Enhancing urban resilience through water ecosystem services in the arid region of Northwest China Postprint

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Abstract

Within the context of global climate change and rapid urbanization, increasing urban resilience (UR) is especially important in the arid region of Northwest China (ANC), where fragile ecosystems and an uneven water distribution create significant sustainability challenges. In this study, a coupled UR-water ecosystem services (WESs) framework was developed on the basis of 1-km resolution remote sensing data for the 2000–2020 period obtained from the Landsat series, Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS), and Global Precipitation Measurement (GPM), among other sources. Within the framework, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was incorporated to provide a WES indicator system. Moreover, entropy weighting was employed to quantify both UR and WES indicators; the coupling coordination degree (CCD) model was used to measure the coupled relationship between UR and WESs; an extreme gradient boosting (XGBoost)-SHapley Additive exPlanations (SHAP) interpretation approach was adopted to identify key drivers and underlying mechanisms; and Geographically Weighted Regression (GWR) was applied to capture spatial distribution characteristics of major driving factors. The results indicated that UR steadily increased from 4.60$×10–3to10.24×10–3, *whereasWESsfollowedaninvertedV − shapedtrend, withapeakvalueobservedin*2010(11.84×$10-3). The CCD remained consistently low (mean: 0.0166–0.0246) and exhibited considerable spatial heterogeneity. Notably, the degree of coordination was greater in the oasis and mountain core areas but significantly lower at desert areas. XGBoost-SHAP model analysis revealed six key drivers influencing various states of the CCD between UR and WESs systems. The contributions of these factors could be ranked as follows: water yield (WY; 24.30%)>farmland area per capita (FP; 21.10%)>gross domestic product (GDP) per capita (GDPC; 19.00%)>soil retention (SR; 14.90%)>population density (PD; 5.42%)>water purification (WP; 4.40%). In contrast, in UR system, WP (53.66%) and SR (31.62%) served as the dominant drivers. Moreover, the dominant drivers shifted from a combination of natural and socioeconomic factors in State I (sustainable high resilience) to primarily socioeconomic factors in State III (unsustainable low resilience). SR and WP exerted positive moderating effects, whereas socioeconomic factors such as GDPC and PD exerted inhibitory effects on the coordination relationship. This research highlights that UR in the ANC region is limited mainly by water scarcity, weak feedback loops, and spatial variability, emphasizing the need for tailored intervention strategies.

Full Text

Preamble

J Arid Land (2026) 18(3): 429-451 Enhancing urban resilience through water ecosystem services in the arid region of Northwest China ZHOU Yuxuan , HE Jia , WANG Shoufeng 1 College of Geographic Science and Tourism, Xinjiang Normal University, Urumqi 830054, China; Xinjiang Laboratory of Lake Environment and Resources in Arid Zone, Xinjiang Normal University, Urumqi 830054, China

Abstract

Within the context of global climate change and rapid urbanization, increasing urban resilience (UR) is especially important in the arid region of Northwest China (ANC), where fragile ecosystems and an uneven water distribution create significant sustainability challenges. In this study, a coupled UR-water ecosystem services (WESs) framework was developed on the basis of 1-km resolution remote sensing data for the 2000–2020 period obtained from the Landsat series, Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS), and Global Precipitation Measurement (GPM), among other sources. Within the framework, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model was incorporated to provide a WES indicator system. Moreover, entropy weighting was employed to quantify both UR and WES indicators; the coupling coordination degree (CCD) model was used to measure the coupled relationship between UR and WESs; an extreme gradient boosting (XGBoost)-SHapley Additive exPlanations (SHAP) interpretation approach was adopted to identify key drivers and underlying mechanisms; and Geographically Weighted Regression (GWR) was applied to capture spatial distribution characteristics of major driving factors. The results indicated that UR steadily increased from 4.60$\times 10 to 10.24\times 10, whereas WESs followed an inverted V-shaped trend, with a peak value observed in 2010 (11.84\times$10). The CCD remained consistently low (mean: 0.0166–0.0246) and exhibited considerable spatial heterogeneity. Notably, the degree of coordination was greater in the oasis and mountain core areas but significantly lower at desert areas. XGBoost-SHAP model analysis revealed six key drivers influencing various states of the CCD between UR and WESs systems. The contributions of these factors could be ranked as follows: water yield (WY; 24.30%)>farmland area per capita (FP; 21.10%)>gross domestic product (GDP) per capita (GDPC; 19.00%)>soil retention (SR; 14.90%)>population density (PD; 5.42%)>water purification (WP; 4.40%). In contrast, in UR system, WP (53.66%) and SR (31.62%) served as the dominant drivers. Moreover, the dominant drivers shifted from a combination of natural and socioeconomic factors in State I (sustainable high resilience) to primarily socioeconomic factors in State III (unsustainable low resilience). SR and WP exerted positive moderating effects, whereas socioeconomic factors such as GDPC and PD exerted inhibitory effects on the coordination relationship. This research highlights that UR in the ANC region is limited mainly by water scarcity, weak feedback loops, and spatial variability, emphasizing the need for tailored intervention strategies.

