

Article

Spatiotemporal Evolution of Water Yield Services and Multiscale Driving Effects in an Arid Watershed: A Case Study of the Aksu River Basin

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Abstract

The water yield (WY) service is a critical ecosystem service in arid regions, and understanding its spatiotemporal heterogeneity and controls is important for sustainable watershed management. Annual water yield (WY) in the Aksu River Basin (ARB), China, from 2000 to 2020 was simulated using the InVEST model, with validation against observed runoff (NSE = 0.840, R^2 = 0.846, RMSE = 1.787). The results revealed a decline in WY from 66.49 mm in 2000 to 43.15 mm in 2015, while retaining a clear north–south gradient, with higher values in the north. Areas showing decreasing and increasing trends accounted for 45.34% and 3.14% of the basin, respectively. WY exhibited strong spatial autocorrelation (global Moran's I = 0.912–0.941), with high-value clusters in the north and low-value clusters in the south. GeoDetector identified precipitation, temperature, and potential evapotranspiration as key drivers (q = 0.889, 0.880, and 0.832, respectively), with precipitation-related interactions generally exceeding 0.9, indicating enhanced explanatory power through multi-factor coupling. After variable screening and collinearity control, MGWR revealed spatially varying effects of drivers and significant spatial non-stationarity. Overall, despite the declining trend, WY in the ARB maintained a relatively stable spatial structure, with its heterogeneity primarily driven by the coupling of climatic forcing and topographic constraints, providing a scientific basis for zonal water resource management in arid river basins.

Keywords: InVEST; GeoDetector; MGWR; arid inland river basin; ecosystem services



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1. Introduction

Natural ecosystems provide multiple ecosystem services that directly or indirectly support human survival and development, including provisioning, regulating, cultural, and supporting services [1,2]. As a pivotal component of ecosystem services, the water yield (WY) service exhibits strong spatial interactions with carbon sequestration, soil retention, and other key services within the context of ecosystem synergies and trade-offs [3]. In coupled hydrological–ecological–socioeconomic systems characteristic of arid and semi-arid regions, WYs play a critical regulatory role by supporting agriculture, industry, fisheries, and domestic livelihoods [4]. Consequently, analyzing the spatiotemporal trends of regional WYs and identifying their driving forces are essential for alleviating water scarcity,

ensuring water security, optimizing ecosystem benefits, and guiding sustainable water management strategies [5].

WYs describe the process by which ecosystems intercept, infiltrate, and store precipitation through forest canopies, litter, soils, lakes, reservoirs, and other components at specific spatiotemporal scales. This process both satisfies ecosystem water demands and provides external water resources [6,7]. Current research on the spatiotemporal evolution of WYs predominantly relies on hydrological models to simulate their spatial and temporal distributions. Commonly used models include SWAT [8], TOPMODEL [9], self-organizing feature map neural networks [10], and InVEST [11]. Compared with other models, InVEST has been widely applied to assess the dynamics of WYs and their responses to environmental change because it provides spatially explicit outputs [12]. In arid inland basins, InVEST is often integrated with land-use scenario analysis and driver-attribution methods to disentangle and quantify the combined effects of climate variability and land-use change on WYs [13,14]. As research on WYs advances, their driving mechanisms are typically investigated using two methodological approaches. The first employs global-scale algorithms, which assume spatially invariant relationships between WYs and their influencing factors. For instance, Sun et al. [15] used correlation analysis to examine the relationships among natural geographic features, socioeconomic factors, and WY in the Nansi Lake Basin. In contrast, Dai and Wang [16] used GeoDetector to identify climatic variables, particularly precipitation and evapotranspiration, as the main drivers of WYs in the Hengduan Mountains. However, spatial heterogeneity in WYs and their determinants may cause global models to overlook localized spatial interactions. When relationships between dependent and explanatory variables vary across space, spatial non-stationarity arises [17]. The second approach uses local-scale algorithms such as geographically weighted regression (GWR), which accommodates spatial non-stationarity and has been widely applied. For example, Zhang et al. [18] used GWR to identify key drivers of WYs in the Yangtze River Basin. They found that annual precipitation, urban land area, and per capita GDP exerted stronger influences in western regions than in eastern regions. Wang et al. [19] applied GWR to investigate the driving factors of WY on the Qinghai–Tibet Plateau. The results showed that precipitation had a positive effect on WYs across more than 99.8% of the region, whereas temperature (71.9%), net primary productivity (87.2%), and lakes (87.7%) exerted negative effects on WYs. However, GWR assumes that all ecological processes operate at the same geographic scale, which is a fundamental limitation [20]. Because WYs are affected by multiple natural and socioeconomic factors operating across different spatial scales, MGWR addresses this issue by incorporating spatial location information and estimating an optimal bandwidth for each variable. This enables a more comprehensive representation of multiscale ecological processes.

The ARB (Chinese reach) is a major headwater region of the Tarim River and features a typical oasis–desert coupled landscape. The basin is an important agricultural production base in Xinjiang and northwestern China, and it also functions as a crucial ecological barrier for regional ecological security. WYs are a key ecosystem service in arid regions and are highly sensitive to climate change and human disturbances. In recent years, multiple water conservation and ecological restoration projects have been implemented to alleviate water supply and demand imbalances and enhance ecological security. However, evidence on the spatiotemporal responses of WYs and their driving mechanisms under these interventions remains limited. Existing studies rarely characterize the long-term dynamics and spatial persistence of WYs at broad spatial scales. Quantitative attribution of drivers also remains insufficient, particularly regarding scale effects, spatial heterogeneity, and regional differentiation of key factors. Therefore, this study examines the spatiotemporal evolution and driving mechanisms of WYs in the ARB during 2000–2020. WYs are represented by

annual WY, with an emphasis on the joint effects of climatic factors and human activities on WYs across locations and spatial scales. The objectives are to (i) characterize the spatiotemporal patterns of WYs in the ARB from 2000 to 2020 and examine their spatial structure and change persistence; (ii) quantify the main effects and interactions of key natural and socioeconomic factors at the basin scale and identify the dominant drivers of the spatial differentiation and interannual variability of WYs; and (iii) reveal the spatial heterogeneity and scale dependence of the effects of dominant drivers on WYs, clarify differences in their domains of influence, and provide scientific evidence to support zoned strategies for water resource conservation, development, and utilization in arid basins.

2. Materials and Methods

2.1. Study Area

The ARB is located in the northwestern part of the Tarim Basin (Figure S1), Xinjiang Uygur Autonomous Region, China, along the western foothills of the southern Tianshan Mountains (75°35′–82°00′ E, 40°00′–42°27′ N). As a critical transboundary river system in Central Asia, the basin features a stepped topographic gradient descending from north to south and from west to east. The northern region is dominated by the Tianshan Mountains and gradually transitions southward into alluvial plains, with a mean elevation ranging from 1030 to 1060 m [21]. The basin covers approximately 48,000 km². The ARB has a warm temperate, arid continental climate, with a long-term mean temperature of 10 °C and annual precipitation of only 137.7 mm. As the largest source stream of the Tarim River, the Aksu River system consists of two major tributaries that originate in Kyrgyzstan, the Toshgan River and the Kumalak River. These tributaries converge 12 km upstream of Xiqiao Bridge in Aksu to form the mainstem, which eventually flows into the Tarim River at Xiaojiake. River flow is primarily derived from alpine snowmelt and mountain precipitation. The mainstem has a long-term mean annual runoff volume of 6.311×10^9 m³, while the entire basin contributes a mean annual water volume of 8.308×10^9 m³, accounting for 70%–80% of the Tarim River's total flow. This hydrological dominance underscores the basin's strategic ecohydrological importance.

