



# Article Spatial and Temporal Variation in Vegetation Response to Runoff in the Ebinur Lake Basin

Chenglong Yao <sup>1,2</sup>, Yuejian Wang <sup>1,2,\*</sup>, Guang Yang <sup>3,4,\*</sup>, Baofei Xia <sup>1,2</sup>, Yongpeng Tong <sup>1,2</sup>, Junqiang Yao <sup>5</sup>, and Huanhuan Chen <sup>1,2</sup>

- <sup>1</sup> College of Science, Shihezi University, Shihezi 832000, China
- <sup>2</sup> Key Laboratory of Oasis Town and Mountain Basin System Ecology of Xinjiang Production and Construction Corps, Shihezi 832000, China
- <sup>3</sup> College of Water Conservancy & Architectural Engineering, Shihezi University, Shihezi 832000, China
- <sup>4</sup> Key Laboratory of Cold and Arid Regions Eco-Hydraulic Engineering of Xinjiang Production & Construction Corps, Shihezi 832000, China
- <sup>5</sup> Institute of Desert Meteorology, China Meteorological Administration, Urumqi 830002, China
- \* Correspondence: wangyuejian0808@163.com (Y.W.); mikeyork@163.com (G.Y.)

Abstract: The response of spatial and temporal vegetation changes to runoff is a complex process involving the interaction of several factors and mechanisms. Timely and accurate vegetation and runoff change information is an important reference for the water cycle and water resource security. The Ebinur Lake Basin is representative of arid areas worldwide. This basin has been affected by climate change and human activities for a long time, resulting in the destruction of the basin's ecological environment, and especially its vegetation. However, there have been few studies that have focused on watershed vegetation and runoff changes. Therefore, we combined Generalized Information System and remote sensing technology, used SWAT and InVEST models based on the Google Earth Engine platform, and used the vegetation normalization index method to calculate the spatial distribution of vegetation and water production from 2000 to 2020 in Ebinur Lake. Sen's trend analysis and the M-K test were used to calculate vegetation and runoff trends. The relationship between vegetation and runoff variation was studied using bivariate spatial autocorrelation based on sub-basins and plant types. The results showed that the Z parameter in the InVEST model spanned from 1-2. The spatial distribution of the water yield in a watershed is similar to the elevation of the watershed, showing a trend of higher altitude leading to a higher water yield. Its water yield capacity tends to saturate at elevations greater than 3500 m. The local spatial distribution of the Normalized Difference Vegetation Index(NDVI) values and water yield clustering in the watershed were consistent and reproducible. Interannual runoff based on sub-basins correlated positively with the overall NDVI, whereas interannual runoff based on plant type correlated negatively with the overall NDVI.

**Keywords:** Ebinur Lake watershed; bivariate spatial autocorrelation; Google Earth Engine; InVEST model

# 1. Introduction

Vegetation is an important component of terrestrial ecosystems and is a foundation for the survival of other organisms [1,2]. In the context of global climate change, the frequency of droughts, areas affected, and degree of damage are increasing annually [3,4]. Many rivers worldwide are experiencing substantial declines in water flow, with some completely drying. This has resulted in severe effects on humans and the environment [5,6]. Climate change has had a direct impact on precipitation patterns, affected water and sand transport systems, and had a considerable impact on regional ecological security [7]. Therefore, understanding how vegetation responds to variations in runoff is crucial for determining ecological changes.



Citation: Yao, C.; Wang, Y.; Yang, G.; Xia, B.; Tong, Y.; Yao, J.; Chen, H. Spatial and Temporal Variation in Vegetation Response to Runoff in the Ebinur Lake Basin. *Forests* **2023**, *14*, 1699. https://doi.org/10.3390/ f14091699

Academic Editor: Daniel L. McLaughlin

Received: 16 July 2023 Revised: 5 August 2023 Accepted: 18 August 2023 Published: 23 August 2023



