Yue et al., 2021). The model was initiated with $Z = 3.6$, which was gradually increased by 0.2 until maximized values of R^2 , NSE, and Re were obtained. After nearly a thousand tests, optimal values of $Re = 2\%$, $R^2 = 0.98$, and $NSE = 0.63$ were obtained at an input Z value of 8.8.

2.4 Trend Analysis

The Mann-Kendall (M-K) test is a non-parametric method that does not require samples to follow a specific distribution and is not affected by outliers (Mann, 1945; Kendall, 1975). The M-K test is commonly used to identify trends in precipitation and drought under climate change influence (Sheng and Paul, 2004). This study applied the M-K test to detect trends in water yield and climate factors over time. It should be noted that the statistic Z value from the M-K test differs from the seasonal parameter Z required as input into the InVEST model.

2.5.1 Global Spatial Autocorrelation

The present study used Moran's I to express global spatial autocorrelation, analyzing overall correlations between spatial units and assessing whether spatial agglomeration existed. Moran's I ranges from -1 to 1 . Values of $I > 0$ indicate that spatial attribute values have a spatial agglomeration effect with surrounding attribute values, with values closer to 1 indicating more significant spatial agglomeration. Values of $I < 0$ indicate spatial differentiation effects, with values closer to -1 indicating more significant spatial differences, while $I = 0$ indicates no spatial autocorrelation (Tu and Xia, 2008). The spatial weight matrix was set as a simple binary adjacency matrix. Moran's I is calculated as follows (Moran, 1950):

$$I = \frac{n \sum_{i=1}^n \sum_{j=1}^n W_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n W_{ij} \sum_{i=1}^n (x_i - \bar{x})^2}$$

where W_{ij} is the spatial weight matrix of cells i and j ; x_i and x_j are measured values of cells x and y , respectively; $\bar{x}$ is the average measured value of all cells; and n is the number of all evaluation units.

2.5.2 Bivariate Local Moran's I

We used the Local Indicators of Spatial Association (LISA) method to assess the strength of correlation between attributes of each spatial unit and adjacent

units according to local Moran's I (Harries, 2006). Here, $I_i > 0$ indicates that spatial units are highly correlated, including high-high and low-low types; $I_i < 0$ indicates large differences in spatial units, including high-low and low-high types. The formula is as follows (Tepanosyan et al., 2019):

$$I_i = \frac{(x_i - \bar{x}) \sum_{j=1}^n W_{ij}(x_j - \bar{x})}{\sum_{i=1}^n (x_i - \bar{x})^2}$$

This method can be used to study the spatial agglomeration effect of meteorological factors and water yield. High-high and low-low types refer to proportional relationships between meteorological factors and water yield, whereas high-low and low-high types indicate inverse correlations.

3.1.1 Temporal Variation

Precipitation (P), actual evapotranspiration (AET), potential evapotranspiration (PET), and simulated water yield in the WRB from 1985 to 2019 are shown in Figure 3. The annual average P over the study period was 542.09 mm, with no significant temporal trend ($Z = 1.28$, $P > 0.05$). Minimum and maximum P values of 364.26 mm and 766.12 mm occurred in 1997 and 2003, respectively. The average PET was 695.55 mm, showing no significant trend ($Z = 0.43$, $P > 0.05$). The average AET was 458.81 mm, showing a significant increasing trend ($Z = 1.93$, $P < 0.05$), suggesting that more than 80.00% of precipitation in the WRB returned to the atmosphere through evaporation annually. Water yield in the WRB fluctuated and correlated with precipitation, with maximum and minimum values of 261.62 mm and 6.08 mm in 2003 and 1997, respectively. The annual average water yield was 83.14 mm, accounting for approximately 15.33% of annual precipitation. There was an insignificantly increasing trend in water yield over the entire study period ($Z = 0.94$, $P > 0.05$) at a rate of 4.84 mm/10a, with a turning point occurring in 2003.

Fig. 3. Annual precipitation, actual evapotranspiration (AET), potential evapotranspiration (PET) and water yield of the Weihe River Basin, China during 1985–2019

3.1.2 Spatial Variation

As shown in Figure 4, the present study examined spatial distributions of simulated annual water yield. In 1985, overall basin water yield was high, with main water-producing areas located in the Beiluo River Basin, the northern Jinghe River Basin, and the upper reaches of the Weihe River. From 2005 to 2015, annual water yield decreased from east to west and from south to north, with main water-producing areas including the Weihe River mainstream and the southern

Qinling Mountains. Low water yield areas were located in the Jinghe River and Beiluo River basins. Global Moran' s I values obtained by the Geoda model ranged from 0.38 to 0.68, indicating that water yield had a significant spatial agglomeration effect.

Fig. 4. Spatial distribution of water yield in the Weihe River Basin, China. (a) 1985; (b) 2005; (c) 2015; (d) average.

