Ecozone-dependent reorganization of multifactor interactions controls actual evapotranspiration across arid mountain-basin systems

MA Zhenrong, WANG Yongdong, ZHOU Zhibin, CHEN Yusen

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Abstract

Actual evapotranspiration (ETa) is a key regulator of land-atmosphere water and energy exchanges in arid regions. However, the coupled effects of its controlling factors along mountain-basin gradients remain poorly quantified, limiting precise water resource management. Based on multi-sourced data (2001-2022) from Xinjiang Uygur Autonomous Region, China, this study analyzed the spatiotemporal patterns of ETa across five eco-zones: the Altay Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, and Kunlun Mountains. Using Mann-Kendall and Theil-Sen trend analyses, GeoDetector, and Random Forest model, we quantified the contributions and interactions of seven environmental drivers: air temperature, precipitation, soil moisture, wind speed, net radiation, vapour pressure deficit, and leaf area index. The multi-year mean ETa over Xinjiang was 193.15 (($\pm$)21.16) mm/a, showing a distinct “high in mountains and low in basins” spatial pattern. A significant increasing trend of 1.60 mm/a was observed regionally, yet with clear spatial divergence, i.e., ETa increased in the major mountain ranges but decreased or stabilized in the hyper-arid Tarim Basin and transitional Junggar Basin. Water-supply factors (precipitation and soil moisture) explained about 40% of the spatial variance individually, while factor interactions enhanced the explanatory power substantially (maximum interaction gain (Δq) = 0.18), indicating that bivariate and nonlinear combinations captured ETa patterns more effectively than single driver. Interaction regimes were strongly ecozone-dependent and varied between wet and dry years. Through comparing the wet year (2003) with the dry year (2022), we found a reorganization of dominant interaction pairs: the hyper-arid Tarim Basin shifted from hydrothermal control to vegetation-water-stress coupling; the Junggar Basin maintained persistent vegetation-energy coupling; the Altay and Tianshan Mountains strengthened vegetation-mediated interactions during drought; and the Kunlun Mountains transition from hydrothermal to moisture-aerodynamic control. These results clarify how complex topography and vegetation physiology modulate macroclimatic forcing in this arid mountain-basin system. These findings offer a process-based foundation for ecohydrological zoning, and provide critical insights for adaptive water ecosystem management and sustainable development in response to the “warming and wetting” trending global drylands.

Full Text

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Ecozone-dependent reorganization of multifactor interactions controls actual evapotranspiration across arid mountain-basin systems

MA Zhenrong[1,2], WANG Yongdong[1,2*], ZHOU Zhibin[1,2], CHEN Yusen[1,2]

[1] National Engineering Research Center for Desert-Oasis Ecological Construction Technology, Xinjiang Institute of Ecology and Geography, Chinese Academy of Sciences, Xinjiang 830011, China;

[2] University of Chinese Academy of Sciences, Beijing 100049, China

Abstract: Actual evapotranspiration (ETa) is a key regulator of land-atmosphere water and energy exchanges in arid regions. However, the coupled effects of its controlling factors along mountain-basin gradients remain poorly quantified, limiting precise water resource management. Based on multi-source data (2001-2022) from Xinjiang Uygur Autonomous Region, China, this study analyzed the spatiotemporal patterns of ETa across five eco-zones: the Altay Mountains, Junggar Basin, Tianshan Mountains, Tarim Basin, and Kunlun Mountains. Using Mann-Kendall and Theil-Sen trend analyses, GeoDetector, and Random Forest model, we quantified the contributions and interactions of seven environmental drivers: air temperature, precipitation, soil moisture, wind speed, net radiation, vapour pressure deficit, and leaf area index. The multi-year mean ETa over Xinjiang was 193.15(($\pm$)21.16) mm/a, showing a distinct "high in mountains and low in basins" spatial pattern. A significant increasing trend of 1.60 mm/a was observed regionally, yet with clear spatial divergence, i.e., ETa increased in the major mountain ranges but decreases or stabilized in the hyper-arid Tarim Basin and transitional Junggar Basin. Water-supply factors (precipitation and soil moisture) explained about 40% of the spatial variance individually, while factor interactions enhanced the explanatory power substantially (maximum interaction gain (Δq)=0.18), indicating that bivariate and nonlinear combinations captured ETa patterns more effectively than single driver. Interaction regimes were strongly ecozone-dependent and varied between wet and dry years. Through comparing the wet year (2003) with the dry year (2022), we found a reorganization of dominant interaction pairs: the hyper-arid Tarim Basin shifted from hydrothermal control to vegetation-water-stress coupling; the Junggar Basin maintained persistent vegetation-energy coupling; the Altay and Tianshan Mountains strengthened vegetation-mediated interactions during drought; and the Kunlun Mountains transition from hydrothermal to moisture-aerodynamic control. These results clarify how complex topography and vegetation physiology modulate macroclimatic forcing in this arid mountain-basin system. These findings offer a process-based foundation for ecohydrological zoning, and provide critical insights for adaptive water ecosystem management and sustainable development in response to the "warming and wetting" trend in global drylands.