Keywords

urban resilience; water ecosystem services (WESs); coupling coordination degree; Extreme Gradient Boosting (XGBoost); SHapley Additive exPlanations (SHAP); Northwest China; arid region Citation:

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1 Introduction

Against the backdrop of global urbanization and climate change, water ecosystem services (WESs) are increasingly degraded or lost under mounting pressures. This degradation undermines urban resilience (UR) and creates a self-reinforcing feedback loop (Seto et al., 2012; Macedo and Madaleno, 2022; Jahan and Singh, 2023; Pattison and Cooke, 2024; Ruiz Serrano et al., 2024).

The Social-Ecological Systems (SES) framework provides a fundamental lens for understanding the complex interplay and bidirectional feedback mechanisms between human societal development and ecological system functions (Ostrom, 2009; Folke et al., 2016). WESs enhance a city' s resistance to and recovery from external shocks by provisioning water resources, regulating runoff, and purifying the environment (Grimm et al., 2008). Simultaneously, improving UR can effectively mitigate the destructive impact of human activities on WESs, thereby facilitating a virtuous cycle between the UR and WESs systems (Ahern, 2011). Amid the dual pressures of global urbanization and climate change, achieving coordinated coupling between UR and WESs has become an urgent imperative for sustainable development (Das et al., 2024).

In recent years, as critical components of SES, both UR and WESs have attracted increasing research attention. Research on UR has evolved from single-disciplinary approaches toward multidimensional perspectives, receiving particular emphasis in recent studies (Wang et al., 2018; Liu et al., 2021; Elsharqawy et al., 2022). Meanwhile, as a branch of ecosystem services (ESs), WESs have developed rapidly, with modeling and quantification now widely employed in their analysis (Brauman et al., 2007; Leal Filho et al., 2020; Ha and Bastiaanssen, 2023; Ha et al., 2023). However, existing research has predominantly focused on singular dimensions, frequently overlooking the feedback loop between WES degradation and increasing vulnerability in UR. (Costanza et al., 2014). Research on the coupling between UR and WESs currently faces two major gaps: (1) a lack of quantitative assessment of their coupled relationship; and (2) an insufficient understanding of their nonlinear coupling dynamics and underlying mechanisms, coupled with a notably limited application of coupled calculation and interpretable machine learning methods in this specific domain (Ryo et al., 2019; Sharifi, 2020). These research gaps are particularly pronounced in the arid region of Northwest China (ANC). The inherent ecological vulnerability of this region renders it imperative to elucidate the coupling relationships and underlying mechanisms between UR and WESs.

The ANC, located in the hinterland of Northwest China and deep within the Eurasian continent, is characterized by an arid climate with an annual precipitation generally below 400.0 mm (Yao et al., 2019). This harsh moisture regime fundamentally underpins its highly fragile ecological base, rendering ecosystem stability extremely sensitive to various disturbances (Wang et al., 2025).

Challenges such as uneven water distribution and overgrazing combine to create a complex set of intertwined ecological pressures (Cao et al., 2022). Meanwhile, rapid urbanization processes and spatial concentration of population have led to the frequent occurrence of issues such as groundwater over-extraction, water eutrophication, and a sharp decline in biodiversity. In turn, urbanization further exacerbates environmental degradation. Consequently, the ANC emerges as a critical region for investigating the coupling relationships and mechanisms between UR and WESs under the influence of human activities (Ding et al., 2022; Dan et al., 2024).

Based on the urgent need to address current research gaps and advance sustainable development in arid regions, this study focused on the ANC as a representative case area. Using 1-km resolution remote sensing data spanning 2000–2020 from the Landsat series, Defense Meteorological Satellite Program (DMSP)/Operational Linescan System (OLS), and Global Precipitation Measurement (GPM), among other sources, this study constructed a UR-WES coupling analysis framework. Through objective weighting methods, the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) and Coupling Coordination Degree (CCD) models, Extreme Gradient Boosting (XGBoost)-SHapley Additive exPlanations (SHAP) interpretation machine learning model, and Geographically Weighted Regression (GWR) model, this research quantified UR and WES indicators and examined their coupled relationships and underlying

drivers. This study is structured around a core research question: how to enhance UR in the ANC through WESs? Ultimately, the findings provide scientific evidence to support spatially-targeted policy formulation for water resource management and UR enhancement in the ANC. 2 Materials and methods

2.1 Study area

The ANC region, deeply situated within the hinterland of the Eurasian continent (35°–50°N, 73°–107°E), denotes the vast inland dry area west of the Helan Mountains-Wushaoling line and north of the Qilian-Kunlun mountain belt, encompassing Xinjiang Uygur Autonomous Region, most of the Hexi Corridor (except part of Qilian Mountains in Jiuqu City, Gansu Province), and Alxa League, Inner Mongolia Autonomous Region (Chen et al., 2023). This region features an annual average temperature ranging from approximately -4°C to 12°C, while annual evapotranspiration (approximately 1500.0–3000.0 mm) substantially exceeds precipitation (approximately 50.0–300.0 mm), resulting in a highly uneven distribution of water resources (Wang et al., 2017). The region is dominated by mountains and basins, including major ranges such as the Altay, Tianshan, Kunlun, and Qilian mountains, together with vast basins such as the Tarim and Junggar basins (Fig. 1 [Figure 1: see original paper]) (Wang et al., 2021). The landscape of ANC region is characterized mainly by grasslands, Gobi deserts, and barren lands. Land use is dominated by grassland and unused land, while cropland, forestland, water bodies, and built-up areas collectively account for less than 20.00% of the total area. The ANC region features an arid landscape characterized by a distinctive mountain-oasis-desert system interwoven with urban agglomerations.

