water

Article

Study on the Contribution of Land Use and Climate Change to Available Water Resources in Basins Based on Vector Autoregression (VAR) Model

Mengmeng Jiang [1], Zening Wu [2], Xi Guo [2,*], Huiliang Wang [2] and Yihong Zhou [1]

1 School of Water Conservancy and Civil Engineering, Zhengzhou University, Zhengzhou 450001, China; jmm306@zzu.edu.cn (M.J.); zhouyhong0214@163.com (Y.Z.)
2 Yellow River Laboratory, Zhengzhou University, Zhengzhou 450001, China; zeningwu@163.com (Z.W.); wanghuiliang@zzu.edu.cn (H.W.)
* Correspondence: zzuguoxi@163.com

Abstract: Under the influence of global climate change and urbanization processes, the number of available water resources (AWRs) in basins has become significantly more uncertain, which has restricted the sustainable development of basins. Therefore, it is important for us to understand the relationship between land use (LU) patterns and climate change on AWRs in a basin for sustainable development. To this end, the vector autoregressive (VAR) method was adopted to construct a quantitative model for AWRs in the basin in this study. Taking the Yiluo River Basin (YRB) as an example, the dynamic relationship between the five elements of agricultural land (AD), woodland (WD), grassland (GD), construction land (CD), and annual precipitation (PREP) and AWRs in the basin was studied. The results show the following: (1) The constructed VAR model was stable, indicating that the use of the proposed VAR model to characterize the degree of the effect of LU pattern and PREP on AWRs in the YRB was reasonable and effective. (2) AWRs in the YRB showed a downward trend, and their responses to the change in LU and PREP were delayed. The changes in the AWRs in the YRB tended to occur the year after changes to the LU pattern and PREP occurred. (3) In the long run, the degree of the contribution of each influencing factor to changes to AWRs was 23.76% (AD), 6.09% (PREP), 4.56% (CD), 4.40% (WD), and 4.34% (GD), which meant that the impact of the LU pattern was more than 90%. This study provides new ideas for similar research, water resource allocation, and LU planning in other river basins from a macroscopic perspective.

Keywords: basin management; available water resources (AWRs); land use change; precipitation; vector autoregression (VAR) model

check for updates

Citation: Jiang, M.; Wu, Z.; Guo, X.; Wang, H.; Zhou, Y. Study on the Contribution of Land Use and Climate Change to Available Water Resources in Basins Based on Vector Autoregression (VAR) Model. *Water* **2023**, *15*, 2130. https://doi.org/10.3390/w15112130

Academic Editor: Athanasios Loukas

Received: 26 April 2023
Revised: 26 May 2023
Accepted: 1 June 2023
Published: 3 June 2023

1. Introduction

Globally, runoff is undergoing unprecedented changes, which are having a significantly negative impact on water management and utilization in basins [1]. Runoff is closely related to the water resources of social circulation processes [2], which are the foundation of sustainable development in basins and play an important role in the maintenance of the ecological environment, social stability, and food security [3]. Research has found that the excessive expansion of human activities and global climate change have become the main factors affecting water production in the watershed [4,5]. The former is ultimately reflected in land use (LU) changes through population aggregation and industrial layout changes, while the latter affects the water resources of the watershed through meteorological variables such as precipitation [6,7]. The water yield of the watershed is related to the development and utilization of water resources, the control of flood or drought water security issues, and the maintenance of vegetation species [8,9]. In particular, urbanization and economic development have had unprecedented impacts on LU changes and watershed water production conditions, with many rivers experiencing unsustainable water resource exploitation [6]. The use of water in basins constrains land planning, and unreasonable land development has a negative impact on water resources. For example, the excessive development of agricultural land leads to a shortage of irrigation water [10]. In addition, rainfall changes caused by climate change also have a significant impact on regional water supply [11]. Therefore, in the context of increasingly frequent human activities and climate change, it is crucial to understand the patterns of LU in river basins, clarify the role of climate change on available water resources, and quantify their relationship, which is conducive to the formulation of sustainable management policies and the optimization of the allocation of water and soil resources in the basin.

Generally, the majority of the total water resources calculated using river runoff cannot be developed and utilized due to economic, technological, and ecological protection limitations. Only the available water resources obtained through water extraction processes are available to aid human survival and development [12,13]. Therefore, this portion of water resources is not only affected by climate change, but also by human activities. Due to the natural attributes of these influencing factors, research on the impact of runoff is always based on the physical processes of the water cycle, with little attention being paid to the quantification of AWRs in basins, as well as the impact of human activities (LU) and climate change (PREP) on the social attribute of water resource availability. In fact, this portion of water resources is the key to solving the problem of water resource shortages in basins [14,15].

At present, research on the analysis of factors influencing the changes in water resources in basins can generally be divided into four categories. The first category includes distributed and semi-distributed hydrological models based on physical processes, such as SWAT [16], HSPF [17], and MIKE-SHE [18]. These models analyze the influence of different land types on watershed runoff due to the difference in precipitation–evaporation balance caused by the internal hydrological mechanism [19,20]. However, the application of these models is limited because of the complexity of the data sets, the time required for the parameter calibration and verification processes, and the lack of a predictive function. The second category is the use of artificial intelligence technology or new modeling paradigms, such as using data-driven technology to predict monthly river discharge [21], using the coupled wavelet random forest algorithm to improve the accuracy of evapotranspiration estimation in hydrological models [22], and building machine learning models to simulate soil water content data [23]. Although intelligent models can improve the data accuracy of traditional hydrological models and enable the prediction of river runoff, they require more complex modeling techniques to be used by the managers.

The third category is to take the three-dimensional external factors of society, the economy, and the environment into consideration to conduct quantitative research on the relationship between water and soil resources as a whole. For the social dimension, the Gini coefficient [24–26] was used to evaluate the influence of the relationship between land and water resources on society; for the economic dimension, the energy consumption coefficient was selected to reveal urbanization water resources and energy consumption to evaluate the relationship between water and soil resources [27–29]; for the environmental dimension, water footprint was chosen to measure the impact of LU change on the water environment from the consumption of water resources by land area [3,30]. The fourth category is statistical methods, which include the analysis of runoff changes based on the Mann–Kendall rank correlation test, the exploration of the driving factors of runoff changes at obvious change points based on multiple linear regression analysis [31] and precipitation elasticity coefficient methods [32], discussion of the factors affecting the spatial distribution of river water quality based on the spatial autocorrelation analysis method [33], and the estimation of the impact of (LU) and terrain on river water quality based on the principal component analysis method [34]. Although statistical methods avoid complex physical processes and fully utilize data information, simple regression analysis ignores the dynamic variability of influencing factors or only considers the influencing factors at specific moments (sudden changes). Therefore, a new statistical method that can be used to evaluate the dynamic impact of various types of LU and PREP on water resource changes in basins is urgently needed.

Compared with hydrological models and simple regression analysis, the vector autoregression (VAR) model not only has a simple structure, it also reflects the dynamic nature of influencing factors in the water cycle process. The VAR model proposed by Sims [35] is a method for establishing a model based on the statistical characteristics of data to analyze the relationship between multiple interrelated variables. The VAR model treats each endogenous variable in the system as a hysteresis function of all endogenous variables. It is a joint form of multiple time series autoregressive models, expanding the single variable autoregressive model to a vector autoregressive model composed of multiple time series variables [35]. This model not only analyzes and predicts the relationships between variables in the system from the perspective of dynamic impact mechanisms but also quantifies the impact effects [36,37]. Initially, the VAR model was mainly applied in the economic field to describe the dynamic behavior of economic variables [38]. With time, it was gradually applied in other disciplines. Kumar et al. [39] used the VAR model to analyze the degree of influence of the change in the concentration of one air pollutant on the change in the concentration of other pollutants over time. Xu and Lin [40] used the VAR model to explore the driving factors of CO_2 emissions in China. Wu et al. [41] analyzed the contribution of different management measures to carbon stocks of vegetation through the VAR model, which provided a solid foundation for the formulation of effective management policies. However, there are few studies introducing the VAR model into hydrology to explore the impact of different types of LU areas and precipitation (PREP) on changes to water resources.