Keywords: actual evapotranspiration; arid region; mountain-basin systems, GeoDetector; Random Forest model

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*Corresponding author: WANG Yongdong (E-mail: wangyd@ms.xjb.ac.cn)
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1 Introduction

Actual evapotranspiration (ETa) represents the total flux of water vapor from the land surface to the atmosphere, comprising terrestrial ET (including soil evaporation, plant transpiration, and canopy interception evaporation) as well as evaporation from open water, snow, and ice surfaces (Zhang et al., 2019; Hong et al., 2023). It is the second-largest water loss in the terrestrial water cycle after precipitation and the key regulating variable in the surface energy balance after net radiation, exerting fundamental control on regional hydrothermal coupling, carbon-cycle dynamics, and ecosystem services (Gentine et al., 2019; Elnashar et al., 2021). Globally, more than 60% of terrestrial precipitation is returned to the atmosphere via ET (Rotenberg et al., 2025). Consequently, predicting ETa trends and clarifying its driving mechanisms provides the scientific basis for assessing regional water-resource carrying capacity and sustaining ecosystem service functions (Jung et al., 2010; Jin et al., 2025); and this prediction is particularly important in arid mountain–basin systems, where steep elevational contrasts and strong aridity gradients impose tightly coupled constraints of water supply, energy availability, atmospheric evaporative demand, and vegetation on ETa.

Previous studies have shown that the evolution of ETa is constrained by complex interactions along multi-dimensional environmental gradients, and exhibits strong context dependence and nonlinearity (Di et al., 2023). At the ecosystem scale, stomatal regulation couples water and carbon fluxes, producing strong co-variation between ETa and gross primary productivity (GPP) that can be amplified as leaf area index (LAI) increases (Gan et al., 2018; Zhang et al., 2019).

In arid and semi-arid regions, rising vapor pressure deficit (VPD) strengthens atmospheric demand and can interact with soil moisture and vegetation regulation to intensify drought sensitivity of ET and water-carbon exchange (Novick et al., 2016; Li et al., 2023). Against this background, traditional linear regression models struggle to capture the nonlinear, threshold-based, and saturated responses of ETa to environmental drivers (Ohana-Levi et al., 2022; Rajput et al., 2024). Introducing machine-learning algorithms with strong high-dimensional mapping capabilities (e.g., Random Forest (RF) and neural networks) to approximate the response functions of ETa to multi-source environmental factors has therefore become an important pathway to improve the precision of environmental response predictions (Abdel-Fattah et al., 2023; TR et al., 2023; Chen et al., 2025). To mitigate the limitation of machine-learning models, we couple them with GeoDetector to quantify spatially heterogeneous driver contributions and interaction-enhancement (including nonlinear) effects via variance decomposition, thereby improving both interpretability and predictive credibility for ETa controls (Wang et al., 2022; Kartik et al., 2023; Tao et al., 2023; Kanji and Das, 2025).

Xinjiang Uygur Autonomous Region, China is characterized by a pronounced mountain–basin system in an endorheic (closed) drainage setting, where the Altay Mountains, Tianshan Mountains and Kunlun Mountains enclose two major basins—the Junggar Basin in the north and the Tarim Basin in the south—creating sharp elevational and aridity gradients and strong spatial heterogeneity in water–energy cycles (Cai et al., 2021). Against this topographic backdrop, climate warming is driving a rapid reconfiguration of the regional hydrothermal regime, with growing mismatch between water supply and demand, and increasing ecological vulnerability (Wei et al., 2025; Yu and Zhang, 2025). The widely discussed "warming and wetting" signal is often manifested as short and spatially heterogeneous extreme precipitation that does not fundamentally alleviate long-term aridity (Yao et al., 2022a), while temperature-driven glacier melt may transiently increase runoff but implies progressive depletion of solid water storage over longer time scales (Huss and Hock, 2018; Schuster et al., 2025). Water use and land-cover change further modulate basin water availability and surface fluxes, complicating attribution of ETa controls (Zhao et al., 2024). Under coupled climatic and anthropogenic forcing, regional ecosystems are exposed to systemic risks characterized by escalating water scarcity and salinization, nonlinear vegetation water-stress constraints on ET partitioning, and self-reinforcing warming–ETa feedbacks that intensify land-surface drying and ecotone degradation (Li et al.,