2.2. Data Sources

This study employed multisource datasets spanning 2000–2020. Meteorological data included annual precipitation (PRE), mean temperature (TEM), and monthly potential evapotranspiration (EVA). Land cover (LUCC) data were obtained from the Resource and Environment Science Data Center, Chinese Academy of Sciences (<https://www.resdc.cn/>), for five periods (2000, 2005, 2010, 2015, and 2020). Land cover types were categorized into six classes following the first-level classification framework: cropland, forest, grassland, water bodies, built-up land, and unused land. Topographic data were derived from a 30 m resolution digital elevation model (DEM) obtained from the Geospatial Data Cloud. Slope (SLOPE) and aspect (ASPECT) rasters were generated using the ArcGIS (v10.8) Spatial Analyst module. Soil properties were obtained from the Harmonized World Soil Database (v1.2), including soil texture, sand, silt, and clay fractions, organic carbon content, and root depth. Fractional vegetation cover (FVC) was estimated using the pixel dichotomy model based on MODIS NDVI data from the Google Earth Engine platform. Net primary productivity (NPP) was obtained from the MOD17A3HGF product at a native 500 m resolution. Socioeconomic data included raster-based gross domestic product (GDP) and population density (POP) datasets. All datasets were standardized to the Krasovsky 1940 Albers coordinate system and resampled to 1 km resolution using bilinear interpolation (Table S1). Spatial distribution patterns are shown in Figure S2. DEM, ASPECT, SLOPE,

and LUCC are derived from 2020 data, whereas the remaining variables represent time-averaged spatial patterns over 2000–2020.

2.3. Methods

The InVEST was used to simulate annual WY in the ARB from 2000 to 2020, thereby characterizing the temporal dynamics and spatial heterogeneity of WYs. Based on these outputs, GeoDetector and MGWR were applied to quantify the effects of key natural and socioeconomic factors on WYs from the perspective of spatial differentiation. The overall workflow is shown in Figure 1.

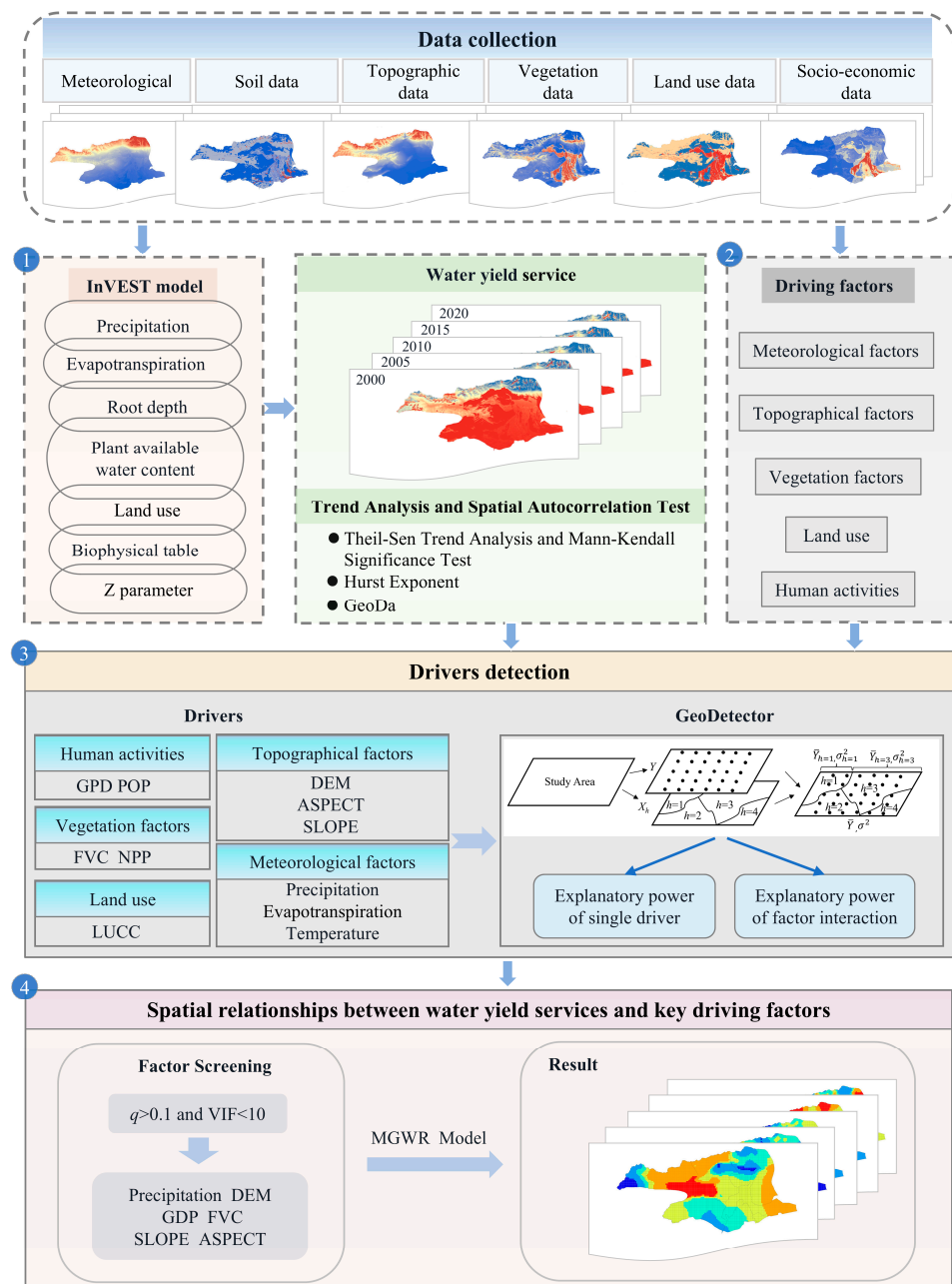


Figure 1. Flowchart of the research framework for assessing water yield (WY) service in the Aksu River Basin (ARB) using the Integrated Valuation of Ecosystem Services and Tradeoffs model (InVEST), GeoDetector (q-statistic), and multiscale geographically weighted regression (MGWR). PRE, precipitation; TEM, temperature; EVA, potential evapotranspiration; DEM, digital elevation model; SLOPE, slope; ASPECT, aspect; GDP, gross domestic product; POP, population density; FVC, fractional vegetation cover; NPP, net primary productivity; LUCC, land use/cover change; VIF, variance inflation factor.

2.3.1. WY Estimation and Model Parameterization

Annual WY was estimated using the InVEST Annual WY module based on the Budyko framework [11]. For each grid cell, WY was defined as the remaining portion of annual precipitation after accounting for actual evapotranspiration (AET). AET is primarily controlled by climatic conditions, such as precipitation and temperature, and by catchment properties, including vegetation cover, soil characteristics, and topography [22]. Required inputs included gridded annual precipitation and potential evapotranspiration, land use maps, and soil properties from the Harmonized World Soil Database, including plant available water content and constraints on rooting depth. For each land use class, rooting depth and the evapotranspiration coefficient were assigned according to Table 1.

Table 1. The biophysical coefficients.

Code	Land Use Type	Vegetated Type	Root Depth (mm)	Kc
1	Cropland	1	100	0.2
2	Forest	1	5000	1.0
3	Grassland	1	1000	0.7
4	Water	0	10	0.8
5	Built-up land	0	500	0.3
6	unutilized land	0	10	0.5

Notes: Vegetation indicator denotes whether a land use/land cover class is vegetated (1) or non-vegetated (0). Root depth is expressed in millimeters (mm). Kc is the crop coefficient used to parameterize evapotranspiration in the InVEST model.

Glacier meltwater correction and parameterization. Runoff generation in the ARB is strongly influenced by glacier meltwater. Because the InVEST annual WY formulation is primarily precipitation driven and does not explicitly represent glacier melt contributions, glacier meltwater was incorporated during parameterization to derive a physically consistent precipitation seasonality parameter Z for the basin. Using 2000 as the baseline year, the estimated glacier meltwater contribution was subtracted from the water input term based on published sources [23,24]. Parameter Z was then calibrated against observed discharge at the Xi Da Bridge hydrological control station reported in the China River Sediment Bulletin. Following sensitivity testing and calibration, Z was set to 2.14 and held constant for 2000–2020 to ensure interannual comparability of WY estimates.

2.3.2. Spatiotemporal Trends, Persistence, and Spatial Autocorrelation of WY

Temporal trends in annual WY during 2000–2020 were quantified at the pixel level using the nonparametric Theil–Sen estimator, which provides a robust median slope for monotonic change and is insensitive to outliers [25]. Trend significance was evaluated using the two-sided Mann–Kendall test, a rank-based, distribution-free procedure widely used for hydroclimatic time series [26]. Trends were classified as significant at $p < 0.05$ and highly significant at $p < 0.01$. By combining the sign of the Theil–Sen slope with the Mann–Kendall significance level, each pixel was assigned to an increasing or decreasing trend category. These pixel-level results were further summarized at the basin scale by calculating the area proportions of each trend category, providing a context for interpreting the driver analysis.