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Vegetation serves as a link in the material cycle and plays an important role in surface energy conversion, climate regulation, and water transfer [8–10]. Vegetation affects surface runoff through land-based water cycle processes such as precipitation interception, surface evaporation, and soil water infiltration [11,12]. The hydrological cycle in arid zones is extremely vulnerable. Therefore, the response of runoff changes to human activity and climate change is highly sensitive [13,14]. For example, simulations of runoff under different scenarios have shown that the aridity of the Alwand Basin in Iran has increased [15]. Arid locations typically have low population densities. Given the water resource limitations, human activities in arid areas are often concentrated around areas that do have water resources [16]. There are relatively few land-use types in dry zones, with land primarily being used for agriculture or construction [17]. However, agricultural irrigation and urban development require substantial amounts of water, making water resources increasingly scarce [18]. Furthermore, some engineering projects aimed at water conservancy, such as dam closures and cross-basin water diversions, may affect runoff. These projects alter the distribution of natural runoff, thereby affecting hydrological processes [19]. In the Minab River Basin of Iran, the increase in land use has led to a considerable reduction in runoff [20]. When human activities involve water resource development and overuse, water resources are more rapidly depleted [19,21]. As global climate change continues, the shift in precipitation patterns has become most pronounced in arid zones, typified by decreasing rainfall, increasing evaporation, decreasing soil moisture, and exacerbating runoff decline [22,23]. Continuous climate change may lead to the collapse of entire ecosystems in arid areas. Therefore, effective measures need to be taken to strengthen water resource protection and management to address the challenges posed by human activities and climate change.

The Ebinur Lake Basin is part of the "Silk Road Economic Belt", and its soil and water security are closely linked to the economy of China. The ecological environment of the Ebinur Lake Basin is affected by human activity and climate change [24]. Grassland degradation, water scarcity, and land desertification are becoming more prominent in this basin [3]. Grassland deterioration is a critical issue, primarily due to overgrazing and reclamation [25]. These activities have reduced grassland cover and caused vegetation deterioration, which has hastened land desertification [26]. Furthermore, water resources in the Ebinur Lake Basin are under increasing strain from economic expansion and rapid urbanization [27]. Ebinur Lake Basin is a region with scarce hydrological data. There are fewer hydrological stations within the watershed. Obtaining hydrological data is only point data. In this context, many researchers have studied the internal causes of lake area changes, runoff (channel flow) changes, land-use changes, and soil salinization to address increasingly prominent water resource problems [27–29]. Water scarcity in the Ebinur Lake Basin has been linked to a decrease in runoff caused by climate change and an increase in water demand caused by increasing the expansion of cultivated land and plantation [28,30]. Different types of land use have different impacts on vegetation and runoff [19,27,30]. Compared to bare land, surface runoff covered by vegetation is more likely to exhibit gradual characteristics, with runoff time concentrated over a longer period of time rather than a brief peak [19]. The impact of different vegetation on runoff is also different. The runoff of herbaceous plants and forests started significantly later than that of shrubs [31]. To date, the relationship between vegetation and runoff (overland flow) in the Ebinur Lake Basin is not clear. For example, it is not yet known whether the temporal and spatial changes in vegetation and runoff in the sub-basin are the same as those throughout the whole basin and how each vegetation type affects runoff. The spatiotemporal changes of vegetation and runoff (overland flow) are interdependent. Examining the spatial and temporal variations between them can help develop strategies for the sustainable use of watershed water resources. Therefore, ecological and environmental monitoring and scientific research have become important tools for protecting the ecological and environmental security of the Ebinur Lake Basin.

In this study, we used the bivariate spatial autocorrelation method to study the relationship between vegetation and runoff changes from the perspective of sub-watersheds and plant types. This research aimed to investigate three scientific questions: (1) how runoff in the watershed varied in space and time; (2) how the vegetation in the watershed changed over time and space; and (3) whether there is a link between vegetation and runoff in watersheds.

# 2. Overview of the Study Area

The Ebinur Lake Basin (Figure 1) (44°02′–45°23′ N, 79°53′–83°53′ E) is a component of the Xinjiang Uygur Autonomous Region's Boltara Autonomous Prefecture. The area has a northern temperate continental arid climate. The difference between the daily and annual temperatures of the basin is large, with hot summers and cold winters. For several years, the average annual precipitation has been 116–170 mm. The annual evaporation rate exceeds 1000 mm. The terrain of the watershed is complex, flanked by mountains on three sides, and is a well-known wind outlet in China, with northwest winds dominating in all years [28]. The watershed vegetation is classified into seven types: alpine vegetation, coniferous forests, agricultural fields, grasslands, meadows, shrubs, and deserts. The basin is relatively rich in species, with up to 36 types of national first- and second-class protected animals. There are 79 plant families and 413 plant species with medicinal potential, primarily Chinese wolfberry, ephedra, licorice, and rare plants such as red Mentha [32].