Distribution of altitude in the arid region of Northwest China (ANC). DEM, digital elevation model.

2.2 Data sources

In this study, the UR system is comprehensively characterized by nine indicators, namely, the population density (PD) (Rafiei-Sardooi et al., 2021), population growth rate (PGR) (Arfanuzzaman and Rahman, 2017), urbanization rate (URA) (Zhang et al., 2016), urban population size (UPS) (Feng et al. 2020), farmland area per capita (FP) (Ding et al., 2016), gross domestic product (GDP) per capita (GDPC) (Liu et al., 2024b), fossil fuel CO emissions (FE) (Diaz et al., 2024), nighttime light intensity (NLI) (Liu et al., 2023), and the nighttime light aggregation index (NLAI) (Hu et al., 2024). The establishment of this indicator system is primarily based on the theory of urban composite ecosystems, aiming to capture the adaptability and developmental resilience of urban systems across multiple dimensions, including demographic dynamics, economic development, and environmental impacts (Elmqvist et al., 2019). The WES system was assessed via three core indicators from the InVEST model, namely, water yield (WY) (Dennedy-Frank et al., 2016), sediment retention (SDR) (Su et al., 2020), and nutrient delivery ratio (NDR) (Redhead et al., 2018). The selection of these indicators is grounded in the ES cascade framework and the classical classification system of water-related services, which aims to represent key functional aspects such as water supply provision, soil conservation, and water quality regulation functions (Potschin-Young et al., 2018).

The datasets employed in this study cover both UR and WESs, which were derived from remote sensing data with a spatial resolution of 1 km. The temporal coverage comprises five time points, i.e., 2000, 2005, 2010, 2015, and 2020. The data sources for the UR and WES systems are summarized in Tables 1 and 2, respectively.

Urban resilience (UR) data sources

Index Unit Data source

Population density (PD) persons/km The premier human geography foundation population datasets-Oak Ridge National Laboratory (ORNL) Population growth rate (PGR) The premier human geography foundation population datasets-ORNL LandScan Viewer Urbanization rate (URA) National Qinghai-Tibetan Plateau/Third Pole Urban population size (UPS) persons/km National Qinghai-Tibetan Plateau/Third Pole Farmland area per capita (FP) /person Resources and Environmental Science Data Platform Gross domestic product (GDP) per capita (GDPC) USD/person Geographic Data Sharing Infrastructure, global Fossil fuel carbon dioxide (CO emissions (FE) g C/(m Global Environmental Database (GED) Nighttime light intensity (NLI) nW(cm National Earth System Science Data Center Nighttime light aggregation index (NLAI) National Earth System Science Data Center Water ecosystem service (WES) data sources

Index Unit Data source

Precipitation (PRE) Potential evapotranspiration (PET) Land use/land cover (LULC) Digital elevation model (DEM) National Centers for Environmental Information (NCEI) Soil data China soil map based harmonized world soil database (HWSD) (v.1.1; 2009); National Qinghai-Tibetan Plateau Data Center/Third Pole Environment Data Center Biological table Yang (2020); Ding (2021); and An et al. (2022)

2.3.1 Analysis methods

In this study, an analytical framework was established to assess the coupling relationship between UR and WESs, comprising six key components, namely, data collection, conceptual framework development, data processing, CCD model analysis, XGBoost-SHAP interpretation model analysis, and GWR analysis (Fig. 2 [Figure 2: see original paper]).

The UR indicator system was developed on the basis of existing research (Wang et al., 2025)

and encompasses three dimensions, i.e., population, economy, and environment. The WES indicators were derived from the InVEST model and include WY, soil retention (SR), and water purification (WP) services (Fig. 2). These services, with dual natural and socioeconomic attributes, interact with UR through complex networks, while anthropogenic activities exert feedback influences on WESs and shape UR demands.

The data were standardized before the CCD model was applied to evaluate the degree of UR–WES coordination, which was classified into four types (Zhang et al., 2025), namely, State I (sustainable high resilience), State II (unsustainable high resilience), State III (unsustainable low resilience), and State IV (sustainable low resilience). Key drivers were then identified using XGBoost-SHAP model analysis, and their spatial heterogeneity was analysed with GWR (Fig. 2).

Urban resilience (UR)–water ecosystem services (WESs) coupling analysis framework. PD, population density; PGR, population growth rate; UPS, urban population size; URA, urbanization rate; GDPC, gross domestic product (GDP) per capita; NLAI, nighttime light aggregation index; NLI, nighttime light intensity; FE, fossil fuel carbon dioxide (CO) emissions; FP, farmland area per capita; PRE, precipitation; PET, potential evapotranspiration; LULC, land use/land cover; CCD, coupling coordination degree; XGBoost-SHAP, Extreme Gradient Boosting-SHapley Additive exPlanations; GWR, Geographically Weighted Regression.

2.3.2 UR indicator construction

To develop the UR index system, we adopted a 1-km grid as the basic unit to integrate the natural

and socioeconomic attributes of the study area. Drawing upon previous research, an indicator system was developed on the basis of population, economic, and environmental dimensions through methods such as expert consultation, adhering to the principles of comprehensiveness, representativeness, and feasibility (Wang et al., 2025). Specifically, population resilience (POP) was represented by PD, PGR, and UPS; economic resilience (ECO) was measured on the basis of URA, GDPC, NLI, and NLAI; and environmental resilience (ENV) was captured by FP and FE. All the indicators were considered positive, except for NLAI, which was classified as negative. POP, ECO, and ENV were derived from the weighted sum of three categories of standardized basic indicators.