The Hurst exponent can be used to predict future change trends in WY time series and is widely applied to analyze long-term change trends in meteorological, hydrological, and ecological time series [27]. The calculation method follows Lai et al. By combining the Theil–Sen slope and the Hurst exponent, future change trends in the WY time series were classified into four types: persistent increase (Slope > 0 , $H > 0.5$), future decline (Slope > 0 , $H < 0.5$), persistent decrease (Slope < 0 , $H > 0.5$), and future increase (Slope < 0 ,

$H < 0.5$). The resulting persistence categories were mapped to depict their spatial patterns, and the area proportions of each category were summarized at the basin scale to support subsequent driver analyses.

Spatial dependence in annual WY was evaluated using global and local Moran's I statistics [28]. Global Moran's I was used to test whether WY exhibited significant spatial autocorrelation across the basin, whereas local indicators of spatial association (LISA, local Moran's I) were used to identify statistically significant clusters and spatial outliers. These diagnostics provide an explicit characterization of the spatial organization of WY, providing a context for subsequent interpretation of spatial heterogeneity and driver attribution analyses [29,30]. For LISA, WY was aggregated to a $3 \text{ km} \times 3 \text{ km}$ fishnet grid constructed in ArcGIS 10.8. Spatial weights were specified using first-order queen contiguity (i.e., adjacency within a 3×3 neighborhood). Statistical significance was assessed using permutation tests with 999 randomizations, and local clusters were reported at $p < 0.01$. LISA outcomes were classified into four standard types: High–High and Low–Low clusters, indicating spatial concentrations of similar WY values, and High–Low and Low–High outliers, indicating locations where WY contrasts with surrounding neighbors.

2.3.3. Driver Attribution and Interaction Analysis

GeoDetector was used to quantify the spatially stratified heterogeneity of annual WY and to evaluate the explanatory power of candidate drivers and their interactions [31]. Analyses were performed in R using the GD package. In this study, the factor detector and interaction detector were used to (i) rank the dominant drivers of the spatial differentiation of WY and (ii) assess whether pairs of drivers exhibit enhancement, independence, or weakening effects when considered jointly.

Factor detector: The explanatory power of an explanatory variable X for the spatial variation of WY was quantified using the q -statistic. The q -statistic measures the extent to which the stratification of X explains the spatial differentiation of WY by comparing within-stratum variance with the overall variance. The q value ranges from 0 to 1, with larger values indicating stronger explanatory power.

Interaction detector: Interaction effects were evaluated by comparing the q value of each driver with the q value after overlaying two drivers, $q(X_1)$, $q(X_2)$, and $q(X_1 \cap X_2)$. This comparison identifies whether the joint explanatory power is greater than, equal to, or less than the individual effects, thereby indicating enhancement, independence, or weakening relationships. Following prior evidence and considering data availability [32,33], eleven drivers were selected to represent climatic, topographic, vegetation, socioeconomic, and land cover conditions (Table S2).

2.3.4. Multiscale Spatial Effects of Drivers

MGWR was used to quantify spatially varying relationships between annual WY and its potential drivers, and to assess whether the influence of each driver operates over a distinct spatial extent [34]. Unlike conventional GWR, which constrains all covariates to share a single bandwidth, MGWR estimates a separate bandwidth for each explanatory variable. This allows regression coefficients to vary across space at variable-specific spatial scales [35,36]. In MGWR, WY is regressed on multiple explanatory variables with a spatially varying intercept and spatially varying regression coefficients, where each coefficient is calibrated using its own bandwidth.

To ensure comparability and to test whether the multiscale specification improves model performance, both GWR and MGWR were calibrated using the same kernel type (Gaussian) and the same bandwidth search procedure (golden section search) implemented in MGWR 2.2. Model fit was evaluated using the residual sum of squares (RSS), the

corrected Akaike information criterion (AICc), the coefficient of determination (R^2), and adjusted R^2 [37,38]. The resulting local coefficients, together with the variable-specific bandwidths, were used to identify where each driver exerted positive or negative effects on WY and to determine whether such effects were predominantly local or basin-wide in scale.

3. Results

3.1. Spatiotemporal Patterns and Dynamics of WY in the ARB

3.1.1. Accuracy of WY Estimates

Observed natural streamflow data from 2000 to 2020 were obtained from measurements at the Aksu West Bridge hydrological station, as reported in the China River Sediment Bulletin. These observations were used to calibrate and validate the hydrological module of the InVEST model (Figure 2). Model performance was evaluated using the Nash–Sutcliffe efficiency (NSE), the R^2 , and the root-mean-square error (RMSE). The validation yielded $NSE = 0.840$, $R^2 = 0.846$, and $RMSE = 1.787$, demonstrating that the InVEST model effectively simulates WY in the ARB.

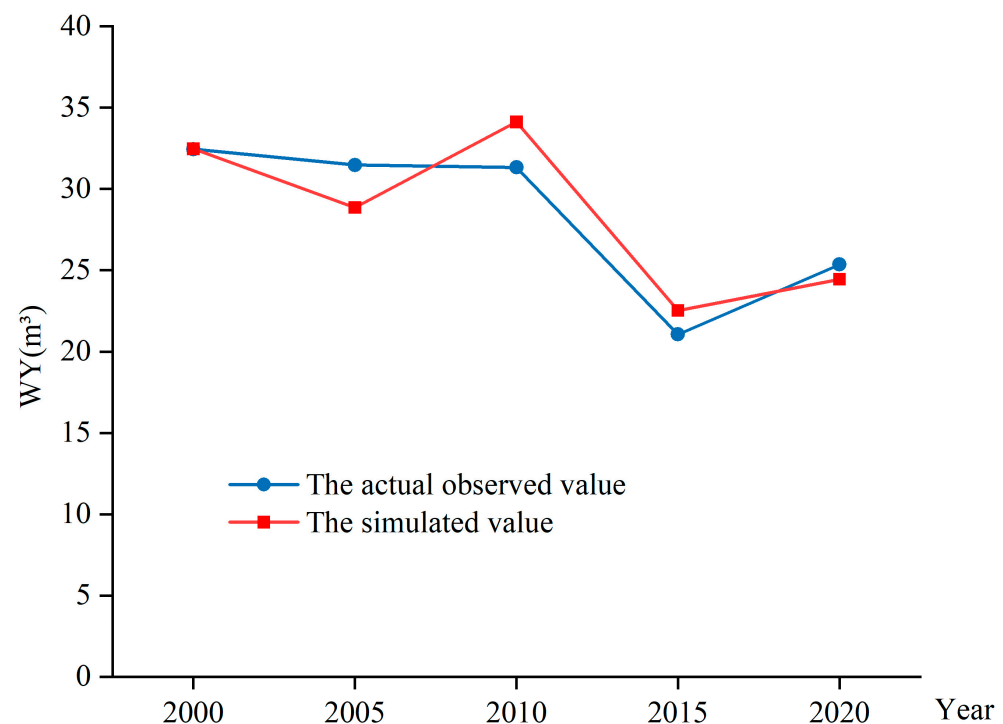


Figure 2. Comparison between observed and simulated water yield (WY) in the Aksu River Basin (ARB) for model validation (2000–2020).

3.1.2. Spatial Patterns and Interannual Variability of WY

During the period from 2000 to 2020, the interannual variations in precipitation, AET, WY depth, and total WY within the basin are presented in Figure 3. The maximum annual average precipitation was 193.1 mm, the minimum was 140.12 mm, and the overall average was 169.22 mm, indicating a total decrease of 52.98 mm over the study period. AET ranged between 96.97 mm and 126.59 mm, with a mean of 111.25 mm, declining at an average annual rate of 1.53 mm/year. AET accounted for 66% of total precipitation, while the precipitation decline rate was 1.6 times that of AET. WY depth demonstrated significant temporal variability, peaking in 2000 (66.49 mm) and reaching its lowest value in 2015 (43.15 mm). Total WY fluctuated between $21.06 \times 10^8 \text{ m}^3$ and $32.46 \times 10^8 \text{ m}^3$, exhibiting an overall decreasing trend.