Figure 1. Ebinur Lake Basin.

# 3. Data and Methods

# 3.1. Data Sources

The interaction between vegetation and runoff has predominantly been investigated by constructing sample plots [31]. However, to date, actual measured data gathered in the experimental region have been limited. Therefore, we used easily accessible remote sensing data in our study. The water production module of the InVEST model (Figure 2) is a tool used for assessing natural capital management and the sustainable use of water resources [27].



Figure 2. InVEST model water production module.

The water production module was used to evaluate the quantitative and distribution properties of water resources and the impact of factors such as hydrographic conditions, precipitation, and evapotranspiration [33–35]. For this model, data on precipitation, reference evapotranspiration, land use, soil data, soil moisture content, a digital elevation model (DEM), and biophysical tables are required. Table 1 summarizes the data used in the study.

Table 1. Dataset descriptions, processing, usage, and sources used in this study.

Туре	Data	Description	Processing and Usage	Source	
Hydrological	Surface water volume	Reflects the total amount of surface water in the region during the year	Used to calibrate data and calculate water production modulus	Bortala Autonomous Prefecture Hydrological Bulletin 2000–2020	
Remote sensing	Precipitation	Monthly precipitation data with a spatial scale of 1 km resolution	Exploring the spatial distribution differences of precipitation for calibrating InVEST	National Tibetan Plateau Data Center (http://data.tpdc.ac.cn (accessed on 18 April 2023)) [36]	
	Potential evapo- transpiration	Monthly potential evapotranspiration dataset with a spatial scale of 1 km	Used for calibrating InVEST	National Tibetan Plateau Data Center (http://data.tpdc.ac.cn (accessed on 18 April 2023)) [36]	
	Land use	Landsat images generated through manual visual interpretation	Used for calibrating InVEST	Google Earth Engine Remote Sensing Cloud Computing Platform Download Land Use Classification Maps for Each Year from 2000 to 2020 [37]	
	DEM	Digital elevation model with a resolution of 30 m	Calculating watershed boundaries and describing terrain undulation data for calibrating InVEST	National Tibetan Plateau Data Center (http://data.tpdc.ac.cn (accessed on 18 April 2023)) [36]	
	NDVI	Maximum NDVI value synthesized over 16 days based on Terra satellite global vegetation index at 250 m	Analyzing the spatiotemporal changes in NDVI and discussing the relationship between runoff and vegetation cover	Google Earth Engine Remote Sensing Cloud Computing Platform Calculate NDVI for Each Year from 2000 to 2020	
Soil	Soil data	Contains all attributes of soil (HWSD) Dataset (v1.2)	Calculating soil water content for calibrating InVEST	National Tibetan Plateau Data Center (http://data.tpdc.ac.cn (accessed on 18 April 2023)) [38]	
Other data	Biophysical table	Reflects the attributes of soil coverage and LULC, including LULC encoding, plant evapotranspiration coefficient (Kc), and root depth	Used for calibrating InVEST	Literature [25] and InVEST user guide [39]	

## 3.2. Data Analysis

3.2.1. InVEST Water Production Model

Vegetation and runoff data have been used to establish water balance models, Lorenz curves, and Budyko data to explore the relationship between vegetation and runoff [40–42]. However, modeling using these methods only reflects the linear relationship between the two and does not visualize their spatial relationship. Therefore, this study used the water production module of the InVEST model, which is based on the water balance principle, to determine the water production of each raster in the watershed and to obtain the spatial distribution of runoff.