The standardization and weighting methods are described in Section 2.3.4. This system provides a comprehensive representation of the capacity of cities to withstand external shocks and respond to risks stemming from multiple dimensions.

WES indicator construction The WES indicator system was established on the basis of the ES evaluation approach of the InVEST v.3.15.0 model, and three modules, namely, WY, SDR, and NDR, were selected. These modules yield indicators of WY, SR, and WP, respectively.

The WY module is developed on the basis of the Budyko (1974) hydrological coupling curve and the water balance principle. Notably, WY in each grid cell is calculated as the difference between precipitation and actual evapotranspiration, expressed as follows (Yang et al., 2023): where is the WY for land use type in pixel (mm); AET is the actual evapotranspiration of pixel (mm); is the precipitation of pixel (mm); PET is the potential evapotranspiration (PET) of pixel (mm); is a non-physical empirical param related to natural climate and soil properties; AWC is the available water capacity for plants of pixel (mm); and Z is a seasonal constant that characterizes precipitation patterns within the study area. The parameters employed in the WY module are derived from An et al. (2022).

The SDR module assesses soil retention (SR) capacity by quantifying SR in each grid cell using terrain, soil, and related datasets. The formulas are as follows (Wang et al., 2023b; Hou et al., 2024):

SEDRET =RKLS where RKLS is the potential soil loss of pixel (t/(hm a)); USLE is the actual soil loss of pixel (t/(hm a)); SEDRET is the actual soil conservation of pixel (t/(hm is the rainfall erosivity factor of pixel mm/(hm is the soil erodibility factor of pixel h/(MJ mm)); LS is the topography factor of pixel is the cover-management factor of pixel ; and is the support practice factor of pixel (Ding, 2021).

The NDR module aims to estimate nitrogen export on the basis of land use/land cover (LULC) and associated parameters. This in turn facilitates the assessment of the WP capacity in the study area, as the nitrogen output is inversely proportional to WY. The calculation is as follows (Wu et al., 2021): where is the pollutant output of pixel (kg/(hm a)); Load is the pollutant output coefficient of pixel (kg/(hm a)); and is the pollutant retention effectiveness for land use type . The

parameters employed in the NDR module were derived from Yang (2020).

Calculation of UR and WES indices In this study, UR and WESs were quantified by applying the entropy method in ArcGIS v.10.8 (Environmental Systems Research Institute Inc. (ESRI), Redlands, USA) to determine indicator weights for addressing the high internal variability, nonnormal distribution, and disorderly characteristics of indicators in the ANC region. The entropy method offers an objective weighting framework by quantifying indicator variation, identifying sensitive factors, and reducing the subjective bias in weight determination. This approach is particularly suitable for arid region, which are characterized by high spatial heterogeneity and generally low indicator levels (Ma et al., 2020; Liu et al., 2021). The equations are as follows (Egbueri and Agbasi, 2022):

Data standardization: 0.001 (is a positive indicator) 0.001 (is a negative indicator) where is the foundational indicator within the standardized UR and WES systems; is the data entry in the original matrix, with denoting the region and evaluation indicator, respectively; and max and min are the maximum and minimum values of indicator respectively. To facilitate the subsequent calculations using the natural logarithmic function, we adjusted the normalized values by adding 0.001 to the original values.

The indicator proportion ( ) can be calculated as follows: 1, 2, 3, 1, 2, 3, where is the total number of regional samples; and is the total number of evaluation indicators.

The entropy value ( ) can be calculated as follows: 1, 2, 3, ···, ; 1, 2, 3, ···,) Weights ( ) are calculated as follows: 1, 2, 3, The UR and WES indices (UR , WES , POP , ECO , and ENV) are calculated as follows:

1 ENV

where , and are the numbers of indicators in the UR, WES, POP, ECO

and ENV indicator systems, respectively. Pearson correlation analysis Pearson correlation analysis was applied to assess the linear relationship between UR and WESs.

The correlation coefficient is calculated as follows (Zhou et al., 2017; Schober et al., 2018; Baak et al., 2020): where is the correlation coefficient; are the observed values of two variables at the sample point; denote the sample means of the two variables; and is the sample size.

The correlation strength was classified as strong (>0.7000), moderate (0.3000< $ $0.7000), or weak ($ $0.3000).

The significance of the Pearson correlation coefficient was assessed using Student' s -test. The statistic was calculated, and the associated degree of freedom ( ) was determined as follows: where is the -test statistic. If <0.050, the correlation is statistically significant.

CCD model A CCD model was employed to assess the dynamic equilibrium of the UR-WESs relationship on the basis of the quantified UR and WES indices. The calculation is as follows (Lü et al., 2023; Peng et al., 2023; Liu et al., 2024a): where denote the two indicators required for CCD calculation; is the degree of coupling; is the comprehensive development index; α and β are the weights of the two indicators, α=β=0.5 (Yu et al., 2024); and is the CCD, with values ranging from 0 to 1. Based on natural gaps, we divided the study area into four states (State I (0.1500–0.6300), State II (0.0700–0.1500), State III (0.0000–0.0200), and State IV (0.0200–0.0700)) (Xiao et al., 2023b; Jiang et al., 2024).