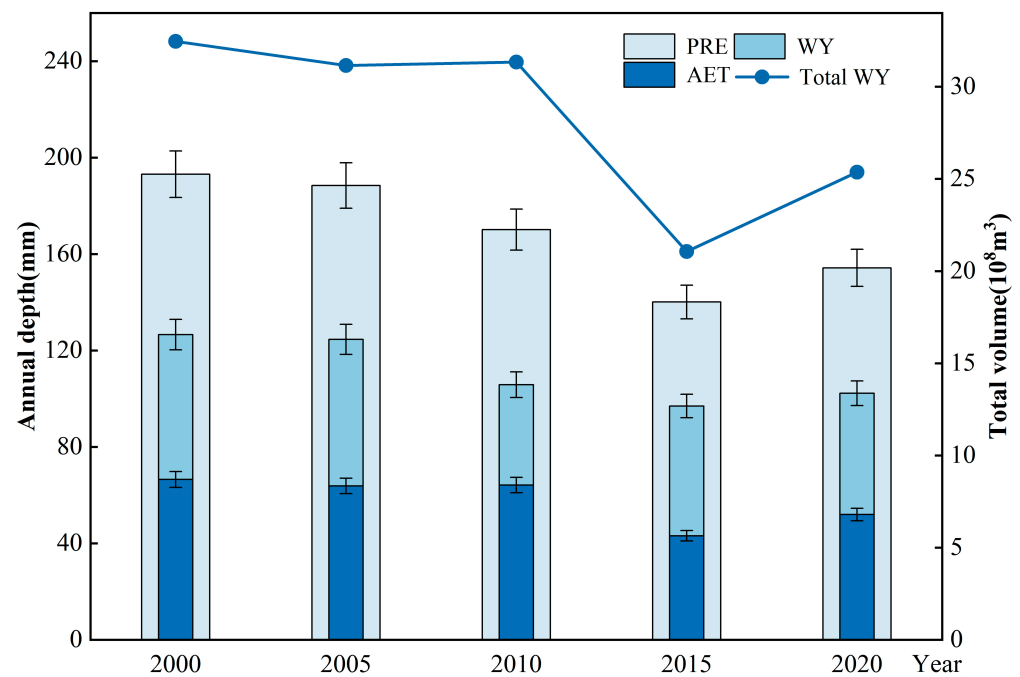


Figure 3. Interannual variations in precipitation (PRE), actual evapotranspiration (AET), water yield depth (WY), and total water yield (Total WY) in the Aksu River Basin (ARB) from 2000 to 2020. Bars represent annual depth (mm), and the line denotes total water yield (10^8 m^3).

From 2000 to 2020, WY in the ARB exhibited pronounced spatial heterogeneity and a persistent north–south gradient, with higher values in the northern upstream mountainous headwaters and lower values across the central–southern plains and desert zones (Figure S3). This pattern is consistent with the basin’s physiographic transition from the upstream mountains to the downstream oasis–desert plain, where spatial contrasts in water inputs and evaporative losses likely contribute to the observed spatial variability in WY. Consistent with the basin-wide water-balance signal in Figure 3 (precipitation decreased more than AET), the overall spatial configuration of WY remained broadly stable, whereas the magnitude of high-WY zones weakened over time. Specifically, the basin-wide maximum WY decreased from 917 mm in 2000 to 646.5 mm in 2020 (−29.5%), with intermediate maxima of 785.6 mm (2005), 725.05 mm (2010), and 668.25 mm (2015), indicating a sustained decline in peak WY.

To delineate spatial trends in WY, the Theil–Sen trend analysis was combined with the Mann–Kendall test (Figure 4a). Areas exhibiting highly significant, significant, and non-significant increases were predominantly concentrated in Akqi County, comprising only 3.14% of the total area. In contrast, regions showing highly significant, significant, and non-significant decreases accounted for 45.34% of the study area, primarily located in the northern and southeastern zones. At the annual scale, WY reflects the residual of precipitation after evapotranspiration losses; therefore, the dominance of decreasing trends is consistent with the basin-wide decline in precipitation reported in Figure 3. Short-term projections of WY were derived by integrating Theil–Sen median trends with Hurst index values (Figure 4b). These projections largely align with historical patterns observed from 2000 to 2020. Northern subregions—including Akqi County, northern Wushi County, and northern Wensu County—displayed sustained increases, accounting for just 2.89% of the basin. However, 45.39% of the area is projected to undergo persistent declines, while stable trends are anticipated across a substantial portion. Notably, these stable zones correspond to areas with historically low WY (Figure S3), indicating a general decline in the basin’s WY capacity.

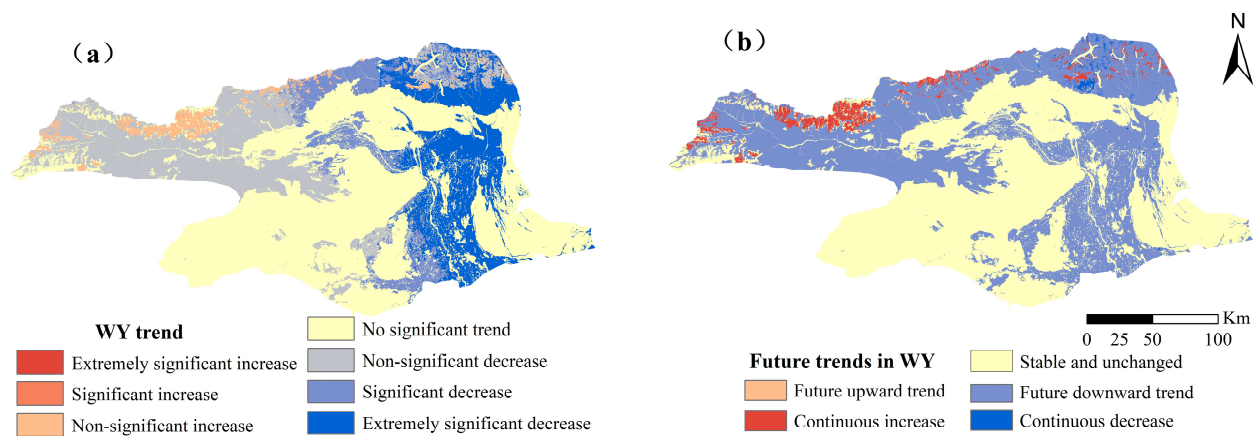


Figure 4. Spatial patterns of historical trends and projected future changes in water yield (WY) across the Aksu River Basin (ARB) during 2000–2020: (a) Historical WY trend categories: extremely significant increase, significant increase, non-significant increase, no significant trend, non-significant decrease, significant decrease, and extremely significant decrease. (b) Projected future WY trend categories: continuous increase, future upward trend, stable and unchanged, future downward trend, and continuous decrease.

Global spatial autocorrelation results, measured using Moran's I based on grid-level mean annual WY from 2000 to 2020, are presented in Table 2. The results indicated that global Moran's I values were all above 0.912 ($p < 0.001$), suggesting strong positive spatial autocorrelation and statistically significant clustering of WY within the study area. This satisfies the prerequisite for applying the GWR and MGWR models [37]. During both 2000–2010 and 2010–2020, Moran's I showed an initial decline followed by an increase, with an overall upward trend, indicating progressively stronger spatial clustering of WY over time.

Table 2. Spatial pattern of WYs in the ARB from 2000 to 2020.

Year	Moran's I	Z-Score	p -Value
2000	0.921	135.335	0.001
2005	0.912	133.632	0.001
2010	0.936	135.752	0.001
2015	0.916	134.999	0.001
2020	0.941	136.474	0.001

While global spatial autocorrelation captures overall spatial patterns, it does not reveal local variation in WY. Therefore, it is necessary to further examine localized aggregation and dispersion between grid cells and their surrounding neighborhoods. Local spatial autocorrelation analysis using LISA cluster maps identified four types of spatial association in WY: High–High, Low–Low, Low–High, and High–Low (Figure 5). No High–Low clusters were detected, implying that high-WY locations rarely occurred as isolated outliers surrounded by low-WY neighborhoods, and that high-WY patterns tended to be spatially contiguous. Low–Low clusters dominated (>48.2% of the basin), mainly distributed in the southern low-WY region (e.g., Kalpin County, Awat County, southern Aksu City, and southern Wushi County), indicating an extensive background of persistently low WY. In contrast, Low–High clusters accounted for only 0.11%–0.49% and were concentrated in northern Wensu County, reflecting limited localized low-WY patches embedded within relatively higher-WY surroundings. Compared with 2000, the proportion of High–High clusters increased by 3.41% in 2020 and was mainly concentrated in northern and west-

ern Akqi County, suggesting an enhancement of high-WY clustering in this upstream headwater area.