2012; Yao et al., 2018; Zhang et al., 2020; Liu et al., 2025; Yang, 2025). Together, the coupled terrain–climate–human system of Xinjiang, spanning strongly contrasting ecozones and steep environmental gradients, provides an ideal natural region for testing ecozone-dependent, interaction-driven controls on ETa and the reorganization of dominant driver interactions.

However, diagnostics based solely on long-term means or linear trends can obscure the nonlinear, threshold- and interaction-amplified responses that are often activated by climatic extremes and high-frequency hydroclimatic variability (Nordling et al., 2025). In climatically fragile arid Xinjiang, alternating extreme wet and dry conditions may impose stronger ecohydrological impacts than slowly evolving trends, making an extreme-scenario perspective essential for detecting system behavior near water-stress limits (Mutti et al., 2019; Gu et al., 2021; Wang et al., 2023). Comparing ETa dynamics between representative wet and dry years not only helps reveal potential resilience thresholds, but also tests whether dominant controls on ETa reorganize—that is, whether the relative importance and interaction structure among climatic and land-surface factors shift under contrasting moisture backgrounds (Liu et al., 2020). Here, we use standardized precipitation evapotranspiration index (SPEI) to delineate wet versus dry conditions because it jointly reflects precipitation supply and evaporative demand across time scales, making it particularly suitable for arid regions with strong atmospheric demand (Chen et al., 2019; Hissan and Parveen, 2025).

Despite growing recognition of nonlinear and interaction-amplified ETa controls, a systematic framework to benchmark these processes across diverse hydroclimatic contexts is lacking. Specifically, it remains unclear how ecozone-dependent interaction regimes reorganize under contrasting moisture backgrounds. Therefore, the following questions are pointed out in this study: (1) how do ETa patterns and trends vary across ecozones? (2) do interactions outweigh single factor, and which driver pairs dominate? and (3) under wet vs. dry conditions, do dominant pairs reorganize across ecozones? This study provides a comparative framework for predicting ETa controls, which can be extended to other regions with similar environmental gradients. By identifying how dominant interaction pairs reorganize under shifting hydroclimatic conditions, our findings offer a systematic approach for cross-ecosystem comparisons and process-based insights for water resource management in arid environments.

2 Materials and methods

2.1 Study area

The Xinjiang Uygur Autonomous Region is located in northwestern China, in the interior of the Eurasian continent (34°25′–49°10′N, 73°40′–96°23′E). It covers an area of 1.66 × 10^6 km^2 and is the largest province in China by land area (Yang et al., 2018). Its topography is characterized by a "three mountains enclosing two basins" pattern (Altay, Tianshan, and Kunlun mountains enclosing the Junggar and Tarim basins; Fig. 1) (Chen et al., 2024), which imposes pronounced mountain–basin gradients in water supply and energy demand. The study area has a typical temperate continental arid climate, with precipitation decreasing from west to east, from north to south, and from mountains to plains (Gao et al., 2010; Liu et al., 2018). Water resources depend mainly on mountain precipitation and cryospheric meltwater, whereas the plains receive little precipitation and experience strong evaporation (Yang et al., 2022). About 84% of the

Division of ecozones (R1-R5) of the study area, China.

Figure 1: Division of ecozones (R1-R5) of the study area, China.

region lies in arid to hyper-arid zones (aridity index<0.65) and multi-year mean precipitation is mostly <150 mm, while potential ET (PET) often exceeds 1000 mm, indicating a strong water-energy imbalance (Zhao et al., 2024).