Therefore, this study attempts to explore the dynamic impact of human activities and climate change on the number of AWRs via the VAR model. The main research content of this study includes: (1) AWRs in the basin were calculated and their temporal changes analyzed, and the VAR model was applied to analyze the response of AWRs in the basin to LU patterns and annual PREP. (2) Taking the Yiluo River Basin (YRB) in China as the research area, the dynamic impact of LU and PREP on AWRs was clarified, and the contribution of these two factors to the AWRs' changes was quantified. (3) The application of the VAR model in the hydrological field was expanded, providing new ideas for basin managers to explore the interaction between water and land resources in basins and resource management planning. The novelty lies in considering the social attributes of water resources, proposing a quantitative method for AWRs in the basin, and combining VAR models to explore the contribution rates of different LU and PREP to AWRs' changes in basins.

2. Materials and Methods

2.1. Study Area

Yiluo River is the largest first-level tributary below Sanmenxia in the Yellow River in China [42]. It is mainly composed of Yi River and Luo River, among which, the Luo River is the main flow and Yi River is the first tributary of the Luo River. The Yiluo River Basin (YRB) is located in the middle reaches of the Yellow River Basin between Sanmenxia and Huayuankou, between 109°17′ E~113°10′ E and 33°39′ N~34°54′ N. It flows through Shaanxi and Henan provinces in a total of 18 counties (cities), covering an area of 18,881 km^2. The topography of the YRB is complex. Mountainous and hilly areas cover a large portion of the area, and natural secondary forests and plantations are the main vegetation. The YRB has a long history of agricultural production and a wide range of industrial categories, and the tertiary industry has undergone rapid development in this area, which has increased the need for the development and utilization of water and soil resources in the basin. Obviously, it is necessary to understand the dynamic response of AWRs to the changes in LU and climate in the basin.

The geographical location, LU distribution, and flowing regions of the YRB are shown in Figure 1. The data collected in this study include historical precipitation data, annual LU, and water resource data. Annual precipitation data were obtained by using Tyson polygon interpolation, based on the original data collected during precipitation observation stations in the YRB, from the China Hydrological Yearbook—Hydrological Data of Yellow River Basin [43]. The annual LU data were derived from the Chinese LU/LC dataset created by Yang and Huang [44]. The spatial resolution of land cover (LC) was 30 m, and the average overall accuracy (OA) of the data reached 79.31%. The clip tool of the ArcGIS platform was used to cut the data set. Land use data at 30 m resolution in the YRB from 2001 to 2019 were obtained. Data regarding water resources in the YRB in 2001–2019 were obtained from the Comprehensive planning for YRB [42], the water resources bulletin in Shaanxi Province (accessed on 12 December 2022, http://slt.shaanxi.gov.cn/zfxxgk/fdzdgknr/zdgz/szygb/index.html), and the water resources bulletin in Henan Province (accessed on 12 December 2022, https://slt.henan.gov.cn/bmzl/szygl/szygb/). Additionally, the cross-validation method was used to determine the consistency of data from different sources. The selected variables were AWRs and the area of land use type, including agricultural land (AD), woodland (WD), grassland (GD), construction land (CD), and annual precipitation (PREP). In order to eliminate the influence of heteroscedasticity as much as possible and reduce the influence caused by the different dimensions of the measurement units of the variables, logarithm transformation was carried out on all variables; therefore, the processed variables were LNAWR, LNAD, LNWD, LNGD, LNCD, and LNPREP.

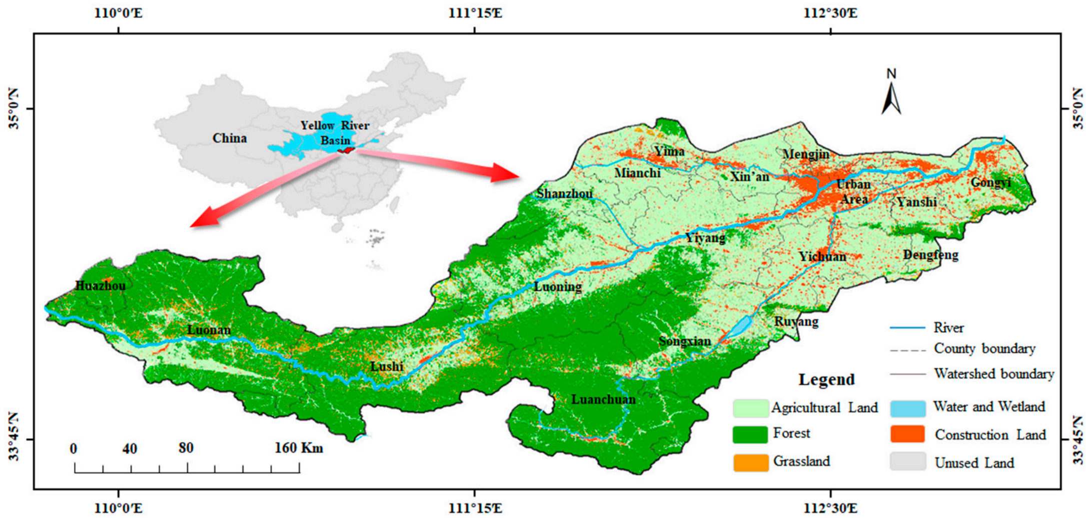

Figure 1. The geographical location, LU distribution, and flowing regions of YRB.

2.2. Calculation of AWRs in the Basin

AWRs in basins include surface water and shallow groundwater [45]. The former occupies a large proportion in the process of water resource utilization in a basin and changes with the amount of surface water resources, while the latter accounts for a relatively small portion, and the water supply is stable due to the difficulty in its exploitation [46]. According to China's Technical Specification for Forecasting Analysis of Water Resources Supply and Demand [47] and relevant research results [12], the formula for calculating AWRs in a basin is as follows:

$$W_{aq} = W_{saq} + W_{uaq} \tag{1}$$

$$W_{saq} = W_{sq} - W_{eq} - W_{fq} \pm W_{tq} \tag{2}$$

$$W_{uaq} = \xi * W_{uq} \tag{3}$$

where W_{aq} is the number of AWRs in the whole basin, 10^8 m^3; W_{saq} is AWRs from surface water in the basin, 10^8 m^3; W_{uaq} is AWRs from groundwater in the basin, 10^8 m^3; W_{sq} is the amount of surface water, 10^8 m^3; W_{eq} is water demand for the eco-environment inside the river, 10^8 m^3; W_{fq} is the unusable flood discards, 10^8 m^3; W_{tq} is the transfer water inter-basin, 10^8 m^3; ξ is the coefficient of groundwater extraction; W_{uq} is the amount of groundwater, 10^8 m^3.