The equations used are as follows:

$$Y_{XJ} = \left(1 - \frac{AET_{XJ}}{P_X}\right) \times P_X,\tag{1}$$

$$\frac{AET_{XJ}}{P_X} = \frac{1 + \omega_X R_{XJ}}{1 + \omega_X R_{XJ} + \frac{1}{R_{XJ}}},$$
(2)

$$R_{XJ} = \frac{K_{XJ} \times ET_0}{P_X},\tag{3}$$

$$\omega_X = Z \frac{AWC_X}{P_X},\tag{4}$$

where  $Y_{XJ}$  denotes the annual water yield of the study area,  $AET_{XJ}$  is the average annual actual evapotranspiration,  $P_X$  is the average annual precipitation, and  $R_{XJ}$  is the dimensionless drying index obtained from the ratio of potential evapotranspiration to precipitation.  $ET_0$  is the average annual potential evapotranspiration.  $K_{XJ}$  is the vegetation evapotranspiration coefficient corresponding to different land-cover types in the raster cell, whose values can be obtained by consulting the data. *Z* is a seasonal parameter used to characterize the seasonality of precipitation.  $AWC_X$  is the available water content of the plant, and its value is determined by soil depth, soil texture, and organic matter content. In this study, the plant available water capacity (PAWC) calculated from soil data was used instead of the  $AWC_X$  [43]. The equation used is as follows:

$$PAWC = 54.509 - 0.132 \text{ Sand} - 0.003(\text{Sand})^2 - 0.055 \text{ Silt} - 0.006(\text{Silt})^2 - 0.738 \text{ Clay} + 0.007(\text{Clay})^2 - 2.688c + 0.501(C)^2,$$
(5)

where sand is the soil sand content, silt is the soil powder content, clay is the soil clay content, and *C* is the soil organic matter content.

## 3.2.2. Correlation Analysis

Bivariate spatial autocorrelation analysis was used to describe the spatial correlation and dependency characteristics of the two geographical features. Unlike traditional spatial autocorrelation analysis, which considers only one variable, bivariate spatial autocorrelation analysis can more accurately show the spatial relationships between geographical phenomena [44]. The specific equations are as follows:

$$I = \frac{\sum_{a=1}^{c} \sum_{b=1}^{c} W_{ab}(x_{\alpha} - \overline{x}) (y_{j} - \overline{y})}{N^{2} \sum_{a=1}^{c} \sum_{b=1}^{c} W_{\alpha\beta}}$$
(6)

where *I* is the global spatial autocorrelation index, *c* is the number of research units,  $W_{ab}$  is the spatial weight matrix,  $x_a$  and  $y_a$  are the values of the independent and dependent variables in spatial units *a* and *b*, respectively, and N<sup>2</sup> is the variance of all samples. The specific equations are as follows:

$$I_a = z_a \sum_{j=1}^{c} W_{ab} Z_b \tag{7}$$

where  $I_a$  represents the local spatial relationship between the independent and dependent variables in study unit *a*.  $Z_a$  and  $Z_b$  are the standardized values for the variance of the observation values of study units *a* and *c*. The distribution map of local indicators of spatial association (LISA) formed can show the clustering and differentiation characteristics of independent and dependent variables in the local region. The SWAT model is widely used in the field of hydrological research [15,20]. In this study, we only used DEM data to generate watershed boundaries and sub-watershed boundaries through SWAT models. This study refers to the nonparametric linear regression technology and uses Theil–Sen trend analysis and the Mann–Kendall test method to study the spatial and temporal change trend of NDVI and runoff in Ebinur Lake Basin from 2000 to 2020 [15,45]. We used ArcGIS (version 10.2) to create images.

## 4. Results

#### 4.1. Calibration and Validation of InVEST

The results obtained from the InVEST water production module represented the total amount of water produced in the input catchment. Given that the area of the delineated watershed was not the same as the catchment area of the measured data, the simulated water production values could not be directly compared with the measured surface water volume. The water production modulus was used to compare the differences between the simulated and measured values (Figure 3). The sensitive factor affecting the model was the parameter Z. Therefore, we calibrated the Z parameter based on the water production modulus obtained from the hydrological bulletin of the Bortala Autonomous Prefecture from 2000 to 2020. We used correlation coefficients for several tests between the simulated and measured values to select the optimal Z value, as shown in Table 2. The correlation coefficient between the simulated and measured values of water production. Most of the Z values were in the range of 1–2. When precipitation tended to be stable, close to the multi-year average, the Z value did not change significantly. When the precipitation exceeded the average, Z increased.



Figure 3. Simulation results and measured values.