According to China' s ecological-function zoning, researchers divided the study area into five ecological functional zones (Yao et al., 2022a; Fig. 1). To ensure terminological consistency and clarity, we show the formal definitions of these zones and the corresponding abbreviated names used throughout the subsequent analysis in Table 1. The general environmental characteristics of these ecozones are as followed: the Altay Mountains (R1) are a high-cold mountainous region

with moderate precipitation; the Junggar Basin (R2) is a semi-arid to arid transitional basin with low elevation and limited moisture; the Tianshan Mountains (R3) feature high elevation gradients and serve as a vital "water tower" with relatively higher precipitation; the hyper-arid Tarim Basin (R4) is a low-lying desert basin with extreme dryness and high temperature; and the Kunlun Mountains (R5) constitute a high-altitude, cold, and extremely arid mountain region with sparse precipitation. Under such strong water-energy mismatch, concentrated oasis systems, intensive engineering, and land-use interventions, the study area shows systematic shifts in ETa partitioning and water balance along mountain-basin and oasis-desert gradients, enabling an ecozone-resolved assessment of how interaction-enhanced controls on ETa—and their relative importance—reorganize under contrasting wet and dry conditions (Yao et al., 2022a).

Fig. 1 Division of ecozones (R1-R5) of the study area, China. DEM, digital elevation model. The figure is based on the standard map (GS(2024)0650) provided by the National Platform for Common Geospatial Information Services (http://bzdt.ch.mnr.gov.cn/), and the boundary of the base map has not been modified.

Table 1 Classification of the five ecozones

No.	Ecozone name	Geographic name	Landscape
R1	Altay-western Junggar mountain forest-steppe zone	Altay Mountains	Mountain
R2	Junggar Basin desert zone	Junggar Basin	Basin
R3	Tianshan mountain forest-steppe zone	Tianshan Mountains	Mountain

No.	Ecozone name	Geographic name	Landscape
R4	Tarim Basin–eastern Xinjiang desert zone	Tarim Basin	Basin
R5	Pamir–Kunlun–Altun alpine frigid desert–steppe zone	Kunlun Mountains	Mountain

2.2 Data collection and preprocessing

ETa was derived from the Penman–Monteith–Leuning Version 2 (PML_V2) product, which provides 8-d composite data at 500-m resolution. Hydro-climatic drivers, including air temperature, total precipitation, net radiation, wind speed, and soil moisture, were obtained from the ERA5 (the fifth generation ECMWF (European Centre for Medium-Range Weather Forecasts) reanalysis for the global climate and weather for the past 8 decades)-Land reanalysis dataset. We calculated Terrestrial water vapour pressure deficit (VPD) based on ERA5-Land temperature and dewpoint variables. Vegetation dynamics were represented by the Moderate Resolution Imaging

Spectroradiometer (MODIS) leaf area index (LAI) 8-d product (MCD15A2H v061), while topographic features were captured via the digital elevation model (DEM) (Table 2).

Table 2 Information of the data used in the study

Dataset	Data product	Spatial resolution	Temporal resolution	Source
Administrative boundary	Xinjiang administrative boundary (GS(2024)0650)	-	-	Tianditu (http://cloudcenter.tianditu.gov.cn)
Ecozones	R1–R5 ecozones	-	-	Peking University GeoData (http://geodata.pku.edu.cn)
ETa	PML_V2 v0.1.8 (coupled ET and GPP) via GEE	500 m (resampled to 1 km)	8-d, monthly, and annual scales	GEE (Zhang et al., 2016; Gan et al., 2018; Zhang et al., 2019)

Dataset	Data product	Spatial resolution	Temporal resolution	Source
Meteorology	ERA5-Land monthly means (T, P, SM, Wind, R_n, and VPD)	Native grid (resampled to 1 km)	Monthly	Copernicus Data Store (Muñoz-Sabater et al., 2021)
Drought index	HSPEI	1 km	Multi-scale (1/12-month)	10.57760/sciencedb.ecodb.00090
Topography	DEM	30 m (resampled to 1 km)	-	USGS/NASA LP DAAC (Farr et al., 2007)
Vegetation	MOD15A2H.061	500 m (resampled to 1 km)	8-d	GEE/LP DAAC

Note: ETa, actual evapotranspiration; PML_V2, Penman–Monteith–Leuning Version 2; ET, evapotranspiration; GPP, gross primary productivity; GEE, Google Earth Engine; T, air temperature; P, total precipitation; SM, soil moisture; Wind, wind speed; R_n, net radiation; VPD, vapour pressure deficit; HPSEI, high spatial resolution (1 km) standardized precipitation evapotranspiration index; DEM, digital elevation model; USGS, United States Geological Survey; NASA, National Aeronautics and Space Administration; LP DAAC, Land Processes Distributed Active Archive Center. "-" means no value.