2.3. Construction Steps in VAR Model between AWRs and LU and Precipitation in the Basin

The premise of establishing a VAR model for multiple time series is that variables need to be stable. The purpose of modeling is to analyze the influence mechanism among variables, quantify the influence degree, and predict variables. If $\boldsymbol{y}_t$ represents the column vector of k-dimensional endogenous variables (the number of variables is k), p is the lag period of the model, denoted as VAR (p). The mathematical expression is as follows:

$$\boldsymbol{y}_t = c + \boldsymbol{\alpha}_1 \boldsymbol{y}_{t-1} + \cdots + \boldsymbol{\alpha}_p \boldsymbol{y}_p + \boldsymbol{\varepsilon}_t \tag{4}$$

where c is constant; $\boldsymbol{y}_{t-i}, i = 1, 2, \ldots, p$ is the lagged endogenous variable; $\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_n$ is the column vector of the matrix of coefficients to be evaluated for $\boldsymbol{y}_t$; $\boldsymbol{\varepsilon}_t$ is the vector generalization of the random perturbation term. The model-constructing steps mainly include the following two parts:

Step (1): Stability test of variables

The stationary time series variable that passes the unit root test is the necessary condition for constructing a VAR model. The Augmented Dickey–Fuller (ADF) test and the nonparametric Phillips–Perron (PP) test are the most commonly used unit root tests [48]. The long-term relative stability between stable variables is the basis of the VAR model. Therefore, Johansen and Juselius proposed the Johansen co-integration test in 1988 [49], which tested the co-integration relationship of variables through the maximum likelihood matrix. After the system variables pass the stationarity test and co-integration test, the first step in constructing a VAR model is to determine the appropriate lag period, which also reflects the dynamic characteristics of the interaction between variables. The information criteria for judging the length of lag period include the likelihood ratio test (LR), the final prediction error (FPE), Akaike Information Criteria (AIC), Schwartz Bayesian Criteria (SC), and the Hannan–Quinn information criteria (HQ) [50].

Step (2): Stability test of VAR model

Only when the constructed VAR model is stable is simulation analysis feasible. The principle of the stability test of the model is to introduce a specific characteristic coefficient to solve the characteristic root of the difference equation obtained by the differential processing of the model. If all the eigenvalues are in the unit circle (the unit circle is a circle with the origin as the center and the radius of 1, located in the coordinates with the horizontal axis as the real number axis and the vertical axis as the imaginary number axis), the VAR model constructed is stable; otherwise, the model is unstable. Only a stable VAR model has practical analytical significance [51].

2.4. Analysis of VAR Model between AWRs and LU and Precipitation in the Basin

The idea of analyzing the influence relationship with a time series is to consider how the influence of the disturbance term is transmitted to each variable and the degree of disturbance that each variable undertakes. The former is an impulse response function (IRF), and the latter is variance decomposition. The VAR model is not a traditional theoretical model, with too many coefficients to directly reflect the relationship between variables; therefore, the IRF and variance decomposition explain and describe the VAR model. The IRF test reflects the dynamic feedback process of system variables to random disturbance terms through the impact of impulse from a system on variables in the current and future periods, so as to obtain the explainability of one variable by another variable in the system and analyze the importance of the variable. The principle of the IRF is as follows:

$$y_{it} = \sum_{j=1}^{k} \left(\theta_{ij}^{0} \varepsilon_{jt} + \theta_{ij}^{1} \varepsilon_{jt-1} + \theta_{ij}^{2} \varepsilon_{jt-2} + \theta_{ij}^{3} \varepsilon_{jt-3} + \ldots \right) \; t = 1, 2, \ldots, T \tag{5}$$

where Equation (5) is the expression of the Vector Moving Average (VMA) under the order of infinite; $\boldsymbol{\varepsilon}_t = (\varepsilon_{1t}, \ldots, \varepsilon_{kt})'$ is a random disturbance term; y_{it} is the variable; θ_{ij}^{0}, θ_{ij}^{1}, θ_{ij}^{2}, $\theta_{ij}^{3} \ldots$ is the response function of y_j caused by the impulse of y_j, and then, the cumulative response function of the j perturbation term from an infinite past to present time point y_j is $\sum_{q=0}^{\infty} \theta_{ij}^{(q)}$.

Some random error terms from variables will be generated in the process of an IRF analysis, which all contain important information about the relationship between variables. Therefore, variance decomposition is used to explain this information as a whole. The analytical idea is that when there is no sequence correlation for the disturbance term, Equation (6) can be obtained according to the cumulative response function obtained using Equation (5):

$$E\left[\left(\theta_{ij}^{0} \varepsilon_{jt} + \theta_{ij}^{1} \varepsilon_{jt-1} + \theta_{ij}^{2} \varepsilon_{jt-2} + \theta_{ij}^{3} \varepsilon_{jt-3} + \ldots \right)^{2} \right] = \sum_{q=0}^{\infty} \left(\theta_{ij}^{(q)} \right)^{2} \sigma_{ij} \\ i, j = 1, 2, \ldots, k \tag{6}$$

where σ_{ij} is the covariance matrix of the perturbation term vector. If the covariance matrix is assumed to be a diagonal matrix, then the variance of y_i is

$$\mathrm{var}(y_i) = \sum_{j=1}^{k} \left\{ \sum_{q=0}^{\infty} \left(\theta_{ij}^{q} \right)^{2} \sigma_{jj} \right\} \; i, j = 1, 2, \ldots, k \tag{7}$$

where σ_{jj} is a member of the assumed diagonal matrix.

Then, the variance of y_i is decomposed into k kinds of unrelated influences, so as to obtain the contribution of each variable to the impact of endogenous variables of the system, as shown in Equation (8):

$$RVC_{j \to i}(\infty) = \frac{\sum_{q=0}^{\infty} \left(\theta_{ij}^{q} \right)^{2} \sigma_{jj}}{\mathrm{var}(y_i)} = \frac{\sum_{q=0}^{\infty} \left(\theta_{ij}^{q} \right)^{2} \sigma_{jj}}{\sum_{j=1}^{k} \left\{ \sum_{q=0}^{\infty} \left(\theta_{ij}^{q} \right)^{2} \sigma_{jj} \right\}} \\ i, j = 1, 2, \ldots, k \tag{8}$$

In other words, the relative variance contribution rate (RVC) reflects the influence of the j variable on the i variable through the difference of the influence of each variable on the system disturbance (relative contribution rate).

2.5. Error Correction Model Analysis

The error correction model (ECM) usually appears as a supplementary model of the VAR model. The VAR model explains the long-term relationship between variables, while the ECM explains the short-term relationship. The principle of the ECM is to treat the error correction term as an explanatory variable and build a short-term model together with other explanatory variables, as shown in Equation (9):

$$\Delta \boldsymbol{y}_t = \boldsymbol{\gamma} \boldsymbol{ecm}_{t-1} + \boldsymbol{\beta}_i \Delta \boldsymbol{x}_t + \boldsymbol{\varepsilon}_t \tag{9}$$

3. Results

3.1. Temporal Variation in AWRs and PREP in YRB

Figure 2 reveals the temporal variation in the annual AWRs and PREP in the YRB from 2001 to 2019. The maximum AWR was 4.29 × 10^9 m^3 in 2003, with the highest PREP of 335.50 mm that year. The minimum AWR was 8.06 × 10^8 m^3 in 2008, while the minimum PREP was 513.15 mm in 2013. It could be seen that the trend of AWRs and PREP was declining overall in the period 2001–2019, and their fluctuation curves were similar. The change in the LU pattern is mainly reflected in the change in different land types. The LU types in the basin were divided into agricultural land (AD), woodland (WD), grassland (GD) and construction land (CD). Table 1 shows the change in LU coverage and dynamic attitude in the YRB during 2001–2019. As can be seen from Table 1, AD and WD were the main LU types in the YRB, and the area of AD and GD was gradually decreasing, while there was a continuous increase in the area of WD and CD.