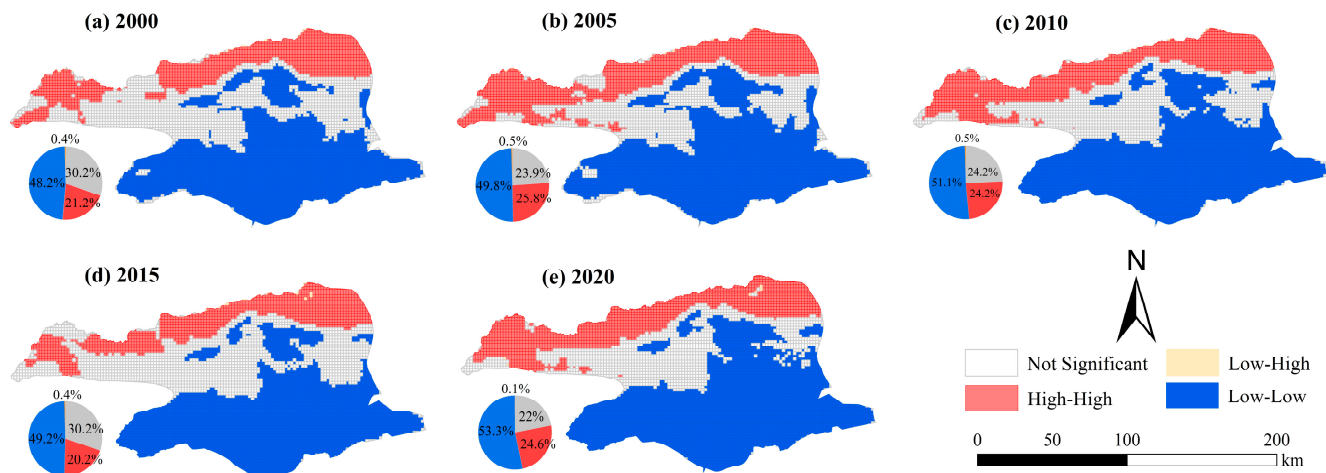


Figure 5. Local indicators of spatial association (LISA) cluster maps of water yield (WY) in the Aksu River Basin (ARB) for 2000, 2005, 2010, 2015, and 2020. High–High and Low–Low denote significant spatial clustering of high and low WY, respectively, whereas Low–High denotes low-WY cells surrounded by high-WY neighbors; cells labeled “not significant” indicate non-significant local autocorrelation. Pie charts show the area proportions of each LISA category in the corresponding year.

3.2. Dominant Drivers and Interaction Effects on WY

GeoDetector analyses were conducted in R using the GD package to identify key drivers of WY in the ARB. The factor detector indicated the following descending order of explanatory power for the spatial heterogeneity of WY: climatic factors > topographic factors > human activities > vegetation factors (Figure 6). All variables were significant at $p < 0.01$. PRE, TEM, EVA, DEM, and SLOPE were the dominant factors, with q values of 0.889, 0.880, 0.832, 0.767, and 0.683, respectively, indicating strong explanatory power for spatial heterogeneity. ASPECT, FVC, and GDP also had q values above 0.1, indicating moderate explanatory power, but weaker effects than the dominant climatic and topographic factors. POP and NPP had the lowest q values, indicating minimal explanatory power for the spatial distribution of WY. These results support that the pronounced north–south contrast in WY (higher in the upstream mountains and lower in the downstream plains/deserts) is primarily structured by hydroclimatic conditions (PRE, TEM, and EVA) together with topographic background (DEM and SLOPE).

To assess how interactions among driving factors affect the spatial heterogeneity of WY, an interaction detector was used (Figure 7). The results showed that the joint effects of human, climatic, vegetation, and topographic variables on the spatial variation of WY were substantially stronger than those of most individual factors. Specifically, when climatic variables (PRE, TEM, and EVA) were overlaid with other factors, the explanatory power consistently exceeded 0.7. Among these, interactions involving precipitation had the highest explanatory strength and occurred most frequently, with q values exceeding 0.9. In addition, interactions between human activity indicators and topographic factors ($q > 0.17$), as well as vegetation factors ($q > 0.12$), were also important contributors to the spatial variability of WY. These findings highlight the importance of interactions between natural conditions and anthropogenic influences. Natural factors directly alter environmental conditions and modulate WY, whereas human activities reshape land cover and soil characteristics, introducing spatially heterogeneous hydrological responses that indirectly but rapidly affect WY. The frequent high explanatory power of precipitation-related interactions ($q > 0.9$) indicates that WY is shaped by coupled effects (e.g., climate–topography

and climate–human interactions), which helps explain why strong spatial clustering and regional contrasts are observed across the basin.

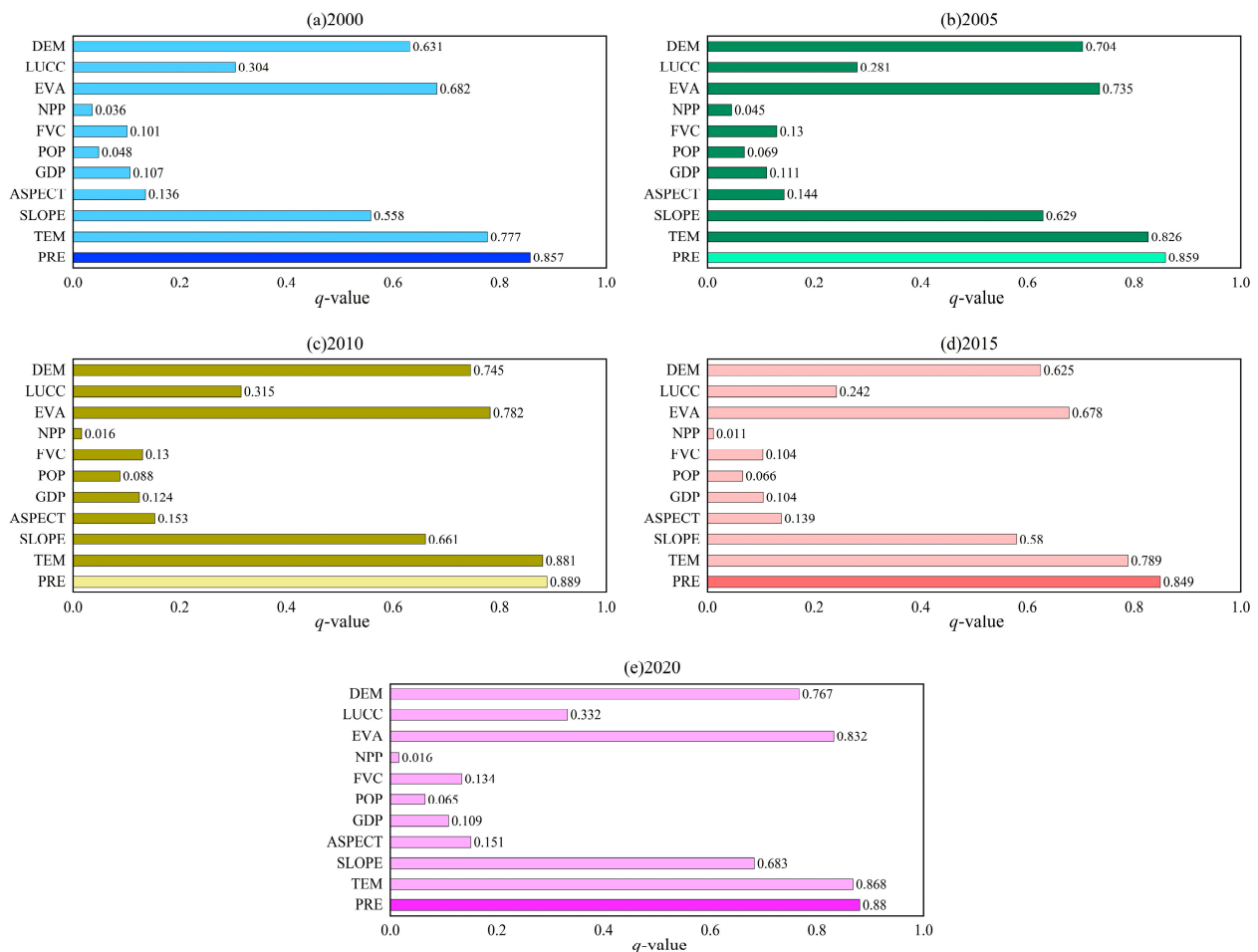


Figure 6. Explanatory power (q-statistic) of individual driving factors for the spatial heterogeneity of water yield (WY) in the Aksu River Basin (ARB), quantified using the GeoDetector factor detector for 2000, 2005, 2010, 2015, and 2020. Factors include precipitation (PRE), temperature (TEM), potential evapotranspiration (EVA), elevation from the digital elevation model (DEM), slope (SLOPE), aspect (ASPECT), gross domestic product (GDP), population density (POP), fractional vegetation cover (FVC), net primary productivity (NPP), and land use/land cover change (LUCC).