Name						Value					
Year	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
Z	1	1.5	1	1	11	1.7	1	1.6	1	1.7	11
Year	2009	2008	2007	2006	2005	2004	2003	2002	2001	2000	
Z	2	1	1.1	1	1.2	1	1.5	1.6	1	1	

Table 2. Z parameters.

# 4.2. Spatial Patterns of Interannual Water Content and NDVI

Based on the water production module of the InVEST model, the annual water yield of the basin was estimated for 2000–2020 (Figure 4). Areas with higher water yields were in the upper part of the basin, and smaller areas were in the lower part. The spatial distribution of the water content in the basin was similar to the elevation of the basin. This indicated that the higher the elevation, the higher the water content. The maximum water content from 2000 to 2020 was recorded in 2016, with a maximum value of 993.38 mm. The minimum water content depth was recorded in 2008, with a value of 393.04 mm. The multi-year average water production was 682.938 mm.



Figure 4. Multi-year average water production and DEM schematic (2000–2020).

The relationship between runoff production depth and elevation was further divided based on the spatial distribution of water production and DEM elevation values from 2000 to 2020 (Figures 4 and 5). The study area was divided into three zones with low, medium, or high values. The elevation of the low-value zone was 162–1250 m, which is in the red area of the spatial distribution of water production (Figure 4). The elevation of the middle-value zone was 1250–3000 m, which is within the red and light-blue zones of the spatial distribution of water production (Figure 4). The elevation of water production of water production (Figure 4). The high-value area was 3000–4603 m above sea level and was within the light-blue and blue areas of the spatial distribution of water production (Figure 4). There was a saturation point in the high-value area (Figure 5). Its water production capacity tended to saturate at an elevation of 3500 m or more. The water production capacity of the land type was higher because of the presence of snowy mountains above 3500 m in elevation.



Figure 5. Relationship between runoff production depth and elevation values.

Based on the Google Earth Engine platform, NDVI was downloaded and calculated for each year from 2000 to 2020 (Figure 6). We use red lines to divide the watershed into low value areas, median areas and high value areas based on the trend of the data. The blue line represents the saturation line of runoff at altitude. The maximum NDVI value was 0.6936 in 2003, and the minimum NDVI value was 0.6091 in 2020, with a multi-year average NDVI value of 0.6193. The maximum NDVI values were spatially distributed in the northern and southeastern mountainous areas of the basin, where the main vegetation types were alkaline vegetation and coniferous forests. The minimum NDVI values excluding water bodies were distributed in the marginal areas of the basin. There were large desert areas between the arable land and grasslands, and the NDVI values for desert vegetation were the lowest. The vegetation in the study area was characterized by the distribution of natural plants around it and agricultural fields in the middle.



Figure 6. Multi-year average NDVI and vegetation type distribution diagram (2000–2020).

# 4.3. Interannual Water Content and NDVI Trend Analysis

The temporal and spatial trends of interannual water content and NDVI from 2000 to 2020 were analyzed and tested for significance using the Theil–Sen median trend analysis method (Figure 7a,b). The NDVI values in the middle of the watershed showed a significant increasing trend (Figure 7a). Based on the plant type diagram, cultivated plants showed a significant increase (Figure 5). A significant decrease in NDVI values occurred in the northern part of the watershed. No significant changes were observed in the other areas. In general, the spatial pattern of runoff did not change significantly (Figure 7b). Water content decreased significantly in the central part of the watershed.



**Figure 7.** Schematic diagram of NDVI and water production changes from 2000 to 2020: (**a**) trend change in NDVI; (**b**) trend change in runoff.

# 4.4. Interannual Water Yield and NDVI Autocorrelation Analysis Based on Sub-Basins

A bivariate spatial autocorrelation analysis was performed between the interannual water yield and NDVI values in the sub-basins (Figure 8). The Moran's I was positive from 2000 to 2020, with a range of 0.048–0.263. Its two variables showed a strong positive spatial correlation, that is, the more water yielded, the greater the NDVI value within the sub-basin. Moran's I index in 2002 was the highest at 0.101. The Moran's I index in 2010 was the lowest at 0.048. Most of the 24 sub-watersheds were distributed in quadrants 1, 2, and 3.



Figure 8. Moran's index based on interannual water yield and NDVI in sub-basins.