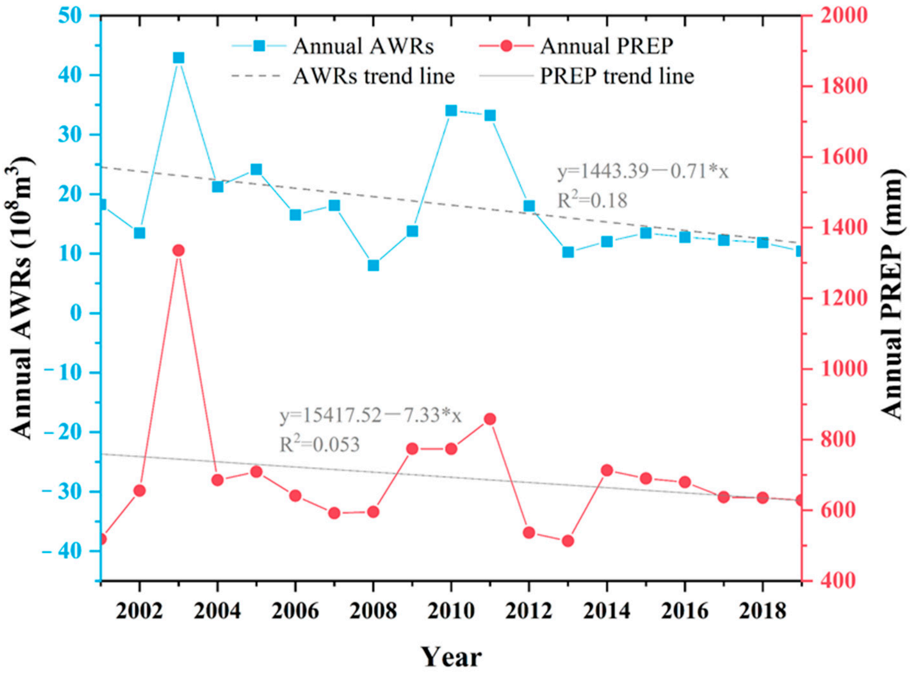

Figure 2. Temporal variation in AWRs and PREP in YRB during 2001–2019.

Table 1. Land use coverage and dynamic attitude in YRB from 2001 to 2019.

Land Use Type	Coverage (%)			Dynamic Attitude (%)	
	2001	2010	2019	2001–2010	2010–2019
Agricultural land	46.82	44.70	42.61	−2.12	−2.10
Woodland	40.92	42.30	45.71	1.38	3.41
Grassland	7.62	6.85	4.09	−0.77	−2.76
Water and wetland	0.37	0.49	0.52	0.11	0.03
Construction land	4.27	5.66	7.08	1.39	1.41
Unused land	0.00	0.00	0.00	0.00	0.00
Total	100.00	100.00	100.00		

3.2. Establishment of VAR Model

In order to eliminate the influence of heteroscedasticity as much as possible and reduce the influence caused by different unit dimensions of variables, logarithmic transformation was adopted on all variables. The area of wetland and unused land changed slightly; therefore, VAR modeling was carried out for the time series of annual AWRs and the area of land use type, including agricultural land (AD), woodland (WD), grassland (GD), construction land (CD), and annual precipitation (PREP).

(1) Test of stationarity

The first step in VAR modeling is to test whether the variable time series are stationary. The variables after logarithmic processing were LNAWR, LNAD, LNWD, LNGD, LNCD, and LNPREP. The results of the unit root test on the variables are summarized in Table 2. The ADF statistic of other time series were all greater than the critical value of 5% except PREP; therefore, their unit root process could not be rejected, which meant the time series was non-stationary. However, the sequence of AWRs and the area of AD after first-order difference and other sequences after second-order difference did not have unit roots, which were the stationary time series. Therefore, a VAR model could be constructed to describe the influence relationship among variables in the YRB.

Table 2. Stationarity test of time series of variables in YRB.

Variable	ADF Test Statistic	*p* Value	Critical Values at Different Significance Levels			Conclusion
			1%	5%	10%	
LNAWR	−3.297	0.0667	−4.380	−3.600	−3.240	Unstable
D (LNAWR)	−4.991	0.0000	−3.750	−3.000	−2.630	Stable
LNAD	−2.253	0.4600	−4.380	−3.600	−3.240	Unstable
D (LNAD)	−3.692	0.0042	−3.750	−3.000	−2.630	Stable
LNWD	0.388	0.9966	−4.380	−3.600	−3.240	Unstable
D (LNWD)	−2.207	0.2036	−3.750	−3.000	−2.630	Unstable
DD (LNWD)	−7.858	0.0000	−3.750	−3.000	−2.630	Stable
LNGD	1.235	1.0000	−4.380	−3.600	−3.240	Unstable
D (LNGD)	−0.447	0.9020	−3.750	−3.000	−2.630	Unstable
DD (LNGD)	−3.382	0.0116	−3.750	−3.000	−2.630	Stable
LNCD	0.218	0.9959	−4.380	−3.600	−3.240	Unstable
D (LNCD)	−2.422	0.1356	−3.750	−3.000	−2.630	Unstable
DD (LNCD)	−5.872	0.0000	−3.750	−3.000	−2.630	Stable
LNPREP	−3.915	0.0019	−3.750	−3.000	−2.630	Stable

Note: D represents the first-order difference; DD represents the second-order difference.

(2) Test of Johansen cointegration

The results of the Johansen cointegration test conducted on the stationary sequence after difference of variables in the YRB are shown in Table 3. When the number of cointegration equations was 0, the statistics of trace and Max-Eigen were 64.8863 and 42.4523, respectively, both of which were greater than the critical value of 5%. Therefore, the null hypothesis of "there are 0 cointegration relations" was rejected. This indicated that there was a long-term equilibrium relationship among the series of AWRs and the area of AD, WD, GD, CD, and PREP in the YRB at the significant level of 5%. Thus, it could be verified that the VAR model was of practical significance in quantitatively expressing the relationship between LU pattern and PREP on AWRs in the YRB.

Table 3. Johansen cointegration test of variables in YRB.

		Trace Test		
H0: rank = r	eigenvalue	Trace statistic	Critical values at 5%	*p* value
None *	0.9410	64.8863	63.8761	0.0410
At most 1	0.5763	22.4339	42.9153	0.8981
At most 2	0.3327	9.5539	25.8721	0.9426
		Max-Eigenvalue Test		
H0: rank = r	eigenvalue	Max-Eigen statistic	Critical values at 5%	*p* value
None *	0.9409	42.4523	32.1183	0.0019
At most 1	0.5762	12.8799	25.8232	0.8127
At most 2	0.3326	6.0675	19.3870	0.9529

Note: * represents that the null hypothesis is rejected at the significance level of 10%.

(3) Selection of the lag period for VAR

The statistics of FPE, AIC, LR, SC, and HQ applied to the time series of the VAR model in the YRB were calculated using Eviews9.0 software (as shown in Table 4). The optimal lag period was selected to be 1 under the information criterion. In other words, the number of parameters in the VAR model was the most appropriate at this time, and the model parameters could be estimated effectively. Then, the parameters of the VAR model for AWRs were preliminarily estimated through the Eviews9.0 software.

Table 4. Selection of the lag period for VAR model in YRB.

Lag	LogL	LR	FPE	AIC	SC	HQ
0	−191.8878	NA	191.7975	19.7500	17.3094	18.3107
1	−186.9326	28.6519	698.3145 *	27.0577 *	27.8129 *	27.0496 *
2	−174.1036	11.9737	1652.9160	27.4804	28.9909	27.4644

Note: * represents that the null hypothesis is rejected at the significance level of 10%.

(4) Stability test of VAR model

Stability testing of the built VAR model was carried out, as shown in Figure 3. The results showed that the reciprocal values of all unit roots of the model were less than 1, which meant they were all within the unit circle. This indicated that the constructed VAR model was stable, and it was reasonable and effective for quantitatively representing the effect degree of LU and PREP on AWRs in the YRB with the VAR model.