3.3. Spatial Heterogeneity and Scale Dependence of Driver Effects

To explore spatial relationships between WY and key influencing factors, variables with q values greater than 0.1 were first selected. Multicollinearity was then assessed, and variables with variance inflation factors (VIF) greater than 10 were excluded before spatial heterogeneity analysis. GWR and MGWR were then used to model the spatial distribution of WY in the ARB. Because LUCC data were not suitable for quantitative modeling in the MGWR framework, six variables were ultimately selected as independent variables: PRE, DEM, SLOPE, ASPECT, GDP, and FVC. Model results (Table 3) showed that MGWR achieved higher R^2 and adjusted R^2 values than GWR, together with lower AICc and RSS. These results indicate that MGWR better addresses spatial non-stationarity and captures the spatial heterogeneity of WY in the ARB. This conclusion is consistent with Hu et al. [39], who evaluated the applicability of multiscale models for identifying drivers of ecosystem services.

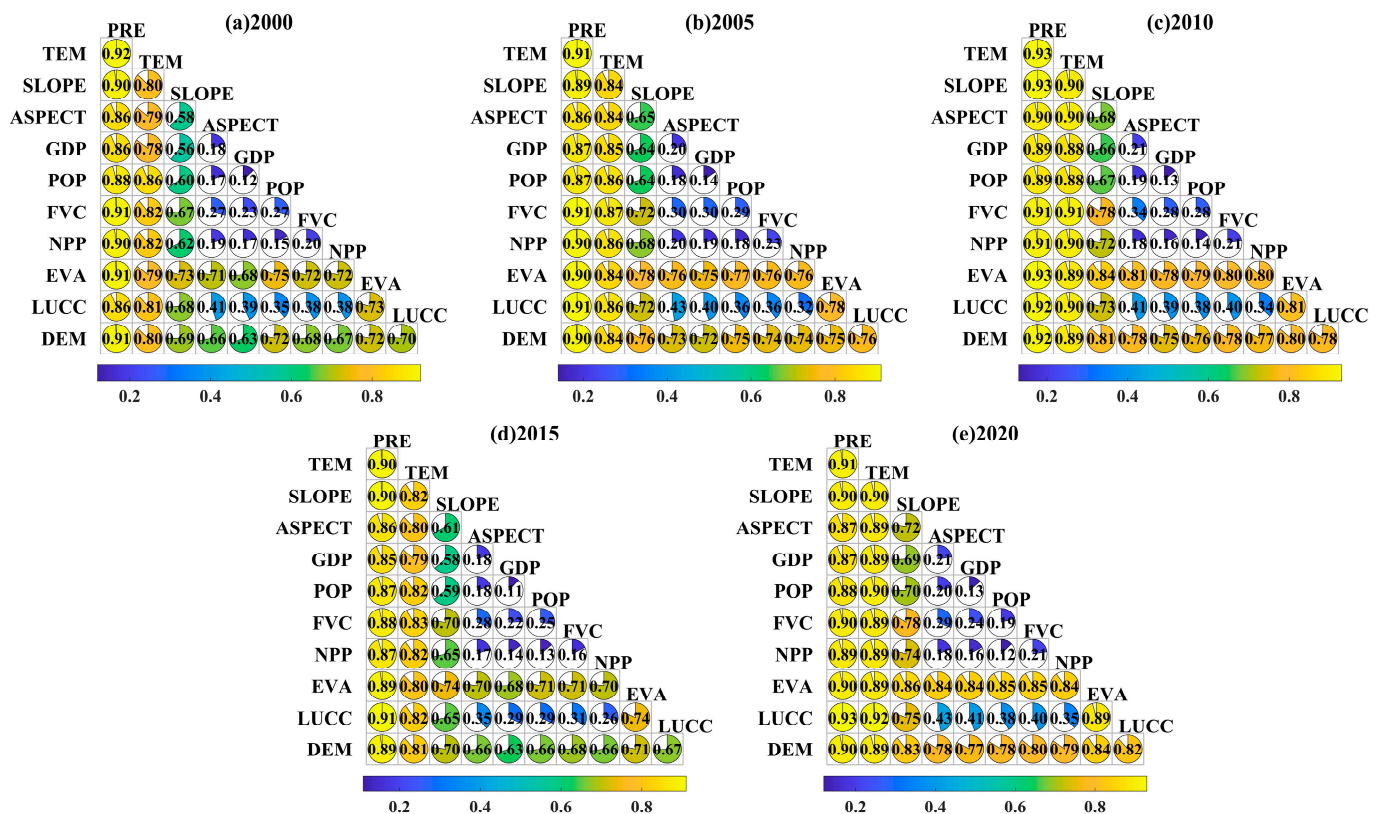


Figure 7. Interaction detector results (q-statistic) from GeoDetector showing the joint explanatory power of paired driving factors on the spatial heterogeneity of water yield (WY) in the Aksu River Basin (ARB) for 2000, 2005, 2010, 2015, and 2020. Numbers within circles denote q-values for factor interactions, and colors indicate the magnitude of q (higher values represent stronger joint explanatory power). Factors include precipitation (PRE), temperature (TEM), potential evapotranspiration (EVA), elevation from the digital elevation model (DEM), slope (SLOPE), aspect (ASPECT), gross domestic product (GDP), population density (POP), fractional vegetation cover (FVC), net primary productivity (NPP), and land use/land cover change (LUCC).

Table 3. Comparative analysis of GWR and MGWR models.

		R^2	Adjusted R^2	RSS	AICc
2000	GWR	0.870	0.870	742.538	4572.068
	MGWR	0.988	0.986	67.060	−6694.768
2005	GWR	0.866	0.866	763.394	4729.946
	MGWR	0.985	0.983	84.053	−6197.790
2010	GWR	0.890	0.890	628.938	3622.906
	MGWR	0.992	0.990	43.985	−8852.936
2015	GWR	0.843	0.843	894.515	5635.656
	MGWR	0.980	0.977	114.788	−4175.485
2020	GWR	0.858	0.858	812.444	5085.770
	MGWR	0.986	0.984	79.394	−6339.929

Notes: R^2 , coefficient of determination; Adjusted R^2 , adjusted coefficient of determination; RSS, residual sum of squares; AICc, corrected Akaike information criterion. Higher R^2 /Adjusted R^2 and lower RSS/AICc indicate better model performance.

Using 2020 as a case study, this section applies the MGWR model to estimate spatially varying regression coefficients between WY and its driving factors, thereby elucidating the spatial response of WY in the ARB. The analysis further distinguishes positive and negative effects of each factor on WY at the grid scale. According to the regression results (Table 4), each factor is assigned an individual bandwidth, allowing the model to account

for multiscale spatial heterogeneity and to better reflect the spatial distribution and intensity of each variable's influence.

Table 4. Statistics of regression coefficients of the MGWR model in 2020.

Driver Factor	Mean	Standard Deviation	Minimum	Median	Maximum	VIF	Bandwidth
PRE	0.838	0.671	−0.118	0.548	2.123	7.107	46
DEM	−0.166	0.128	−0.557	−0.173	0.203	8.200	70
GDP	0.112	0.448	−0.010	0.0625	0.590	1.615	46
FVC	0.085	0.216	−0.238	0.012	1.455	1.549	46
SLOPE	0.082	0.068	−0.158	0.083	0.291	3.987	146
ASPECT	−0.0002	0.035	−0.267	0.0001	0.240	1.084	70

Notes: PRE, precipitation; DEM, elevation from the digital elevation model; GDP, gross domestic product; FVC, fractional vegetation cover; SLOPE, slope; ASPECT, aspect. Coefficient statistics (mean, standard deviation, minimum, median, and maximum) summarize the distribution of local MGWR coefficients across grid cells. VIF is the variance inflation factor used to assess multicollinearity. Bandwidth indicates the optimal spatial scale (number of neighboring observations) used for each predictor in MGWR.