3.2 Response of Water Yield to P and LULC

According to the water yield model principle, P and AET are the main factors affecting simulation results, with AET largely influenced by LULC. This study designed two scenarios to explore changes in water yield under different LULC and P conditions (Table 3). Scenario 1 examined water yield changes under different P intensities, with 1997, 2003, and 2010 representing dry, wet, and average years, respectively. Scenario 2 examined water yield changes under different LULC conditions.

Table 3. P and LULC under different scenarios

Index	Scenario 1	Scenario 2
P	1997, 2003, 2010	2010
LULC	2010	1990, 2010, 2019

Note: P, precipitation; LULC, land use/land cover.

3.2.1 Change in Water Yield under Scenario 1

Scenario 1 results showed that basin water yield changed significantly under different P conditions (Fig. 5). As P increased from less to more, water yield changed accordingly. Maximum water yield during a wet year (675.40 mm) exceeded that during a dry year (133.53 mm) by a factor of 5, and exceeded that during a normal year (365.20 mm) by a factor of 2. Average water yield varied greatly with changing P in 1997, 2003, and 2010, with values of 6.36, 264.63, and 72.96 mm, respectively. The spatial distribution of water yield was consistent with that of P, which was concentrated in southern and eastern areas, corresponding with the main water-producing areas of the WRB.

Fig. 5. Spatial distributions of annual precipitation (P, a-c) and water yield (d-f) in the Weihe River Basin, China under scenario 1

3.2.2 Spatial Correlation between Water Yield and P

The bivariate Moran's I of P and water yield obtained by the Geoda model ranged from 0.30 to 0.80, showing a positive correlation ($P > 0.05$). LISA agglomeration maps of P and water yield showed aggregations mainly of high-high and low-low correlation relationships (Fig. 6). Areas with high-high relationships were concentrated in the southern and eastern WRB, while areas with low-low relationships were concentrated in the northern Jinghe River and Beiluo River basins.

Fig. 6. Spatial distribution of the relationship between annual precipitation and water yield in the Weihe River Basin, China in 1997 (a), 2003 (b) and 2007 (c)

3.2.3 Change in Water Yield under Scenario 2

Scenario 2 results showed that LULC had no significant effect on water yield but impacted its spatial distribution (Fig. 7). There were minimal differences between maximum and average water yield in the basin across 1990, 2010, and 2019, with maximum values of 468.10, 466.88, and 474.54 mm, respectively, and average values of 140.07, 140.9, and 142.85 mm, respectively. Land use type distribution had some impact on the spatial characteristics of water yield. As shown in Figure 7, areas of higher water yield correlated with grassland and farmland, such as the northern Jinghe River and upper reaches of the Weihe River.

Fig. 7. Spatial distributions of LULC (land use/land cover) types (a-c) and water yield (d-f) in the Weihe River Basin, China under scenario 2

3.2.4 Water Yield under Different LULC

ArcGIS 10.2 spatial analysis was used to identify zones of water yield for each land use type under scenario 2. As shown in Figure 8, water yield fluctuations differed among LULC types. Water yields from farmland, forestland, grassland, water body, and construction land continued to increase over the study period, whereas unused land first increased then decreased. The maximum and minimum average water yields were obtained for unused land and water body, at 162.40 and 131.58 mm, respectively.

Fig. 8. Water yield of different LULC (land use/land cover) types in the Weihe River Basin, China

LULC in the WRB changed significantly during the study period. As shown in Table 4, farmland, grassland, and construction land areas changed substantially. Farmland area decreased by 4146.83 km², while water yield increased by 20.00 mm. Forestland, grassland, and construction land areas increased by 498.42, 1624.8, and 1791.96 km², respectively, while water yield increased by

11.34, 24.31, and 12.53 mm, respectively. Unused land area decreased by 9.71 km², while water yield decreased by 17.44 mm. These results indicated that forestland, grassland, unused land, and water body areas had positive correlations with water yield, whereas farmland had a negative correlation. However, grassland and farmland were the dominant land use types in the WRB, accounting for over 80% of the basin's area in 2020. Therefore, water yield was larger in grassland and agricultural land.

Table 4. Changes of LULC (land use/land cover) types of the Weihe River Basin, China from 1990 to 2020

	Farmland Index (km ²)	Forestland (km ²)	Grassland (km ²)	Construction (km ²)	Unused (km ²)	Water (km ²)	Total (km ²)
1990	58,723.94	21,432.95	49,592.64	2,111.34	1,100.00	1,000.00	133,960.87
2020	54,577.11	21,931.37	51,217.44	3,903.30	1,090.29	1,441.36	134,160.87
Change		+498.42	+1,624.80	+1,791.96	-9.71	+441.36	+200.00
	4,146.83						

4.1 Effects of Various Factors on Water Yield

Combined examination of trend analysis, spatial analysis, and scenario analysis results showed that precipitation was the most direct factor affecting regional water yield, consistent with relevant research (Jiang et al., 2016; Li et al., 2021). Regarding AET, it directly participates in the hydrological cycle process (Lewis and Allen, 2017). With emerging challenges from global climate change, AET has gradually increased in recent decades (Fig. 3). This increase may accelerate the hydrological cycle and affect temporal and spatial distributions of hydrological elements (Gusev et al., 2019; Cheng and Li, 2020). AET is affected not only by meteorological factors (temperature, wind speed, relative humidity, and sunshine hours) but also by land use conditions (Lang et al., 2017).