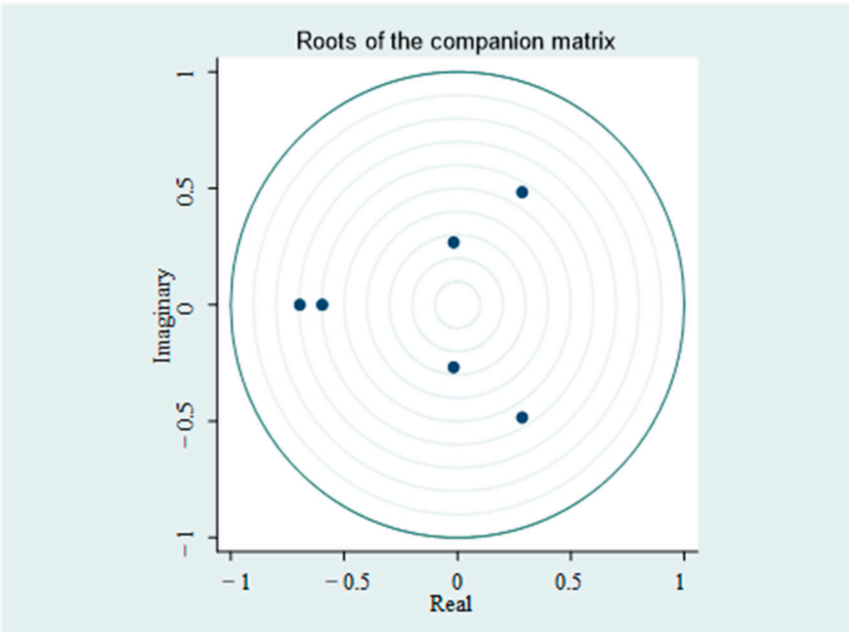

Figure 3. Stability test of VAR model in YRB.

3.3. VAR Analysis Results

(1) The dynamic response of AWRs to change in LU and PREP in YRB

The response of AWRs in the YRB to changes in the LU pattern and PREP was determined based on the basic principle of the IRF, as shown in Figure 4, where the horizontal axis refers to the lag period, and the vertical axis refers to the response value. The response of AWRs in the YRB to the area of AD (Figure 4a), WD (Figure 4b), and GD (Figure 4c) was 0, and they showed negative fluctuations from the second year. The fluctuation coefficients were −0.239, −0.104, and −0.102, respectively, reflecting the hysteresis quality in the impact of changes. Finally, the positive and negative fluctuations tended to 0. This was because the PREP was intercepted by the vegetation layer and soil layer, avoiding the direct impact of rainwater on the ground and leading to runoff in the basin being regulated and water sources being conserved. In the short term, the number of surface water resources decreased and then increased slowly. Conversely, the increase in CD (Figure 4d) had a positive effect on AWRs in the second year, with a coefficient of 0.064, and a negative effect in the third year. This is because CD changed the natural circulation path of water, which increased the water resources in the basin in the short term. However, in the long term, the water resources presented a decreasing trend due to the increase in the human consumption of water resources. The impact of PREP (Figure 4e) began from the second year, and the pulse effect was first positive and then negative, and then fluctuated around 0.

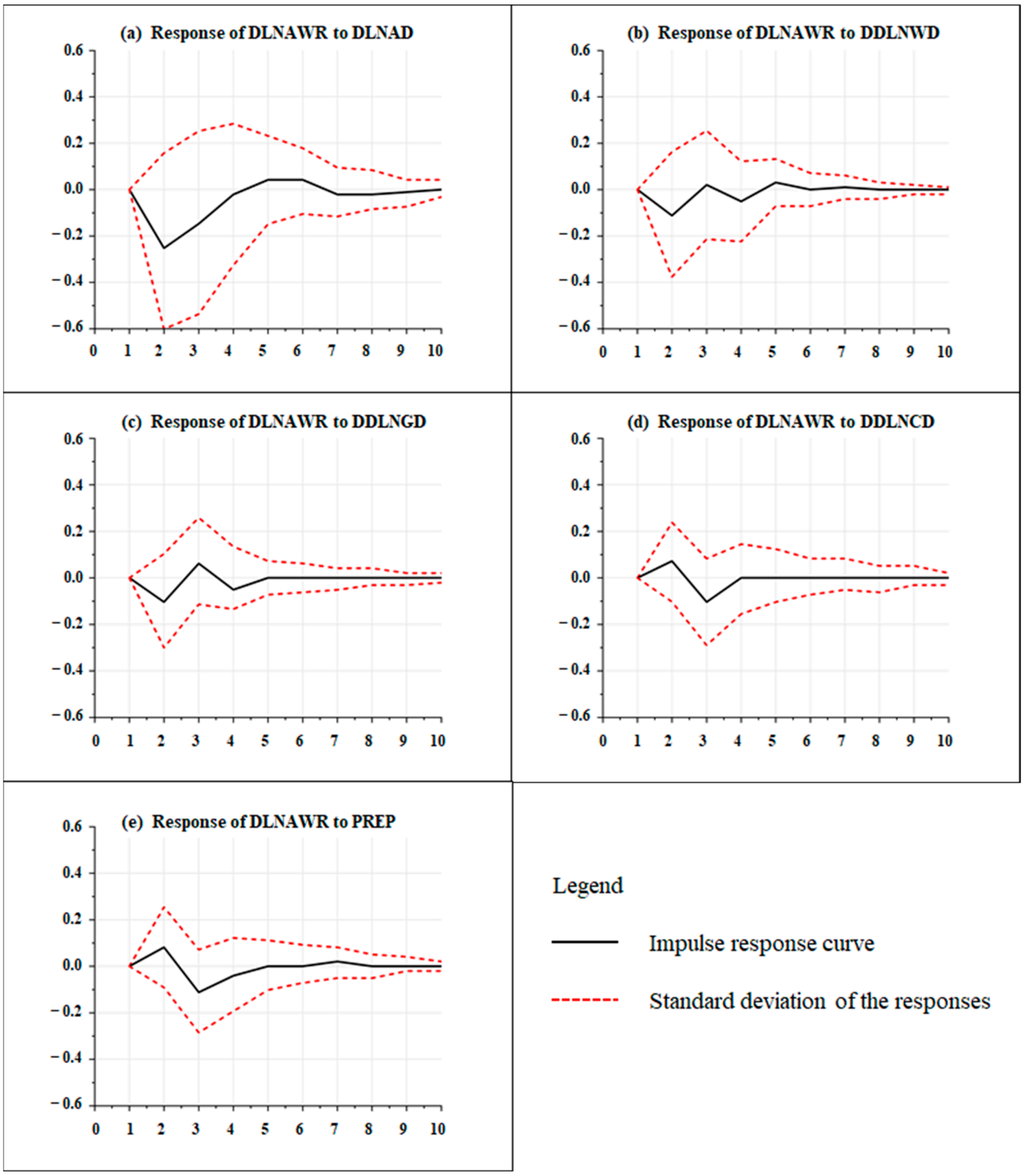

Figure 4. Response curve of AWRs to LU and PREP.

(2) Contribution of LU and PREP changes to AWRs' changes in YRB

Based on the basic principle of variance decomposition, the contribution degree of AD, WD, GD, CD, and PREP to the changes in AWRs in the YRB was analyzed, and the results are displayed in Table 5. In addition to the contribution of AWRs themselves in the YRB, the contribution rates of AD, WD, GD, CD, and PREP to AWRs' changes were 23.76%, 4.40%, 4.34%, 4.56%, and 6.09%, respectively. In general, the impact of LU on AWRs' changes was much higher than that of PREP.

Table 5. Results of variance decomposition of AWRs in YRB.