To align with the monthly and annual analytical scales, we aggregated the 8-d PML_V2 ETa using a summation method: 8-d data were first summed to monthly totals and subsequently into annual totals, defined as the cumulative sum of terrestrial (vegetation transpiration, soil evaporation, and canopy interception) and open-water evaporation components. For meteorological drivers and LAI, monthly and annual values were calculated using the arithmetic mean.

All spatial layers were re-projected to the World Geodetic System 1984 (WGS84) and clipped to the study area. Continuous variables (ERA5-Land and DEM) were resampled from their native resolutions to 1 km using bilinear interpolation, while categorical layers (e.g., land cover) utilized nearest-neighbor resampling. Quality control involved masking non-land pixels and addressing outliers. Given the robust coverage of the selected satellite and reanalysis products over the arid region of the study area, less than 1% of pixels required gap-filling, which was implemented via temporal linear interpolation.

3 Methods

3.1 Identification of extreme years

Extreme years were identified using the gridded 12-month SPEI (SPEI-12) at the whole Xinjiang (XJ) domain, a metric widely applied in agricultural drought monitoring (Bhardwaj et al., 2025). Monthly SPEI-12 values were spatially averaged and summarized to an annual series, with the maximum and minimum years defined as the wettest and driest, respectively. SPEI-12 is based on the standardized climatic water balance and is commonly used in arid regions (Vicente-Serrano et al., 2010). Wetness–dryness classes used for mapping and zonal statistics followed commonly adopted SPEI thresholds (Table 3) (Rasouli Majd et al., 2025).

3.2 Inter-annual trend analysis

Inter-annual trends in annual ETa at the 1-km grid-cell scale (2001–2022; n=22) were quantified using the Mann–Kendall (MK) test and the Theil–Sen median slope estimator (Mohammad et al., 2022).

Serial autocorrelation was addressed by applying Yue–Pilon trend-free pre-whitening (TFPW) to grid-cell series with ( )18 valid annual values, and MK, Theil–Sen slope, and P-values were computed from the adjusted series. Field significance was evaluated using Benjamini–Hochberg false discovery rate (FDR) control (q-value<0.05). Outputs comprised spatial layers of Theil-Sen slope, MK, and an FDR-based significance mask for zonal statistics and mapping.

Table 3 Classification of dry and wet periods

Data range	Trend	Probability (P’)	ΔP’
SPEI( )2.00	Extremely wet (EW)	0.977–1.000	0.023
1.50≤SPEI( )1.99	Severely wet (SW)	0.933–0.977	0.044
1.00≤SPEI( )1.49	Moderately wet (MW)	0.841–0.933	0.092
−0.99≤SPEI( )0.99	Near normal (N)	0.159–0.841	0.682
−1.49≤SPEI≤−1.00	Moderate drought (MD)	0.067–0.159	0.092
−1.99≤SPEI≤−1.50	Severe drought (SD)	0.023–0.067	0.044
SPEI≤−2.00	Extreme drought (ED)	0.000–0.023	0.023

Note: standardized precipitation evapotranspiration index (SPEI) classification is reference form Rasouli Majd et al. (2025).

3.3 Attribution and interaction analysis of ETa drivers

Spatial attribution and interaction effect of ETa drivers were conducted using GeoDetector, which quantifies explanatory power via spatially stratified heterogeneity (Wang et al., 2010). Analyses were implemented on the harmonized 1-km grid for annual ETa during 2001–2022 and monthly ETa during the identified wettest and driest years. Factor and interaction detectors were applied to evaluate single-factor contribution (q_1 or q_2), pairwise joint effect (q_{12}), and net interaction gain $\Delta q = q_{12} - \max(q_1, q_2)$, where $\max(q_1, q_2)$ is the maximum q-value of the two individual drivers. Risk detector was used to identify directional associations between drivers and ETa via mean value comparisons across strata.