Combining the interannual water yield and NDVI (LISA) cluster analysis, high–high clustering was found in sub-basins 3, 5, 8, and 20 (Figure 9). Sub-basin 8 was the area where the maximum NDVI value was recorded, and the maximum water yield was also recorded in that area. Therefore, the spatial autocorrelation between the two was relatively high. The only area with low–high clustering was sub-basin 13, which was in the middle reaches of the basin and had stable low–high clustering of NDVI and water yield over the last 21 years. The low–low clustering areas were sub-basins 2, 6, and 12, which were downstream of the study area. The high–high clustered sub-basins and low–low clustered sub-basins had a contiguous distribution.

## 4.5. Interannual Water Yield and NDVI Autocorrelation Analysis Based on Vegetation Type

A bivariate spatial autocorrelation analysis was performed between the interannual water yield of the vegetation types and NDVI values (Figure 10). Moran's I index was negative from 2000 to 2020, showing a strong dispersion trend. Moran's I index was the highest in 2008, at -0.116, and the lowest in 2018, at -0.340. Vegetation was divided into seven types: alpine vegetation, coniferous forests, cultivated plants, grasslands, meadows, shrubs, and desert (Figure 5). Given the discrete distribution of vegetation types, they were divided into 162 vegetation areas. The samples were distributed across all four quadrants, mainly in quadrants 2 and 4.



Figure 9. LISA clustering analysis of interannual water production versus NDVI based on sub-basins.



Figure 10. Moran's index of interannual water yield and NDVI based on vegetation type.

Based on the LISA clustering analysis of interannual water yield and NDVI based on vegetation types (Figure 11), the vegetation types with high–high clustering included meadows and grasslands. Meadows in the north were highly clustered for the last 21 years. The year with high–high clustering in grasslands was 2008, with one year of occurrence. The grasslands in other years were generally in a low–high concentration state. Meadows and alpine vegetation exhibited high–low clustering and low–low clustering, respectively, and were located in the south and west of the watershed. The vegetation types with low to high concentrations included grasslands and agricultural fields located in the middle of the watershed.



Figure 11. LISA cluster analysis of interannual water yield and NDVI based on vegetation type.

#### 5. Discussion

# 5.1. Factors Potentially Affecting Changes in Vegetation and Runoff

The changes in vegetation and runoff were influenced by various natural and anthropogenic factors. The current study concluded that water production was positively correlated with precipitation, PAWC, and DEM and negatively correlated with NDVI and PET (Figure 12a). The positive correlation between water production and elevation is the highest. Our results showed that the spatial distribution of water production in the watershed was similar to the elevation of the watershed, with a trend of increased water production at higher elevations. This is because of the presence of snow-capped mountains at higher elevations and iceberg meltwater, which is the main source of water supply in the basin [46,47]. The negative correlation between NDVI and elevation is strongest, as arable land is generally located in plain areas. The proportion of arable land in annual NDVI values is relatively high (Figure 12a). Melting icebergs can provide a large amount of water resources. Climate is an important factor that influences vegetation change and runoff. Different climatic conditions affect vegetation growth and the rate of water evaporation, which has an impact on runoff volume [7,44]. Different hydrological conditions, such as rainfall, evapotranspiration, and soil moisture content, also affect vegetation and runoff [11,12,48]. The higher the effective rainfall, the more suitable the conditions for vegetation growth, and the lower the runoff volume over shorter timescales [48]. The results of this study also showed that precipitation is one of the main causes of regional runoff variability (Figure 12b). There was no significant decrease in runoff in the upstream area, but a change occurred owing to the different amounts of annual iceberg snow melt upstream and precipitation being significantly higher upstream than downstream (Figure 12b). Runoff from the lakes and deserts in the lower reaches did not change. There was no significant increase in runoff at the margins of the basin. However, changes occurred because of variations in snow and ice melt in the high mountains caused by annual differences in precipitation [46,47]. The InVEST model is greatly influenced by precipitation. Among the 21 years analyzed, 2008 had the lowest water production and precipitation. The error between the simulated and measured values was also the largest, indicating that precipitation had the most direct effect on changes in runoff in the study area (Figure 3). The Z parameter is 1 because the lowest adjustable parameter value can only be 1. Topographic conditions are key factors affecting vegetation and runoff. There are differences in vegetation growth conditions and

runoff distribution between mountainous and plain areas. The border between mountains and plains is a large area of grasslands and meadows, which grow with a small grass blade area and, therefore, have lower NDVI values, indicating that grasslands in arid areas are more drought tolerant [49].