Period	S.E.	DLNAWR	DLNAD	DDLNWD	DDLNGD	DDLNCD	LNPREP
1	0.4230	100.0000	0.0000	0.0000	0.0000	0.0000	0.0000
2	0.5250	67.8792	20.6738	3.8886	3.7686	1.4782	2.3114
3	0.5684	58.4357	23.4246	3.4198	4.4665	4.5407	5.7124
4	0.5733	57.7600	23.1236	4.1345	4.3900	4.5223	6.0693
5	0.5756	57.3152	23.4113	4.3887	4.3555	4.5056	6.0234
6	0.5771	57.0252	23.7692	4.3685	4.3327	4.4863	6.0179
7	0.5776	56.9308	23.7429	4.3916	4.3364	4.5243	6.0739
8	0.5778	56.9007	23.7303	4.4027	4.3401	4.5433	6.0827
9	0.5779	56.8695	23.7605	4.4007	4.3409	4.5468	6.0813
10	0.5780	56.8509	23.7596	4.4008	4.3433	4.5559	6.0892

(3) Analysis of ECM in YRB

The ECM between AWRs and areas of LU and PREP was constructed through the analysis of the VAR model, as shown in Table 6 and Equation (10). In the short term, the influence of LU and PREP on AWRs in the YRB was significant. Under the condition that other variables remained unchanged, when AD increased by 1 unit, AWRs increased by 550.23 units. When the area of WD, GD, and CD increased by 1 unit, the AWRs in YRB decreased by 2041.71, 264.53, and 468.03 units, respectively, while when PREP increased by 1 unit, AWRs increased by 22.74 units.

$$\begin{aligned} DLNAWR(-1) &= 550.2299 * DLNAD(-1) - 2041.7050 * DDLNWD(-1) \\ &-264.5290 * DDLNGD(-1) - 468.0315 * DDLNCD(-1) \\ &+22.7362 * LNPREP(-1) - 145.7459 \end{aligned} \tag{10}$$

Table 6. The ECM between AWRs and LU and PREP in YRB.

Variable	DLNAD	DDLNWD	DDLNGD	DDLNCD	LNPREP	Constant
Test result	550.2299 **	−2041.7050 ***	−264.5290 ***	−468.0315 ***	22.7362 ***	−145.7459 ***
	(224.5070)	(189.0030)	(27.4488)	(49.2207)	(3.7975)	
	[2.4508]	[−10.8025]	[−9.6372]	[−9.5088]	[5.9871]	

Note: ** and *** represent that the null hypothesis is rejected at the significance level of 10%, 5% and 1% respectively.

4. Discussion

This section details the dynamic effects of each LU area and PREP on AWRs in the basin and how these findings relate to and differ from previous studies.

(1) Explanation of the hysteresis of AWRs in YRB

On the whole, the pulse response curves of AWRs in the YRB are smooth (Figure 4), indicating that the response of AWRs in the basin to changes in the pattern of LU and annual PREP is slow. This means that the impact of LU pattern adjustment on water resources in the first year manifests in the second year. In previous studies [52], the water yield of a river under natural conditions and water demand under an LU pattern were mainly considered in the process of water resource allocation in the basin. This study found that when managers allocate water resources in the second year, changes in AWRs in the basin caused by changes in the LU pattern in the previous year should also be considered. For example, the expansion of CD driven by economic development will lead to the increase in AWRs in the next year; therefore, the water resource allocation scheme in the basin should be adjusted in time to avoid the unnecessary wastage of water resources. Similarly, in the process of LU planning in a basin, it not only needs to meet the needs of human social and economic development [51,53], it also needs to consider the impact of LU types on watershed AWRs. Thus, the contradiction between the expansion of WD and GD for ecological restoration and the increase in CD for social and economic development can be alleviated.

(2) Difference between LU and PREP on AWRs change

Most studies have shown that surface vegetation can reduce water resources in basins, but the degree of reduction has not been quantified [54,55]. Through the VAR model constructed in this study, it was found that the contribution rates of AD, WD, GD, CD, and PREP to changes in AWRs were 23.76%, 4.40%, 4.34%, 4.56%, and 6.09%, respectively. In other words, the change in AR area is the focus of consideration in YRB LU planning. WD and GD can also help reduce AWRs in the YRB on the basis of the analysis of the VAR model constructed in this study [56], both in the short and long term (Figure 4 and Table 5). This is because forest canopies can weaken the direct impact of PREP on the surface, and the developed root system can effectively increase the infiltration of soil to rainfall, the water-holding capacity of which will continue. The increase in the area of AD leads to the increase in AWRs in the YRB in the short term, because human farming activities and fertilizer application change the original water-holding characteristics of the land, leading to increased surface runoff. Meanwhile, with the consumption of water resources by crops, the long-term impact results include a decrease in AWRs in the basin. There are abundant human activities on CD that cause great levels of water consumption [57], which will cause the negative growth of AWRs in the YRB in the short run. However, in the long run, the impervious area increases gradually with social development, leading to an increase in surface runoff and even extreme precipitation events, which generate a greater flood risk in the basin [58]. AWRs, as water resources, are closely related to PREP, as is shown in most studies [59]. Therefore, the comprehensive impact of LU pattern changes on AWRs in different periods should be considered in water resource allocation in basins. The total change in AWRs caused by the change in the land area of different types may increase in the short term but may lead to a decrease after long-term development.

(3) Contributions and limitations of the model

This study introduced the VAR model to establish a research framework for the calculation of AWRs of the basin and to quantify the contribution of changes in LU and PREP to the change in AWRs based on the easy-to-access statistical data. Quantifying the impact degree helped us to determine the direction basin managers should take explore how human activities and climate change affect AWRs in the basin, which provides a new way for basin managers to optimize land layout and water resource allocation. However, this study only considered the impact of rough LU types on AWRs without the further classification of land types. For example, there may be significant differences in the effects of different forest cover types, including arbors, broad-leaved forests, and shrubs, on AWRs. At the same time, the specific effects of human activities and climate change on the water quality of the basin were not considered. In the future, multivariate data fusion will be considered to expand the model and improve the data. The effect of more detailed influencing factors on AWRs and water quality will be explored from the perspective of the whole basin, so as to improve the comprehensiveness of basin management measures.

5. Conclusions

In order to understand the changes in AWRs and the main influencing factors from the perspective of the whole basin and strengthen the management of water and land resources in the sustainable development of the basin, this study calculated the AWRs in the YRB and introduced the VAR model to quantitatively analyze the impacts of different land types and PREP changes on AWRs, and their long-term and short-term impacts were quantified.

(1) Overall, the AWRs in the YRB showed a downward trend, and the time series of AWRs and the area of AD, WD, GD, CD, and PREP were stable after logarithmic and differential processing. The Johansen cointegration test was used to determine that there was a long-term stable relationship between the area of different land types, annual PREP, and AWRs in the basin, indicating that the constructed VAR model was feasible.

(2) There was a lag in the response of AWRs to changes in LU and PREP in the YRB in the current year, which occurred in the next year. The impacts of different land types on AWRs in the YRB were different. Meanwhile, the same land type had different effects on AWRs in different periods in the YRB. In the long run, the contribution degree of each influencing factor to changes in AWRs was 23.76% (AD), 6.09% (PREP), 4.56% (CD), 4.40% (WD), and 4.34% (GD), which lay the foundation for land planning in the YRB.

(3) The framework proposed in this study quantified AWRs in the YRB and analyzed the contribution rates of its influencing factors, indicating that human activities and climate change have different effects on the short-term and long-term effects of AWRs in the YRB. These research ideas and methods can provide new ideas for similar research in other river basins and water resource allocation and LU planning.