Within each ecozone, continuous drivers (temperature, precipitation, soil moisture, wind speed, net radiation, VPD, and LAI) were discretized into six strata using the quantile binning method to satisfy GeoDetector' s stratification requirement. This classification strategy ensures an approximately equal number of samples per stratum, thereby enhancing the statistical stability of the q-statistic. We excluded units with insufficient valid pixels based on a minimum sample-size threshold. Factor-detector significance was evaluated via permutation testing (n=1000), and q-values were additionally normalized to shares for cross-factor comparison in zonal summaries. Interaction patterns were summarized using q_{12} matrices for extreme-year months and aggregated Δq statistics for the multi-year annual analysis; only permutation-significant pairs were retained, and we classified interaction types based on Table 4. Risk detection compared mean ETa among factor strata and assessed monotonicity using Spearman' s rank correlation (ρ). Relationships were reported as positive, negative, or indeterminate (Wang and Xu, 2017; Liang and Xu, 2023) and were benchmarked against RF analysis.

3.4 Model validation and attribution consistency

To independently validate the GeoDetector-based attribution and to characterize both the strength and direction of ETa responses to its drivers, we constructed ETa–environment relationships using RF analysis. RF trains an ensemble of regression trees on bootstrap samples and aggregates their predictions, providing strong nonlinear fitting capacity and robustness, and is well suited to hydro-meteorological regression problems (Breiman, 2001). In this study, the RF model was configured with 500 decision trees.

To ensure a robust evaluation, we employed a dual validation strategy combining independent hold-out validation and out-of-bag (OOB) estimation. For each region and time step, the total sample size was capped at 1×10^5 via random sampling to balance computational efficiency and

Table 4 Categories of interactions between two factors and their interactive relationship

Description	Interaction
$q_{12} < \min(q_1, q_2)$	Weakened and nonlinear
$\min(q_1, q_2) < q_{12} < \max(q_1, q_2)$	Weakened and univariate
$\max(q_1, q_2) < q_{12} < q_1 + q_2$	Enhanced and bivariate
$q_{12} = q_1 + q_2$	Independent
$q_{12} > q_1 + q_2$	Enhanced and nonlinear

Note: q_1 or q_2, single factor contribution; q_{12}, pairwise joint effect.

statistical representativeness. The dataset was then randomly partitioned into training and testing sets. We dynamically adjusted testing size based on the resulting samples (n): 15% for n in [5×10^4, 1×10^5], and 20% for smaller samples ($n<5 \times 10^4$), using a fixed random seed (42) for reproducibility. Model performance was quantified using the coefficient of determination (R^2) calculated on the independent testing set (R^2_{val}) and the internal OOB R^2 (R^2_{OOB}), both of which are reported in the results (Table S1) to ensure the reliability of the driver importance ranking.

Analyses used the same 1-km grid and regional stratification as GeoDetector for annual ETa (2001–2022) and monthly ETa in the identified wettest and driest years. Predictors comprised air temperature, precipitation, soil moisture, wind speed, net radiation, VPD, and LAI. Attribution strength was quantified using permutation importance (PI), calculated with five iterations on testing subsamples. Directional responses were inferred from first-order accumulated local effect (ALE), determined by the linear slope of the ALE curve between the 10th and 90th percentiles. Consistency between methods was evaluated using ρ and the agreement rate between ALE and risk-detector classifications.

4 Results

4.1 Spatiotemporal characteristics of ETa

4.1.1 Spatial pattern and inter-annual evolution of ETa During 2001–2022, mean ETa across XJ was 193.15 (($\pm$)21.16) mm/a, displaying a clear mountain–basin contrast with higher values over the Altay, Tianshan, and Kunlun mountains, and lower values across the Junggar and Tarim basins (Fig. 2a). Mean ETa was the highest in R3 (319.82 ± 54.11 mm/a) and the lowest in R4 (108.76 ± 24.13 mm/a) ecozones; intermediate levels occurred in R1 (275.12 ± 22.35 mm/a), R2 (209.79 ± 24.83 mm/a), and R5 (215.45 ± 75.45 mm/a) ecozones.

Trend estimates (Theil–Sen slope) indicated strong spatial heterogeneity in annual ETa change during 2001–2022 (Fig. 2b). Increasing tendencies were concentrated in major mountainous regions, whereas decreases were more common in

Fig. 2

Figure 2: Fig. 2

basin interiors and along portions of basin margins. The trends within ecozones were spatially divergent, with both increasing and decreasing slopes evident, most clearly in R1 and R3 ecozones (Fig. 2b).