XGBoost-SHAP model In this study, the XGBoost-SHAP interpretable machine learning framework was applied to elucidate the driving mechanisms of the CCD. The XGBoost model, a gradient boosting decision tree algorithm, optimizes its loss function using a second-order Taylor expansion. This method effectively captures complex nonlinear relationships among variables, mitigates overfitting, and achieves high prediction accuracy even for high-dimensional datasets (Chen and Guestrin, 2016; Wang et al., 2023a).

The SHAP method was incorporated to enhance interpretability. Rooted in cooperative game theory and the concept of Shapley values, this method provides a consistent and theoretically grounded quantification of the marginal contribution of each feature variable to model predictions (Lundberg and Lee, 2017; Liu et al., 2025).

By leveraging this integrated model, we systematically assessed the influences of 12 variables from the UR and WES systems across the four CCD state regions. The analysis identified the nonlinear influence pathways of key factors and their critical thresholds, thereby increasing the understanding of the mechanisms underlying the coordinated evolution of human-environment

systems. GWR model The GWR model was employed to investigate the spatial heterogeneity in the influences of the driving factors on the CCD. In the model, the six most important variables (contribution>10.00%) derived from XGBoost-SHAP analysis were incorporated. A separate regression equation is specified for each valid pixel to evaluate local relationships, as follows (Brunsdon et al., 1998; Fotheringham et al., 2002): where is the value of the dependent variable at location (is the index of the explanatory variables, ranging from 1 to ui vi is the regression coefficient that varies with spatial location; is the value of the independent variable; and is the random error term.

3.1 Spatiotemporal variations in UR

Spatially, POP increased notably in Urumqi City, the southern Xinjiang oases, and the Qilian Mountains, whereas it decreased in peripheral rural areas (Fig. 3a [Figure 3: see original paper] and b). The increase in ECO was greatest on the northern slope of the Tianshan Mountains and in the southern Xinjiang oases, with Urumqi City identified as a hotspot (Fig. 3d and e). The spatial pattern of ENV was generally consistent with the overall UR trend, with notable improvement in the urban agglomerations on the northern slope of the Tianshan Mountains and in northwestern Xinjiang (Fig. 3g and h). Overall, UR increased in the urban agglomerations on the northern slope of the Tianshan Mountains and in northwestern Xinjiang, whereas UR decreased at the desert margins (Fig. 3j and k).

Temporally, POP increased steadily from 3.00$ $\times 10 to 4.71 \times 10, with accelerated growth from 2000 to 2005 (Fig. 3c).$ between 2000 and 2020, with faster progress from 2000 to 2010 and stabilization thereafter (Fig. 3l).

3.2 Spatiotemporal variations in WESs

Spatially, WY increased in the Altay, southern Tianshan, and Kunlun mountains but decreased in the northern Tianshan and Qilian mountains (Fig. 4a

[Figure 4: see original paper] and b). SR remained relatively high in the Altay, Tianshan, and Qilian mountains despite an overall decreasing trend, with an increase observed only in the Kunlun Mountains (Fig. 4d and e). WP was concentrated in the Tianshan Mountains, Kunlun Mountains, and Qilian Mountains, with the largest increase occurring in the Kunlun Mountains (Fig. 4g and h). Overall, the Altay, Tianshan, and Qilian mountains constituted high-value zones for WESs, whereas a general decrease was observed on the northern slope of the Tianshan Mountains and in the Qilian Mountains (Fig. 4j and k).

Temporally, WY followed the overall trend in WESs, peaking in 2010 before it notably decreased (Fig. 4c). SR increased steadily until 2015 (from 242\$ $\times$ 10to287 $\times$ 10),beforeitdecreasedsharplyto219 $\times$ 10from2015to2020(Fig.4f).Nitrogenexportincreasedco
shapedtrajectoryfrom2000to2020 : notably,WESsincreasedsubstantiallyfrom8.65 $\times$ 10to11.84 $\times$ 10between20
between 2010 and 2020 (Fig. 4l).

Spatiotemporal distribution of UR indicators in the ANC region from 2000 to 2020. (a–c), population resilience (POP); (d–f), economic resilience (ECO); (g–i), environmental resilience (ENV); (j–l), overall UR. 3.3 Coupling coordination relationship between UR and WESs 3.3.1 Correlation analysis between UR and WESs The Pearson correlation coefficients revealed that the association between UR and WESs gradually strengthened from 2000 to 2020 (=0.0872–0.1192, <0.001). Specifically, WY exhibited very weak positive correlations with POP and ECO that decreased over time but maintained a stable weak negative correlation with ENV (= -0.0058). The correlation between SR and ECO was initially significant (=0.0443) but weakened rapidly to =0.0068, and the correlation of SR with ENV became insignificant after 2010 (>0.050). WP demonstrated statistically significant and increasingly positive correlations with all UR indicators (<0.001), with the WP-ENV pair exhibiting the strongest correlation (=0.1312–0.1797). Overall, the five-year average results confirmed that the UR and WESs in the ANC region were weakly yet consistently positively correlated, with WP emerging as the most stable contributor, while WY and SR indicating limited or declining associations (Table 3).