Author Contributions: All authors contributed to this study's conception and design. Conceptualization, data curation, formal analysis, software, writing—original draft preparation, writing—review and editing, M.J.; supervision, conceptualization, Z.W.; data curation, software, project administration, funding acquisition, X.G.; writing—original draft preparation, H.W.; methodology, visualization, Y.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Key Technologies Research and Development Program of China (2021YFC3000204).

Data Availability Statement: The data set used or analyzed during this study is under study and cannot be shared due to confidentiality. Some of the publicly available datasets are detailed in the manuscript with sources and access.

Acknowledgments: We would like to express our gratitude to the anonymous reviewers for their valuable comments.

Conflicts of Interest: We declare that we have no competing financial interest or personal relationships that could have appeared to influence the work reported in this study.

References

1. Wang, F.; Duan, K.; Fu, S.; Gou, F.; Liang, W.; Yan, J.; Zhang, W. Partitioning climate and human contributions to changes in mean annual streamflow based on the Budyko complementary relationship in the Loess Plateau, China. *Sci. Total Environ.* **2019**, *665*, 579–590. [CrossRef] [PubMed]
2. Lu, S.; Zhang, X.; Bao, H.; Skitmore, M. Review of social water cycle research in a changing environment. *Renew. Sustain. Energy Rev.* **2016**, *63*, 132–140. [CrossRef]
3. Gleeson, T.; Wada, Y.; Bierkens, M.F.P.; van Beek, L.P.H. Water balance of global aquifers revealed by groundwater footprint. *Nature* **2012**, *488*, 197–200. [CrossRef]
4. Aboelnour, M.; Gitau, M.W.; Engel, B.A. Hydrologic Response in an Urban Watershed as Affected by Climate and Land-Use Change. *Water* **2019**, *11*, 1603. [CrossRef]
5. Plummer, R.; Velaniškis, J.; de Grosbois, D.; Kreutzwiser, R.D.; de Loë, R. The development of new environmental policies and processes in response to a crisis: The case of the multiple barrier approach for safe drinking water. *Environ. Sci. Policy* **2010**, *13*, 535–548. [CrossRef]
6. Duan, W.; Chen, Y.; Zou, S.; Nover, D. Managing the water-climate-food nexus for sustainable development in Turkmenistan. *J. Clean. Prod.* **2019**, *220*, 212–224. [CrossRef]
7. Zahabiyoun, B.; Goodarzi, M.R.; Bavani, A.R.M.; Azamathulla, H.M. Assessment of Climate Change Impact on the Gharesou River Basin Using SWAT Hydrological Model. *CLEAN–Soil Air Water* **2013**, *41*, 601–609. [CrossRef]
8. Reheman, R.; Kasimu, A.; Duolaiti, X.; Wei, B.; Zhao, Y. Research on the Change in Prediction of Water Production in Urban Agglomerations on the Northern Slopes of the Tianshan Mountains Based on the InVEST-PLUS Model. *Water* **2023**, *15*, 776. [CrossRef]
9. Robertson, A.D.; Zhang, Y.; Sherrod, L.A.; Rosenzweig, S.T.; Ma, L.; Ahuja, L.; Schipanski, M.E. Climate Change Impacts on Yields and Soil Carbon in Row Crop Dryland Agriculture. *J. Environ. Qual.* **2018**, *47*, 684–694. [CrossRef]
10. Mosleh, Z.; Salehi, M.H.; Amini Fasakhodi, A.; Jafari, A.; Mehnatkesh, A.; Esfandiarpoor Borujeni, I. Sustainable allocation of agricultural lands and water resources using suitability analysis and mathematical multi-objective programming. *Geoderma* **2017**, *303*, 52–59. [CrossRef]
11. Dzirekwa, S.; Gumindoga, W.; Makurira, H.; Mhizha, A.; Rwasoka, D.T. Prediction of climate change impacts on availability of surface water resources in the semi-arid Tugwi Mukosi catchment of Zimbabwe. *Sci. Afr.* **2023**, *20*, e01691. [CrossRef]

12. Jia, S.; Zhou, C.; Yan, H.; Zhou, H.; Tang, Q.; Zhang, J. Estimation of usable water resources and carrying capacity in Northwest China. *Adv. Water Resour.* **2004**, *06*, 801–807. (In Chinese)
13. Wenjing, L. Test Study on the Available Water Resources of Daqing River Basin. Master's Thesis, Hebei University of Engineering, Handan, China, 2014.
14. Pervez, M.S.; Henebry, G.M. Assessing the impacts of climate and land use and land cover change on the freshwater availability in the Brahmaputra River basin. *J. Hydrol. Reg. Stud.* **2015**, *3*, 285–311. [CrossRef]
15. Cosgrove, W.J.; Loucks, D.P. Water management: Current and future challenges and research directions. *Water Resour. Res.* **2015**, *51*, 4823–4839. [CrossRef]
16. Arnold, J.G.; Srinivasan, R.; Muttiah, R.S.; Williams, J.R. Large area hydrologic modeling and assessment part I: Model development. *JAWRA J. Am. Water Resour. Assoc.* **1998**, *34*, 73–89. [CrossRef]
17. Donigian, A.; Bicknell, B.R.; Imhoff, J.C.; Singh, V.P. Hydrological Simulation Program—Fortran (HSPF). In *Computer Models of Watershed Hydrology*; Water Resources Pubns: Littleton, CO, USA, 1995.
18. Zölch, T.; Henze, L.; Keilholz, P.; Pauleit, S. Regulating urban surface runoff through nature-based solutions—An assessment at the micro-scale. *Environ. Res.* **2017**, *157*, 135–144. [CrossRef]
19. Zhaoxi, Z. Assessments of Impacts of Climate Change and Human Activities on the Runoff from the Fenhe River Basin into the Yellow River. Master's Thesis, Zhengzhou University, Zhengzhou, China, 2016.
20. Costa, M.H.; Botta, A.; Cardille, J.A. Effects of large-scale changes in land cover on the discharge of the Tocantins River, Southeastern Amazonia. *J. Hydrol.* **2003**, *283*, 206–217. [CrossRef]
21. Terzi, Ö.; Ergin, G. Forecasting of monthly river flow with autoregressive modeling and data-driven techniques. *Neural Comput. Appl.* **2014**, *25*, 179–188. [CrossRef]
22. Shiri, J. Improving the performance of the mass transfer-based reference evapotranspiration estimation approaches through a coupled wavelet-random forest methodology. *J. Hydrol.* **2018**, *561*, 737–750. [CrossRef]
23. Karandish, F.; Šimůnek, J. A comparison of numerical and machine-learning modeling of soil water content with limited input data. *J. Hydrol.* **2016**, *543*, 892–909. [CrossRef]
24. Huang, X.; Fang, H.; Wu, M.; Cao, X. Assessment of the regional agricultural water-land Nexus in China: A green-blue water perspective. *Sci. Total Environ.* **2022**, *804*, 150192. [CrossRef] [PubMed]
25. Yang, G.; Li, S.; Wang, H.; Wang, L. Study on agricultural cultivation development layout based on the matching characteristic of water and land resources in North China Plain. *Agric. Water Manag.* **2022**, *259*, 107272. [CrossRef]
26. Shang, C.; Wu, T.; Huang, G.; Wu, J. Weak sustainability is not sustainable: Socioeconomic and environmental assessment of Inner Mongolia for the past three decades. *Resour. Conserv. Recycl.* **2019**, *141*, 243–252. [CrossRef]
27. Fan, J.; Kong, L.; Wang, H.; Zhang, X. A water-energy nexus review from the perspective of urban metabolism. *Ecol. Model.* **2019**, *392*, 128–136. [CrossRef]
28. Ramos, E.P.; Sridharan, V.; Alfstad, T.; Niet, T.; Shivakumar, A.; Howells, M.I.; Rogner, H.; Gardumi, F. Climate, Land, Energy and Water systems interactions—From key concepts to model implementation with OSeMOSYS. *Environ. Sci. Policy* **2022**, *136*, 696–716. [CrossRef]
29. Pahl-Wostl, C.; Bhaduri, A.; Bruns, A. Editorial special issue: The Nexus of water, energy and food—An environmental governance perspective. *Environ. Sci. Policy* **2018**, *90*, 161–163. [CrossRef]
30. Wu, H.; Guo, S.; Guo, P.; Shan, B.; Zhang, Y. Agricultural water and land resources allocation considering carbon sink/source and water scarcity/degradation footprint. *Sci. Total Environ.* **2022**, *819*, 152058. [CrossRef]
31. Li, J.; Tan, S.; Chen, F.; Feng, P. Quantitatively analyze the impact of land use/land cover change on annual runoff decrease. *Nat. Hazards* **2014**, *74*, 1191–1207. [CrossRef]
32. Li, E.; Mu, X.; Zhao, G.; Gao, P.; Shao, H. Variation of Runoff and Precipitation in the Hekou-Longmen Region of the Yellow River Based on Elasticity Analysis. *Sci. World J.* **2014**, *2014*, 929858. [CrossRef]
33. Wu, Z.; Jiang, M.; Wang, H.; Di, D.; Guo, X. Management implications of spatial–temporal variations of net anthropogenic nitrogen inputs (NANI) in the Yellow River Basin. *Environ. Sci. Pollut. Res.* **2022**, *29*, 52317–52335. [CrossRef]
34. Chen, J.; Lu, J. Effects of Land Use, Topography and Socio-Economic Factors on River Water Quality in a Mountainous Watershed with Intensive Agricultural Production in East China. *PLoS ONE* **2014**, *9*, e102714. [CrossRef] [PubMed]
35. Sims, C.A. Macroeconomics and Reality. *Econometrica* **1980**, *48*, 1–48. [CrossRef]
36. Lu, M. Vector autoregression (var)—An approach to dynamic analysis of geographic processes. *Geogr. Ann. Ser. B Hum. Geogr.* **2001**, *83*, 67–78. [CrossRef]
37. Gao, T. *Econometric Analysis and Modeling-Application and Example of Eviews*; Tsinghua University Press: Beijing, China, 2006. (In Chinese)
38. Yang, K.; Lee, L.-F. Estimation of dynamic panel spatial vector autoregression: Stability and spatial multivariate cointegration. *J. Econom.* **2021**, *221*, 337–367. [CrossRef]
39. Kumar, U.; Prakash, A.; Jain, V.K. A Multivariate Time Series Approach to Study the Interdependence among O_3, NO_x, and VOCs in Ambient Urban Atmosphere. *Environ. Model. Assess.* **2009**, *14*, 631–643. [CrossRef]
40. Xu, B.; Lin, B. What cause a surge in China's CO_2 emissions? A dynamic vector autoregression analysis. *J. Clean. Prod.* **2017**, *143*, 17–26. [CrossRef]