Coefficients were visualized using the natural breaks method (Figure 8). The coefficient for precipitation has the largest absolute mean value, indicating that precipitation is the dominant factor influencing WY in the basin. Spatial differences in the precipitation coefficient suggest that the sensitivity of WY to precipitation is not uniform across the basin. Areas with larger coefficients indicate a higher responsiveness of WY to precipitation at the annual scale. Precipitation shows an increasing west–east gradient in the northern basin, but the opposite pattern in the central and southern regions. DEM is negatively associated with WY, with the most pronounced negative effects in northern Wensu County. This negative elevation–WY association likely reflects the combined influence of topography-related hydroclimatic conditions (e.g., temperature regime and precipitation phase) and the fact that annual-scale WY estimates may not fully represent high-elevation storage–release processes. GDP shows a positive association with WY, and coefficient magnitudes gradually decline from west to east. Because GDP spatially co-locates with oasis development and human activity intensity, it may act as a proxy for anthropogenic pressure rather than a direct causal driver of WY. FVC has modest mean coefficients, with positive effects mainly concentrated in the northern basin, particularly in western Akqi County. Coefficients for SLOPE and ASPECT range from −0.267 to 0.291, indicating relatively weak influences on WY. The SLOPE coefficient generally declines from the northeastern high-value regions toward peripheral areas. ASPECT coefficients are discretely distributed and converge near zero overall, suggesting minimal impact. Overall, no single factor exerts a purely positive or negative effect. Instead, the spatial distribution of WY in the ARB reflects synergistic interactions among multiple environmental and anthropogenic variables. Overall, the coefficient maps indicate spatial differences in WY sensitivity to precipitation, topography, vegetation, and socioeconomic conditions.

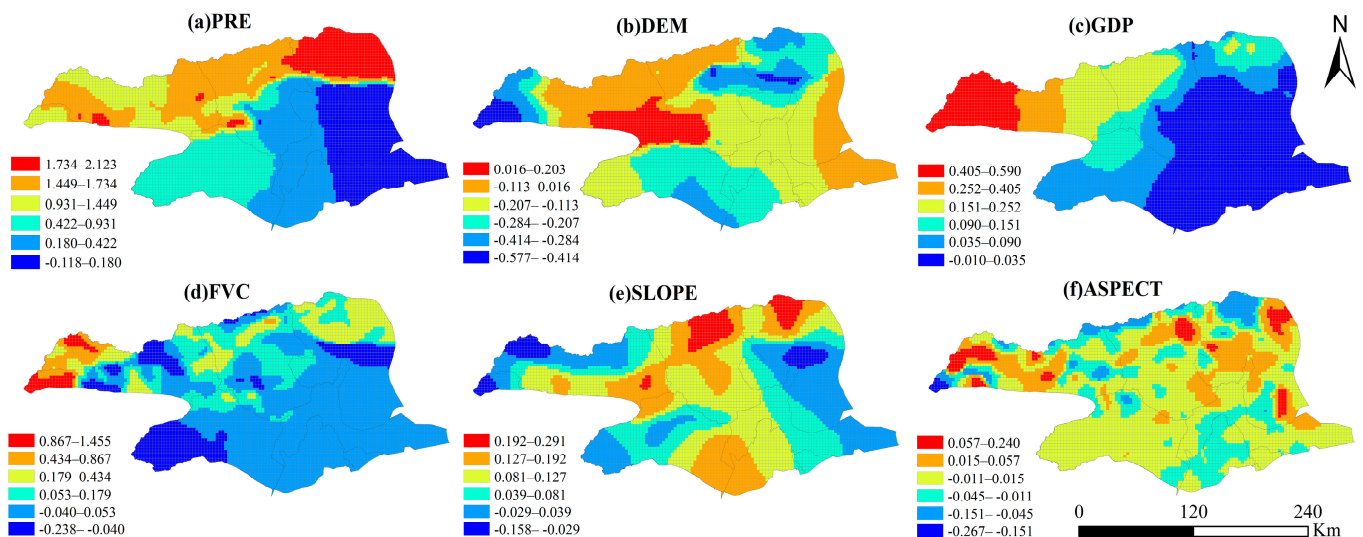


Figure 8. Spatial distribution of multiscale geographically weighted regression (MGWR) coefficients for the relationships between water yield (WY) and selected driving factors in the Aksu River Basin (ARB) (2020). Panels show coefficient estimates for (a) precipitation (PRE), (b) elevation from the digital elevation model (DEM), (c) gross domestic product (GDP), (d) fractional vegetation cover (FVC), (e) slope (SLOPE), and (f) aspect (ASPECT). Positive coefficients indicate a positive association with WY, whereas negative coefficients indicate a negative association.

4. Discussion

4.1. Interpretation of Changes in WY and a Stable Spatial Pattern in the ARB

From 2000 to 2020, annual WY in the ARB exhibited a significant basin-wide declining trend, and areas with decreasing WY accounted for 45.34% of the basin. Despite interannual variability, WY consistently maintained a stable north–south gradient, with higher values in the north and lower values in the south. Previous work likewise reported mean WY depths of 95.67 mm in 2010 and 71.57 mm in 2015, with little overall change in spatial patterns between the two periods [40]. This is consistent with the declining trend and stable spatial gradient found in this study. From a water balance perspective, annual WY is jointly controlled by precipitation inputs and evapotranspiration losses [41]. The persistent “high in the north and low in the south” gradient likely reflects topography-driven background hydrothermal differentiation [42], which reinforces this stable structure by shaping the spatial patterns of precipitation and evapotranspiration. Consequently, basin-scale changes in WY tend to manifest as magnitude adjustments superimposed on an established spatial gradient. The basin-wide level varies with water balance conditions, whereas the gradient direction remains relatively stable.

Trend analysis combined with the Hurst exponent further indicates that approximately 45.39% of the area is likely to continue a declining trajectory, suggesting temporal persistence in WY change. Meanwhile, WY exhibits significant positive spatial autocorrelation (Moran’s $I > 0.912$), and LISA results show the coexistence of High–High clusters in the north and Low–Low clusters in the south. These patterns indicate pronounced spatial clustering and structural organization of WY rather than a random or spatially dispersed pattern [43]. Given these persistence and clustering characteristics, the next step is to identify the dominant drivers and their spatially varying effects to clarify the key controlling processes underlying regional differentiation in WY.

4.2. Combined Dominant Controls and Management Implications

Based on global screening of candidate factors using GeoDetector and spatial regression results from MGWR, PRE, DEM, SLOPE, ASPECT, GDP, and FVC were identified as

the primary drivers explaining spatial differentiation in WY. Overall, this is consistent with existing evidence that WY in arid basins is jointly constrained by meteorological supply and topographic setting, with additional influences from vegetation conditions and human activities [44,45]. GeoDetector further revealed widespread interaction enhancement among factors, suggesting that spatial variability in WY is more likely shaped by multifactor coupling than by any single factor acting independently [31]. Accordingly, MGWR was used to examine how the direction and magnitude of these effects vary across regions.

The results indicate that precipitation has an overall positive effect on WY, suggesting that precipitation supply is a key constraint on annual-scale variability in WY. Previous studies have shown that precipitation variability can substantially regulate WY by directly altering the basin water balance and land surface hydrological processes [14,46]. Accordingly, interannual variability in WY is closely linked to regional precipitation variability and may reflect climate change influences on precipitation regimes [47]. This aligns with the widely reported conclusion that precipitation inputs constitute a primary control on annual WY [18,48].