Regionally averaged ETa exhibited a significantly increasing trend of 1.60 mm/a (P<0.05) with pronounced inter-annual variability (Fig. 2c). ETa rose during the early 2000s, declined to a minimum in 2008 (159.75 mm/a), increased to a peak in 2016 (235.03 mm/a), and then decreased after 2016 with a modest rebound by 2022. Consistent with these trajectories, ecozone-scale series showed increasing tendencies in R3 and R5 ecozones, weak decreases or largely stable conditions in R2 and R4 ecozones, and near-stable behavior in R1 ecozone (Fig. 2d–h).

4.1.2 Spatial distributions of ETa and SPEI in the typical wet and dry years Based on annual mean SPEI series during 2001–2022 (Fig. 3), we selected 2003 and 2022 correspond to the wettest (SPEI=0.52) and driest (SPEI=−0.24) years within the study period, respectively, and for contrasting analysis. Figure 4 shows the monthly trend and spatial distribution of SPEI and ETa in ecozones. Monthly SPEI (−0.99–0.99) indicated predominantly

Fig. 2 Spatial and temporal patterns of actual evapotranspiration (ETa) in Xinjiang (XJ) and its five ecozones during 2001-2022. (a), ETa; (b), ETa trend; (c-f), annual ETa time series and linear trends for XJ as a whole and its five ecozones (R1-R5).

near-normal conditions in 2003, whereas monthly SPEI in 2022 was characterized by generally negative SPEI except in August (0.27), with severe drought occurring in January (−1.77) and February (−1.91) (Fig. 4a and c). Spatially, the year of 2003 showed largely near-normal conditions across XJ with only scattered drought patches in mountainous regions, while the year of 2022 exhibited stronger drought signals in specific ecozones, with R1 and R3 ecozones showing widespread moderate drought and R5 ecozone containing extensive moderate-to-severe drought with localized extreme drought. In contrast, SPEI in R2 and R4 ecozones was comparatively higher in 2022 than in 2003 (Fig. 4a and c). These results indicate that while the year of 2003 and 2022 represent the wettest and driest years at the regional scale, the hydroclimatic conditions in individual ecozone are not perfectly synchronized, characterized by a pronounced contrast between mountain ranges and basin interiors.

ETa displayed distinct seasonal behavior between the two years (Fig. 4b and d). In 2003, mean ETa followed a clear unimodal cycle, peaking in July (37.44 mm/month). In 2022, monthly ETa was more irregular, with a relative low value in May (21.80 mm/month) and a high value in

Fig. 3

Figure 3: Fig. 3

Fig. 4

Figure 4: Fig. 4

Fig. 3 Inter-annual variation of standardized precipitation evapotranspiration index (SPEI) in XJ and its five ecozones during 2001–2022

Fig. 4 Spatial patterns and monthly trends of SPEI (a and c) and ETa (b and d) in 2003 (the wet year) and 2022 (the dry year). ED, extreme drought; SD, severe drought; MD, moderate drought; N, near normal; MW, moderately wet. The details of classification criteria are shown in Table 3.

August (31.56 mm/month). Relative to 2003, ETa was higher in March but lower in May, July, and September. Together, the SPEI and ETa in 2003 established contrasting hydroclimatic backgrounds and associated ETa patterns across ecozones.

4.2 Effects of environmental drivers on ETa

4.2.1 Contributions of environmental drivers at regional and ecozone scales

GeoDetector was used to quantify the multi-year mean contributions of seven environmental

drivers to the spatial heterogeneity of ETa across XJ and its five ecozones during 2001–2022 (Fig. 5). The drivers were grouped into water-supply factors (precipitation and soil moisture), energy-condition factors (net radiation and temperature), vegetation-status factor (LAI), atmospheric-demand factor (VPD), and aerodynamic factor (wind speed). The GeoDetector results indicated that water-supply factors exhibited the highest spatial explanatory power overall, with soil moisture showing the largest multi-year mean *q*-value in XJ and most ecozones, followed by precipitation. Net radiation, LAI, and wind speed contributed at intermediate levels, whereas temperature and VPD showed comparatively lower long-term contributions (Fig. 5).

Fig. 5 Multi-year mean GeoDetector contributions of individual driver across to the spatial heterogeneity of ETa in XJ and its five ecozones during 2001–2022. P, precipitation; SM, soil moisture; R_n, net radiation; T, temperature; LAI, leaf area index; VPD, vapor pressure deficit.