41. Wu, S.; Li, J.; Zhou, W.; Lewis, B.J.; Yu, D.; Zhou, L.; Jiang, L.; Dai, L. A statistical analysis of spatiotemporal variations and determinant factors of forest carbon storage under China's Natural Forest Protection Program. *J. For. Res.* **2018**, *29*, 415–424. [CrossRef]
42. Yellow River Water Conservancy Commission of the Ministry of Water Resources. *Comprehensive Planning for the Yiluo River Basin*; Yellow River Water Conservancy Commission: Zhengzhou, China, 2019. (In Chinese)
43. The Ministry of Water Resources of the People's Republic of China. *Hydrological Yearbook of the People's Republic of China*; Hydrology Bureau of the Ministry of Water Resources, PRC: Beijing, China, 2008. (In Chinese)
44. Yang, J.; Huang, X. The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth Syst. Sci. Data* **2021**, *13*, 3907–3925. [CrossRef]
45. Hu, C.; Wu, Z.; Gao, J.; Xi, X. Calculation of regional available water resources. *Arid Land Geogr.* **2010**, *33*, 404–410. (In Chinese)
46. Chen, X. Research on Water Allocation Management in China. Ph.D. Thesis, Harbin Engineering University, Harbin, China, 2009.
47. The Ministry of Water Resources of the People's Republic of China. *Technical Specification for Forecasting Analysis of Water Resources Supply and Demand*; SL429-2008; China Water&Power Press: Beijing, China, 2009. (In Chinese)
48. Schwert, G.W. Effects of model specification on tests for unit roots in macroeconomic data. *J. Monet. Econ.* **1987**, *20*, 73–103. [CrossRef]
49. Johansen, S.; Juselius, K. Maximum likelihood estimation and inference on cointegration with application to the demand for money. *Oxf. Bull. Econ. Statics* **1990**, *52*, 169–210. [CrossRef]
50. Cao, Y.; Guo, L.; Qu, Y. Evaluating the dynamic effects of mitigation instruments on CO_2 emissions in China's nonferrous metal industry: A vector autoregression analysis. *Sci. Total Environ.* **2022**, *853*, 158409. [CrossRef]
51. Zhao, J.; Mu, X.; Gao, P. Dynamic response of runoff to soil and water conservation measures and precipitation based on VAR model. *Hydrol. Res.* **2019**, *50*, 837–848. [CrossRef]
52. Li, Y.; Han, Y.; Liu, B.; Li, H.; Du, X.; Wang, Q.; Wang, X.; Zhu, X. Construction and application of a refined model for the optimal allocation of water resources—Taking Guantao County, China as an example. *Ecol. Indic.* **2023**, *146*, 109929. [CrossRef]
53. Li, B.; Xiao, W.; Wang, Y.; Yang, M.; Huang, Y. Impact of land use/cover change on the relationship between precipitation and runoff in typical area. *J. Water Clim. Chang.* **2018**, *9*, 261–274. [CrossRef]
54. He, J.; Wan, Y.-R.; Chen, H.-T.; Wang, W.-C. Study on the Impact of Land-Use Change on Runoff Variation Trend in Luojiang River Basin, China. *Water* **2021**, *13*, 3282. [CrossRef]
55. Xu, C.; Fu, H.; Yang, J.; Gao, C. Land-Use and Land Cover Is Driving Factor of Runoff Yield: Evidence from a Remote Sensing-Based Runoff Generation Simulation. *Water* **2022**, *14*, 2854. [CrossRef]
56. Kurzweil, J.R.; Metlen, K.; Abdi, R.; Strahan, R.; Hogue, T.S. Surface water runoff response to forest management: Low-intensity forest restoration does not increase surface water yields. *For. Ecol. Manag.* **2021**, *496*, 119387. [CrossRef]
57. Wu, Z.; Zhang, X.; Guo, X.; Yan, D. Emergy evaluation of ecological and economic value of water and soil resources in residential and industrial land based on energy analysis. *Ecol. Indic.* **2022**, *145*, 109692. [CrossRef]
58. Pasquier, U.; Vahmani, P.; Jones, A.D. Quantifying the City-Scale Impacts of Impervious Surfaces on Groundwater Recharge Potential: An Urban Application of WRF–Hydro. *Water* **2022**, *14*, 3143. [CrossRef]
59. Zhang, Q.; Liu, J.Y.; Singh, V.P.; Gu, X.H.; Chen, X.H. Evaluation of impacts of climate change and human activities on streamflow in the Poyang Lake basin, China. *Hydrol. Process.* **2016**, *30*, 2562–2576. [CrossRef]