**Figure 12.** Possible factors affecting changes in vegetation and runoff. (**a**) Correlation analysis of the main factors of runoff; (**b**) precipitation of meteorological stations in the study area; (**c**) land-use change from 2000 to 2020.

Land-use patterns strongly influence vegetation change and runoff. Human activities change the original state of the land and affect vegetation growth, therefore changing the distribution and amount of runoff [19,20,49]. In the last 20 years, all the land-use types in the watershed have changed, with the most significant changes occurring in grasslands and bare ground (Figure 12c). Some grasslands have become bare land, and some have become forests. Some cultivated land has been converted into grassland, which may be due to the implementation of the Grain for Green project [50]. Shrublands have been transformed into grasslands. Areas that usually contain permanent snow/water have been transformed into bare land. Part of the grassland has become bare land, which could have been caused by environmental damage [27]. Overall, the land types in the watershed are improving, with bare land decreasing and grassland increasing. The results of our study showed that the NDVI significantly increased in the watershed for cultivated plants (Figure 6). This may be because the crops being cultivated differ each year and the cultivated area increased (Figure 12c). The basin was found to be richer in cultivated land planted with crops such as corn, wheat, and cotton. Around its perimeter, the NDVI values have significantly changed, and the significant changes may be where the land-use type is changing to croplands. Cultivated plants in the middle of the area also showed a few highly significant decreases, which may have been caused by the conversion of cultivated land to residential land. The NDVI values of grasslands and meadows changed but not significantly. The area where

they changed was at the border between the mountains and plains. This may have been from changes in vegetation growth caused by climate change.

#### 5.2. Response of Vegetation Change to Runoff

The vegetation cover affects the entire hydrological cycle [51,52]. At different time scales, changes in vegetation cover can have different effects on indicators such as water production, flow production, and runoff coefficient [40,53]. Changes in vegetation cover may affect rainfall infiltration and evapotranspiration [23,24]. Where significant decreases in NDVI values occur in upper mountainous areas, they may be due to deforestation, leading to soil erosion, which causes a decrease in NDVI values (Figure 7a). The reduction in vegetation during the conversion of forested land to other land types may lead to increased rainfall runoff, which, in turn, affects the availability of water resources [54]. In the present study, excluding extreme years of precipitation, water production had continuity in time when the vegetation did not change substantially. In contrast, changes in vegetation cover also affected soil erosion, particularly in mountainous and hilly areas [55]. Under the influence of global climate change, terrestrial water storage is likely to decrease and increase with drought severity [56]. The vegetation response to water production varied at different spatial scales. At small scales, vegetation can increase soil permeability and water storage capacity through the root system, which can affect groundwater recharge and circulation while at large scales [57]. Changes in vegetation cover may have an impact on water balance and hydrological processes in the watershed [40].

Our study found a positive correlation between the interannual water yield of subbasins and the overall NDVI and a negative correlation between the interannual water yield of vegetation types and the overall NDVI (Figures 8 and 10). From both perspectives, there were continuity and reproducibility in the local spatial clustering of NDVI values and water yield (Figures 9 and 11). From the sub-basin perspective, high-high clustering existed in sub-basin 8 from 2000 to 2011, and high–high clustering disappeared in 2012, 2015, 2017, and 2020 in region 8 and reoccurred after its disappearance. High-high clustering occurred in sub-basin 20 in 2011. After one year of continuity, the clustering state no longer occurred, before reoccurring after 2015 and persisting until 2020. Sub-basins 2 and 12 had low-low clustering for 21 years. Sub-basin 6 also had low clustering in most years because sub-basins 2, 6, and 12 also had relatively low NDVI in these areas when interannual water production was low. This may indicate that hydrological processes within the watersheds were influenced by the degree of surface vegetation cover and that higher vegetation cover increased soil water retention capacity and, therefore, interannual water production. Under different vegetation types, the high-high meadow aggregation first occurred in 2000, continued in 2001 and 2002, changed in 2003, and was recorded again in 2004. The meadow maintained low-high clustering, except for the extreme year (2008). Over the last hundred years, precipitation has increased in northern North America where vegetation has increased, whereas precipitation has decreased in central North America and almost all of China [14]. Vegetation is particularly abundant at high northern latitudes and in agricultural and afforested regions [58]. Therefore, the mechanisms of influence at different scales need to be considered when studying the responses of spatial and temporal vegetation changes to water production.