Spatiotemporal distribution of WES indicators in the ANC region from 2000 to 2020. (a–c), water yield (WY); (d–f), soil retention (SR); (g–i), WP (also reflects the situation of nitrogen export); (j–l), overall WESs. 3.3.2 Spatiotemporal distribution of CCD values between UR and WESs The spatiotemporal distribution of the CCD values between the UR and WES indicators from 2000 to 2020 is shown in Figures 5–7. Overall, the CCD values remained low (mean: 0.0166–0.0246) and exhibited an inverted U-shaped trend, first gradually increasing before 2010 (peaking at 0.0246) and subsequently decreasing to 0.0166 in 2020. Spatially, more than 65.00% of the area was classified into State III (CCD<0.0200). The extent of State III areas (e.g., the Junggar, Turpan, and Tarim basins) decreased by 5.30% from 2000 to 2010 but increased again by 7.40% between 2010 and 2020. In contrast, State I areas (0.1500<CCD\$ \$0.6300) were sporadically distributed across oasis cores such as the northern slope of the Tianshan Mountains and the Qilian Mountains (Fig.

5 [Figure 5: see original paper]). For instance, the CCD value in Urumqi City peaked at 0.6300 in 2015 but decreased sharply to 0.0910 by 2020.

As shown in Figures 6 and 7, the ECO-related CCD values were the highest (0.0046–0.0140) and fluctuated considerably, whereas the WY-related CCD values decreased with fluctuations.

Pearson correlation coefficients ( ) between UR and WES indicators Note: A positive Pearson correlation coefficient (>0.0000) indicates a positive linear association between the variables, whereas a negative coefficient (<0.0000) indicates a negative linear association. Owing to the extremely large sample size (based on 1-km resolution raster data), even correlation coefficients with small absolute magnitudes reached a high level of statistical significance <0.001). WY, water yield; SR, soil retention; WP, water purification; POP, population resilience; ECO, economic resilience; ENV, environmental resilience; <0.001 level; <0.010 level; <0.050 level.

Spatiotemporal distribution of CCD values between UR and WES indicators in the ANC region. (a), 2000; (b), 2005; (c), 2010; (d), 2015; (e), 2020; (f), mean of 2000–2020.

The CCD values related to ENV exhibited an increasing trend, while those for the WY/SR combination peaked in 2015. Spatially, the WY- and SR-related CCD combinations exhibited similar patterns, whereas the WP-related CCD combinations revealed spatial clustering in oasis cores such as those on the northern slope of the Tianshan Mountains, particularly after 2005.

Notably, Urumqi consistently remained in State I with respect to the WY-related CCD by 2015, whereas urban clusters in southern Xinjiang temporarily shifted to State II with respect to the WY-POP-related CCD from 2005 to 2010. Moreover, WY-ECO on the northern slope of Tianshan Mountains shifted from State II in 2010 to State IV in 2020. With respect to the WP-ECO, only Urumqi City maintained State I after 2010, whereas the other urban clusters experienced a general decrease. 3.4 Driving factors of CCD and mechanism underlying the effects of WESs on UR using the XGBoost-SHAP model On the basis of the XGBoost-SHAP model, the driving mechanisms underlying the influences of

Spatiotemporal distribution of the CCD values between the UR and individual WES indicators in the ANC region. (a), WY-POP; (b), WY-ECO; (c), WY-ENV; (d), SR-POP; (e), SR-ECO; (f), SR-ENV; (g), WP-POP; (h), WP-ECO; (i), WP-ENV. 12 factors on the CCD were systematically analyzed across different coordination states, and the analysis was extended to the mechanisms through which WESs (WY, SR, or WP) influence UR and its subsystems (POP, ECO, and ENV).

Driving mechanisms of CCD The spatial differentiation of the CCD was governed primarily by six core factors, namely, WY (24.30%), FP (21.10%), GDPC (19.00%), SR (14.90%), PD (5.42%), and WP (4.40%). Across the different coordination states, the driving forces and their effects clearly evolved.

In high-coordination states, natural factors were predominant. State I (sustainable high resilience) was driven mainly by WY (31.47%), NLAI (21.28%), FP (20.44%), and SR (10.43%), with clear threshold effects: notably, WY decreased the CCD below 16.1 mm but increased it

Temporal variation of mean CCD between UR and individual WES indicators. (a), WY-POP; (b), WY-ECO; (c), WY-ENV; (d), SR-POP; (e), SR-ECO; (f), SR-ENV; (g), WP-POP; (h), WP-ECO; (i), WP-ENV. above 86.0 mm, and FP contributed positively to the CCD above 0.1 km /person (Figs. 8a and 9a c). State II (unsustainable high resilience) was driven largely by FP (39.98%), WY (28.13%), and SR (14.51%), where the WY enhancement threshold decreased significantly to 1.5 mm (Figs. 8b and 9d In low-coordination states, the drivers transitioned notably. State III (unsustainable low resilience) was dominated by socioeconomic factors, with GDPC (62.93%) and PD (13.36%) positively driving coordination, whereas WY (5.66%) yielded a negative effect (Figs. 8c and 9g i). In contrast, State IV (sustainable low resilience) was primarily driven by natural factors, namely, WY (32.66%), SR (28.86%), and FP (22.65%), in which WY promoted the CCD across almost the entire range, with an enhancement threshold of 7.6 mm (Figs. 8d and 9j Overall, the CCD driving mechanism evolves from natural-factor dominance in high-coordination states through socioeconomic-factor strengthening in unsustainable states to natural-factor resurgence in low-coordination states. This progression highlights the stage-dependent role of water resources, which supports coordination in high-resilience contexts but can become a constraint under low-resilience conditions because of spatial imbalances in the water supply and demand.