Among topographic factors, DEM shows predominantly negative effects across most areas, with stronger negative effects at higher elevations. In contrast, slope tends to be positive in mountainous and piedmont zones, indicating that topography influences WY through multiple pathways with differentiated net effects. For DEM, the negative association contrasts with the mechanism proposed by Wei et al. [49] for the cold high mountain region of the upper Shule River, where frozen layers restrict infiltration and enhance hillslope convergence, promoting runoff generation. Although high elevations and complex terrain can increase precipitation via orographic lifting and suppress evapotranspiration [24,50], precipitation in high mountain areas is often stored as glaciers and seasonal snow, with a pronounced time lag in release. Because annual scale models have limited representation of snow and glacier accumulation and melt dynamics, upstream contributions to WY may be statistically attenuated, leading to an apparent negative association between elevation and WY. In contrast, steeper slopes typically reduce hillslope storage and infiltration opportunities while enhancing the efficiency of overland and shallow subsurface flow, resulting in a positive influence on annual WY [51]. Aspect shows relatively weak explanatory power and a patchy spatial pattern. This implies that it primarily affects evapotranspiration and soil moisture indirectly through radiation differences and microclimatic conditions, but is unlikely to exert a stable dominant influence at annual and basin scales [52].

In contrast, the regression coefficients for GDP and FVC are smaller in overall magnitude, but their spatial variability is more pronounced. GDP shows weaker coefficients in the central–southern basin, likely because it is concentrated in built-up areas and primarily serves as a proxy for human activity intensity and management inputs rather than a direct determinant of natural WY processes [53]. Local positive effects in the north are more likely to reflect a composite signal of engineering regulation and water use intensity, such as reservoir regulation, canal conveyance and distribution, and irrigation management. These interventions can induce spatial covariation with WY [54]. FVC shows positive effects in the northern basin but weaker effects in the central–southern basin. This may relate to the regulatory role of high-elevation shrub vegetation in enhancing infiltration and reducing surface runoff losses, contributing positively to annual WY [55].

Given the spatially heterogeneous effects of dominant drivers, zoned management should adopt differentiated priorities. In the northern high elevation mountains, where precipitation is dominant, and WY is more sensitive to snow and ice processes, priority should be given to continuous monitoring of headwater inflow and runoff dynamics at key control sections and to limiting land surface and vegetation fragmentation from intensive disturbances such as extraction, road building, and engineering construction. In piedmont

and slope transition zones, where slope is predominantly positive and runoff responses are rapid, management should focus on rapid runoff generation and erosion risk during rainfall and snowmelt periods, supported by slope stabilization and maintenance of key flow paths to dampen runoff variability. In areas where GDP shows strong localized positive effects, it can be treated as a diagnostic signal of intensive water use and management activities, motivating priority audits of water use intensity and conveyance losses, with interventions linked to measurable efficiency indicators. To enhance operational feasibility, we recommend an annual monitoring and assessment scheme integrating runoff at key control sections (annual runoff, wet and dry season flows, and runoff coefficient), water use intensity per unit area, and changes in FVC. The results can be used to iteratively update zoned management priorities and water allocation strategies.

4.3. Limitations and Future Perspectives

The InVEST Annual WY module used in this study is based on the Budyko water–energy balance framework and uses simplified representations of hydrological processes in cold and high-altitude regions. In particular, it does not explicitly simulate glacier mass accumulation or seasonal snowmelt dynamics. Although glacier meltwater was approximated using published sources and subtracted from the water input term, and key parameters (for example, the precipitation seasonality parameter) were calibrated against observed discharge at the Xi Da Bridge station, it remains difficult to accurately reproduce the interannual variability and spatial heterogeneity of snow and glacier melt. This limitation may lead to systematic underestimation of WY in upstream high-elevation areas and increase uncertainty in the assessment [56]. In addition, although MGWR achieved high overall goodness of fit, largely because variable-specific bandwidths capture spatial non-stationarity, the model remains relatively complex [45]. Although multicollinearity was controlled using variance inflation factor screening, some risk of overfitting cannot be fully excluded [57]. Moreover, local model performance was spatially uneven, with relatively low explanatory power in some areas, suggesting that important hydrological or human activity factors may be omitted (Figure S4). Additional variables and further validation are therefore warranted. Consequently, MGWR coefficients are better suited for spatial diagnostics and mechanistic interpretation than for extrapolative prediction.

Future work can proceed in three directions. Methodologically, coupling physically based distributed hydrological models with remote sensing-derived snow and glacier information may improve the representation of hydro-ecological processes in cold arid regions. From a data perspective, incorporating additional key drivers could improve explanatory power in areas with poor local fit. From an application perspective, integrating sensitivity zonation with land use scenarios and ecosystem service models would enable scenario simulations of synergies and trade-offs between WYs and other ecosystem services under alternative management pathways, providing quantitative evidence for integrated basin management.

5. Conclusions

This study integrated the InVEST Annual WY module, GeoDetector, and MGWR to characterize spatiotemporal patterns of annual WY in the ARB during 2000–2020 and to attribute its spatial differentiation to dominant drivers. The main findings are as follows: (1) WY in the ARB exhibited an overall declining trend during 2000–2020, with decreasing areas accounting for 45.34% of the basin, mainly distributed in parts of the northern mountainous region and the southeastern sector. Spatially, WY persistently maintained a stable north–south gradient, with higher values in the north and lower values in the south, indicating a clear and relatively stable spatial structure. (2) At the basin scale, GeoDetector

identified climatic factors (precipitation and potential evapotranspiration) as having the strongest explanatory power for spatial variability in WY, followed by topographic factors (DEM and SLOPE). Significant interaction enhancement was detected among factors, and joint explanatory power was markedly higher than that of individual factors. This indicates that the spatial pattern of WY is jointly shaped by coupled climatic and topographic constraints. (3) MGWR revealed pronounced spatial non-stationarity and scale dependence in driver effects. Precipitation showed an overall positive association with WY, with effect magnitudes weakening from north to south. Elevation exerted a predominantly negative effect, whereas slope showed a predominantly positive effect across most areas. Differences in optimal bandwidths among variables indicate that driver influences operate over distinct spatial extents, underscoring the need for spatially explicit attribution analyses. Overall, dominant controls on WY in the ARB exhibit strong spatial heterogeneity and geomorphological zonation, providing a spatial basis for differentiated strategies in water resource conservation and utilization in arid basins and for subsequent water allocation studies. Moreover, the integrated InVEST–GeoDetector–MGWR framework offers a transferable approach for assessing WYs and attributing spatial patterns in other basins with highly heterogeneous underlying surface conditions.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18020818/s1>, Figure S1. Location of the study area in China. (a) Location of Xinjiang Uygur Autonomous Region (Xinjiang) within China. (b) Location of the Aksu River Basin (ARB) within Xinjiang. (c) Topography and administrative divisions of the ARB, including elevation (m), the river network (Aksu River), and county-level boundaries. Map approval number: GS (2019) No. 1822. Figure S2. Spatial distribution of factors: (a) precipitation (PRE), (b) temperature (TEM), (c) potential evaporation (EVA), (d) digital elevation model (DEM), (e) gross domestic product (GDP), (f) population (POP), (g) fractional vegetation cover (FVC), (h) net primary productivity (NPP), (i) aspect (ASPECT), (j) slope (SLOPE), (k) land use (LUCC; 1 = Cropland, 2 = Forest, 3 = Grassland, 4 = Water bodies, 5 = Built-up land, 6 = Unused land). Figure S3. Spatial distribution of water yield (WY) in the Aksu River Basin (ARB) for (a) 2000, (b) 2005, (c) 2010, (d) 2015, and (e) 2020. Panel (f) shows the mean WY averaged across these five years (2000, 2005, 2010, 2015, and 2020). WY is expressed in millimeters (mm). Figure S4. Distribution of local coefficient of determination (local R^2) from the multiscale geographically weighted regression model (MGWR) at different spatial scales. (a) Basin scale of the Aksu River Basin (ARB). (b) County scale for Aheqi, Keping, Wensu, Wushi, and Aksu. Stacked bars show the percentage of grid cells with local R^2 values in three classes: <0.4, 0.4–0.8, and >0.8. In panel (b), bars within each county correspond to 2000, 2005, 2010, 2015, and 2020 from left to right. Table S1. Data types and sources. Table S2. Determinants of the Spatial Differentiation in WYs in the ARB Region. Notes: WYs, water yield service; ARB, Aksu River Basin; PRE, precipitation; TEM, temperature; EVA, potential evapotranspiration; DEM, digital elevation model; ASPECT, aspect; SLOPE, slope; FVC, fractional vegetation cover; NPP, net primary productivity; POP, population density; GDP, gross domestic product; LUCC, land use/cover change.

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