In arid zones, substantial amounts of surface water are transported to the atmosphere via transpiration from vegetation or evaporation from the land [59]. Since the 1990s, drought trends have increased in Central Asia owing to insufficient precipitation and increased evapotranspiration [14]. The Ebinur Lake Basin is located in Central Asia and is sensitive to vegetation and runoff changes [25]. From 2000 to 2020, the overall vegetation in the basin showed a greening trend. This was due to an increase in cultivated land area in the basin. Cultivated vegetation requires substantial amounts of water for cultivation, irrigation, and fertilization. In recent decades, soil moisture has significantly decreased at the beginning of the growing season due to the continuous increase in temperature and decrease in precipitation, leading to an increase in agricultural droughts [13,60,61]. Meadows are in the

transition zone between high- and low-water production areas, and NDVI values do not vary significantly. Therefore, both values were high and had a high level of aggregation (Figures 4 and 6). Meadows and alpine vegetation have high–low clustering and low–low clustering, respectively, and were located in the south and west of the basin. The two vegetation types differed in their ability to adapt to drought, resulting in relatively low cover at high and low water levels (Figure 11). The low–high clustering vegetation types were grasslands and cultivated plants located in the middle of the watershed. Grasslands had low–high clustering owing to the dominance of dry herbaceous plants in the basin. These are zonal vegetation types under semi-humid and semi-arid climatic conditions. Therefore, when studying the response of spatial and temporal variations in vegetation to runoff in arid zones, the effect of different plant types on runoff needs to be considered.

## 6. Conclusions

This study investigated the relationship between spatial and temporal changes in vegetation and temporal changes in runoff in the Ebinur Lake Basin. The results showed that the spatial distribution of runoff in the watershed was similar to that of elevation: the higher the elevation, the higher the runoff volume. When the elevation was above 3500 m, the regional runoff capacity tended to saturate. The distribution of vegetation was characterized by natural plants in the surrounding areas and cultivated plants in the middle. The runoff trend in the basin was generally not highly variable. Interannual runoff based on sub-basins showed a positive correlation with the overall NDVI. The interannual runoff based on vegetation type showed a negative correlation with the overall NDVI. There was continuity and reproducibility in the local spatial distribution of clusters of NDVI values and runoff in the watershed.

The response of the spatiotemporal characteristics of vegetation to runoff is a complex process that involves the interaction of multiple factors and mechanisms. Except for extreme years (2008), the spatial distribution of water production in the model watershed is basically similar to the real situation. However, the error for extreme years is still significant, and further research should consider more influencing factors for improvement. This study only focuses on vegetation types. We will select specific vegetation for future research. The results of this study showed the relationship between the spatial distribution of water production and vegetation in the study area, which can provide reference for water resource utilization and land planning in the Ebinur Lake Basin. To achieve rational utilization of water resources, local governments should control the scale of agricultural land.

**Author Contributions:** Conceptualization, C.Y.; Methodology, Y.W. and G.Y.; Software, C.Y.; Validation, C.Y.; Investigation, B.X.; Resources, Y.T.; Writing—original draft, C.Y. and Y.W.; Writing—review & editing, B.X. and J.Y.; Visualization, C.Y.; Supervision, Y.W.; Funding acquisition, Y.W., G.Y. and H.C. All authors have read and agreed to the published version of the manuscript.

**Funding:** This research was funded by [the Special project for innovation and development of Shihezi University] grant number [CXFZSK202105, CXFZ202217], [the National Natural Science Foundation of China] grant number [52269006], [Xinjiang Production and Construction Corps] grant number [2021AB021, 2022BC001, 2022DB023], [The Third Xinjiang Scientific Expedition Program] grant number [2021xjkk0804] and [the Program for Youth Innovation and Cultivation of Talents of Shihezi University] grant number [CXPY202223, CXPY202121].

Data Availability Statement: We declare the availability of the data in our manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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