Analysis of the mechanisms through which WESs influence UR Across the different dimensions, the contributions of the WES indicators varied significantly. In the POP dimension, WP was the dominant contributor (50.56%) but exerted only a weakly positive effect overall; whereas WY (28.48%) and SR (20.97%) generated limited influences (Fig. 10a [Figure 10: see original paper]). In the ECO dimension, WY (38.83%), WP (34.30%), and SR (26.87%) were the main contributors, although the influence of WY varied greatly, whereas WP and SR generally contributed positively (Fig. 10b). In the ENV dimension, WP again dominated (51.19%), with a stable positive impact, followed by SR (30.94%) and WY (17.87%), which also yielded overall positive influences (Fig. 10c). At the UR level, WP (53.66%) and SR (31.62%) were the principal drivers, whereas WY (14.72%) played a relatively minor role (Fig. 10d), suggesting that UR is less sensitive to WY than that of CCD system.

SHAP feature summary and importance plots for CCD. (a), State I area; (b), State II area; (c), State III area; (d), State IV area. The grey vertical line in the figure indicates a SHAP value of zero, serving as a reference baseline indicating that the feature does not contribute to model predictions.

This difference in driver importance reflects distinct influence pathways between the WES indicators and UR versus CCD systems. Importantly, this does not contradict the earlier finding that WY is the most critical factor for the CCD.

Rather, the increased sensitivity of the CCD to WY results from water supply-demand imbalances, whereas WP and SR more directly underpin resilience in the UR system. 3.5 Driving mechanism of CCD based on the GWR model Spatial heterogeneity analysis based on the GWR model (=0.83; variance inflation factor (VIF) <2) revealed that among the six key variables examined, WES-related factors (WY, SR, and WP) generally exerted a greater positive influence on the CCD than UR-related factors did (FP, GDPC, and PD). In more than 65.00% of the study area, WY, SR, WP, and FP positively influenced the CCD, with FP exhibiting near-universal positive coverage (99.80%). In contrast, GDPC and PD negatively affected the CCD in more than 74.00% of the region, collectively forming a spatial pattern of positive driving effects in oasis cores versus negative dominance in mountain-desert transition zones.

Regionally, WY exhibited the greatest spatial variability, with notable positive effects dominating except in the transition zones of southern and northern Xinjiang, where negative

SHAP dependency plots for CCD. (a–c), State I area; (d–f), State II area; (g–i), State III area; (j–l), State IV area. reversals occurred (Fig. 11a [Figure 11: see original paper]). SR yielded notable positive effects in the northern Tianshan oases, turning negative along the Junggar and Tarim basin fringes and the eastern Qilian Mountains (Fig. 11b). While WP exhibited concentrated positive effects in the core northern Tianshan areas, its influence was spatially heterogeneous across northwestern Xinjiang and primarily negative along the northern margin of the Tarim Basin and eastern Qilian Mountains (Fig. 11c). In contrast, FP demonstrated stable positive effects throughout the region, which was particularly high in the Qilian Mountains but lower in northwestern Xinjiang (Fig. 11d). GDPC positively influenced the CCD on the northern slope of Tianshan Mountains and the Ili River Valley, whereas its effects turned negative in the Qilian Mountains (Fig. 11e). PD enhanced the CCD mainly in densely populated areas on the northern slope of the Tianshan Mountains and in the Ili River Valley (Fig. 11f).

4 Discussion

On the basis of the spatiotemporal dynamics and driving mechanisms of UR, WESs, and CCD in the ANC region, the fundamental contradictions inherent in coupled UR-WES systems were investigated. Drawing upon the XGBoost-SHAP and GWR model results and considering the spatial structure of the mountain-oasis-desert system, targeted strategies are proposed in three key domains, namely, water resource management, economic regulation, and zonal governance. 4.1 Core contradictions in UR-WESs dual systems First, the inverted V-shaped trajectory of WY, which peaked in 2010, highlighted the central role

SHAP dependency plots for the WESs (WY, SR, and WP) on UR. (a), POP; (b), ECO; (c), ENV; (d), Spatial distribution of the major driving factors based on the GWR model. (a), WY; (b), SR; (c), WP; (d), FP; (e), GDPC; (f), PD.

of water supply-demand imbalances in constraining the CCD. On the demand side, the steady increase in UR indicators (e.g., GDPC, PD, and FP) resulted in increased water consumption,

particularly in the oasis cores (Zhang et al., 2024). On the supply side, forest and grassland degradation in water conservation zones such as the Qilian and Tianshan mountains reduced WY and weakened the hydrological functions of the mountain-oasis system (Wang et al., 2023b). This mismatch, reflected in the decreasing CCD after 2010, reduced the capacity of WESs to sustain UR, thereby amplifying system disequilibrium (Yang et al., 2024).