Water yield varies among different land use types due to differences in soil water content, evapotranspiration capacity, litter water holding capacity, and canopy interception. Unused land had the largest water yield because a greater proportion of precipitation directly penetrated the ground or formed surface runoff (Lang et al., 2017). Increased construction land in the basin has not only increased water resource demand but also changed underlying surface conditions. Construction practices transform the ground surface into an impermeable layer by removing vegetation, leading to decreased evapotranspiration and higher water yield capacity (Sterling et al., 2013; Anache et al., 2017). Water yield capacity of water bodies is weak due to strong surface evaporation. Forestland generated relatively lower water yield because of high transpiration and water interception by deep root systems, litter layers, and dense canopies (Vose et al.,

2011; Li et al., 2021). Grassland and farmland effects on precipitation redistribution were similar to forestland, but their regulation effects were relatively weak due to lower canopy coverage and shallower root depth. Additionally, the wide distribution of these two land types resulted in their dominant contributions to water yield. Previous studies have shown that grassland was the optimal land use pattern for maintaining hydrology (Li et al., 2021). Although considerable land use changes occurred in the basin during the study period, these had no significant effect on water yield, likely because mutual transformations among various land types offset any dominant trend in water yield change due to land use changes (Nie et al., 2011).

Land use is the product of human activities, emphasizing human use of natural lands (Lambin et al., 2003; Goldewijk and Ramankutty, 2004; Liu et al., 2013), which can affect ecosystem processes and components. A series of soil and water conservation projects have been conducted in the basin since the 1950s (Mu et al., 2007), including terrace and sediment dam construction, afforestation, plant restoration, pasture improvement, and returning farmland to forestland or grassland. These projects have significantly improved the ecological environment and water supply functions of the basin (Wang et al., 2017; He et al., 2021). The water balance principle indicates that the difference between water yield and measured runoff represents water consumed by agricultural, urban, and industrial activities, plus changes in reservoir storage (Li et al., 2020). The current study calculated WRB runoff as the sum of measured runoff at Huaxian and Zhuangtou hydrological stations (Fig. 1) over years. Results showed an upward trend in annual water consumption ($Z = 1.56$, $P < 0.01$), which has increased pressure on water resources.

4.2 Limitations of the InVEST Model

The InVEST model has been broadly used to evaluate ecosystem service functions and has achieved good results (Lang et al., 2017; Kim and Jung, 2020; Daneshi et al., 2021). However, some uncertainties exist related to model setup and simplified algorithms (Sharp et al., 2020). For example, the model does not consider complex terrain factors and cannot rigorously describe the water balance process under complex underlying surface conditions (Jiang et al., 2016). Topography affects climate by changing regional hydrothermal conditions, which influence vegetation growth and structure, litter accumulation, and soil physico-chemical properties, consequently affecting water yield (Jia et al., 2014; Maurya et al., 2016).

Additionally, the present study obtained root depth and soil data from the global soil database. The low spatial resolution of these data affected model simulation accuracy to some extent. Moreover, the seasonal parameter Z value used in this study differed slightly from those applied in similar watersheds, indicating that differences in natural conditions can lead to large variations in Z , even between

similar basins. Therefore, verifying the Z value is important before applying the InVEST model.

5 Conclusions

The Weihe River is the largest tributary of the Yellow River and holds strategic significance for ecological environment protection and water resources management in Northwest China. The present study applied the InVEST model to quantitatively evaluate water yield in the WRB from 1985 to 2019 and explored the response of water yield to climate factors and land use types.

The average annual water yield was 83.14 mm, with a slight increasing trend over the study period. The Weihe River mainstream and southern region were the primary water-producing areas. Water yield was comprehensively affected by climate and land use factors. Precipitation was the most direct influencing factor, with its spatial distribution corresponding to that of water yield. In contrast, land use did not significantly affect water yield amount, though variation existed among different land use types. Unused land had the highest water yield capacity, but farmland and grassland contributed most to total basin water yield due to their extensive distribution.

These results can serve as a reference for formulating reasonable and efficient water resources allocation schemes. Additionally, the successful InVEST model application in this study can guide its use in related research under similar natural conditions.

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References

References are preserved exactly as in the original manuscript.

Note: Figure translations are in progress. See original paper for figures.

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