Second, the mainly negative impacts of GDPC and PD on the CCD (as shown by the GWR results) indicated inadequate feedback mechanisms. The GWR results demonstrated that UR-related factors (GDPC and PD) exerted primarily negative effects across most regions, suggesting that economic and demographic expansion failed to promote protective investments in WESs. This phenomenon was further corroborated by the driving mechanisms within the UR system: notably, while WP served as a critical foundation for sustaining both POP and ENV, the rapidly increasing pollution loads generated by the increase in GDPC and PD exerted continuous pressure on WP. This growth pattern has driven the expansion of water-intensive industries, consequently leading to water quality deterioration (decline in WP) and a reduction in the SR capacity (Dasgupta, 2021). Simultaneously, the environmental dimension of UR lagged behind, with underdeveloped urban ecological infrastructure substantially decreasing the buffering capacity of the system against WES fluctuations (Shishegar et al., 2019; Chung et al., 2021).

Finally, the spatial gradient of the CCD from the oasis cores to the desert margins highlighted the role of spatial heterogeneity in exacerbating system conflicts. Degraded forests in upstream water conservation areas reduced the WY supply, thereby increasing water risk in downstream oases (Partelow et al., 2024). Oasis cores, under the influence of high-intensity development, became overly dependent on groundwater, causing the CCD to shift from positive to negative. In desert transition zones, farmland expansion (high FP) overlapped with a decrease in WY, exacerbating system fragility and driving regional-scale degradation (Grison et al., 2023). 4.2 Feasible strategies for increasing UR through WESs First, water resource management should be tailored to address the crucial role of WY and the compensatory functions of SR and WP, as highlighted by the XGBoost-SHAP model results. In the oasis core zones (mainly States I and II areas), where WY served as a primary positive driver but faced overexploitation, the implementation of differentiated water pricing, progressive tariffs, and tradable water footprint credits can curb the expansion of water-intensive industries (Alghamdi et al., 2024; Okolo et al., 2024). At the terminal points of urban drainage systems and across lake/river riparian zones, large-scale development of constructed wetlands and ecological floating bed systems should be implemented to increase the deep purification capacity for pollutants such as nitrogen and phosphorus, thereby stabilizing and enhancing WP, which in turn provides support for achieving UR (Li et al., 2021). At the farmland expansion frontier, basin-scale water quotas should be enforced to ensure ecological water allocation (Zhang and Yang, 2022). Moreover, ecological restoration in water-conservation regions such as the Qilian and Tianshan mountains, through grazing bans, grassland restoration, and forest management, can facilitate the restoration of hydrological functions in the mountain-oasis-desert system (Gao et al., 2025).

Second, economic adjustment mechanisms should be designed to counteract the mostly negative effects of socioeconomic factors, such as GDPC and PD, on the CCD, as indicated by the GWR results. In high-FP regions, optimizing cropping structures by reducing water-intensive crops (e.g., wheat) and promoting drought-resistant cash crops (e.g., goji berry and sea buckthorn) can alleviate agricultural water stress (Fan et al., 2014). In high-GDPC regions (e.g., the northern Tianshan urban agglomeration, often in State III), industrial restructuring should prioritize water-efficient and high-value-added sectors (e.g., the digital economy and renewable energy industries) (Xu et al., 2024). Moreover, decentralized ecological infrastructures (e.g., rain gardens and permeable pavements) and community-based governance mechanisms (e.g., eco-steward initiatives) should be promoted to increase the adaptive capacity of UR to WES fluctuations (Bassett et al., 2025).

Finally, zonal differentiation strategies are essential for addressing the notable spatial heterogeneity in the CCD and its drivers. In water source conservation areas (high-level WY/SR), in addition to strictly implementing ecological conservation red line policies and grazing prohibition measures, establishing and improving a cross-regional horizontal ecocompensation mechanism is essential. This mechanism should ensure that downstream beneficiary areas provide corresponding financial and technical assistance to upstream conservation areas, thereby guaranteeing the long-term and stable maintenance of water retention functions (Cheng et al., 2020; Chi et al., 2024). In oasis cores (higher CCD levels), compact urban planning and the green heart strategy should be implemented alongside efficient irrigation technologies such as mulched drip irrigation to increase the water use efficiency (Zhang et al., 2022; Xiao et al., 2023a; Cao et al., 2024). In desert transition zones (primarily State IV, where WY thresholds are critically low), the implementation of low-disturbance land use practices, such as checkerboard sand barriers, farmland fallowing, and cultivation index regulation, may help reduce system fragility and promote coordinated regional development (Xu et al., 2021; Miti et al., 2025).

5 Conclusions

This study integrated the InVEST model, entropy method, CCD model, XGBoost-SHAP interpretation model, and GWR method to analyze the coupling relationship and driving mechanisms between UR and WESs in the ANC region based on 1-km resolution remote sensing data from 2000 to 2020. The results indicated that UR showed a continuous upward trend, while WESs peaked around 2010 and subsequently declined annually, reflecting a lack of synergistic development between the two systems. The overall CCD remained low with notable spatial heterogeneity. Key drivers shifted according to the coordination state, with water yield and water pressure consistently playing positive regulatory roles. Major constraints identified included water scarcity, insufficient socioeconomic feedback related to WESs, and intensified systemic conflicts due to growing spatial heterogeneity, necessitating differentiated resilience-building strategies. Limitations of this study included inadequate representation of micro-level factors such as water-saving technologies and management efficiency, as well as potential sensitivity issues arising from polarized data distribution between oasis and desert areas. Future research should incorporate multi-source data and focus on the urban scale to conduct multi-scenario analyses, thereby supporting the development of more targeted optimization strategies.

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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