To facilitate comparison of relative importance within each ecozone, we further normalized GeoDetector contributions by converting *q*-values into intra-annual share contributions for aligned years (Fig. 6). At XJ scale, soil moisture and precipitation ranked the highest and together accounted for nearly 40% of across

Fig. 5. Multi-year mean GeoDetector contributions of individual driver across to the spatial heterogeneity of ETa in XJ and its five ecozones during 2001–2022. P, precipitation; SM, soil moisture; R_n, net radiation; T, temperature; LAI, leaf area index; VPD, vapor pressure deficit.

Figure 5: Fig. 5. Multi-year mean GeoDetector contributions of individual driver across to the spatial heterogeneity of ETa in XJ and its five ecozones during 2001–2022. P, precipitation; SM, soil moisture; R_n, net radiation; T, temperature; LAI, leaf area index; VPD, vapor pressure deficit.

Fig. 6. Contribution of GeoDetector to ETa drivers in XJ (a) and its ecozones (b–f) during 2001–2022

Figure 6: Fig. 6. Contribution of GeoDetector to ETa drivers in XJ (a) and its ecozones (b–f) during 2001–2022

the seven drivers, followed by net radiation and VPD, with smaller shares from temperature, wind speed, and LAI. At ecozone scale, driver importance exhibited distinct spatial heterogeneity (Fig. 6). Water-supply factors remained the primary determinants across most ecozones, particularly in R4 and R5 ecozones. In contrast, vegetation-status factor emerged as a more prominent driver in R1 and R2 ecozones, where the contributions were comparable with or exceeded that of individual hydro-climatic variable. While most ecozones were characterized by a clear hierarchy of drivers, the R3 ecozone displayed a more balanced contribution, with relatively narrow disparities between the explanatory power of moisture-supply and energy-availability factors.

To validate the robustness of our findings, we compared GeoDetector results with RF model (Fig. S1). At both regional and ecozone scales, ETa was consistently governed by moisture-supply factors, which exhibited stable and positive associations with ETa across all ecozones. Conversely, atmospheric moisture demand exerted a dominant negative influence. While minor discrepancies occurred in the ranking of secondary drivers (e.g., wind speed and net radiation), the result of ρ confirmed a moderate-to-high consistency between q-value and RF permutation importance across most ecozones (median ρ=0.41–0.64; Table S2). Furthermore, the agreement rate between ALE-derived and risk detector-based responses exceeded 67% in all ecozones (Fig. S1), underscoring the reliability of the identified hydro-climatic controls on ETa dynamics.

Fig. 6 Contribution of GeoDetector to ETa drivers in XJ (a) and its ecozones (b–f) during 2001–2022

Interaction detector results revealed a multi-factor control regime across XJ, characterized by ubiquitous bivariate and nonlinear enhancements among all driver pairs (Fig. 7). At the regional scale, vegetation–atmosphere coupling dominated the interaction, with the coupling of LAI and temperature and the coupling of LAI and VPD yielding the highest interaction. Spatially, these

Fig. 7

Figure 7: Fig. 7

interactions exhibited pronounced heterogeneity: in R1 and R3 ecozones, the coupling of LAI with energy availability was the primary determinant of ETa variance. Conversely, in R2, R4, and R5 ecozones, the interaction between LAI and atmospheric moisture demand became more prominent. Notably, in R5 ecozone, an additional aerodynamic–moisture constraint emerged as a key interaction. Overall, these findings underscore that ETa processes in XJ are governed by complex interactive effects, where vegetation-mediated regulation varies significantly according to local hydrothermal and topographic conditions.

4.2.2 Comparison of dominant drivers in the typical wet and dry year Driver contributions of intra-annual ETa exhibited pronounced seasonal shifts and inter-annual differences between 2003 and 2022 (Figs. 8 and S2). In the wet year, vegetation and hydrological factors dominated the growing-season ETa variance, particularly in the mountainous ecozones. Conversely, in the dry year, the relative importance shifted toward energy-related and atmospheric-demand factors, with the most significant increases observed in the arid basins and alpine zones. While wind speed exhibited highly episodic and region-specific variability, the overall seasonal rankings underscore a fundamental transition in ETa controls from moisture-supply to energy-driven factors during extreme years.

GeoDetector analysis revealed that interaction explanatory power consistently exceeded that of individual drivers across both years, with bivariate and non-linear enhancements predominating the interaction (Figs. 9 and S3). At the regional scale, the coupling of soil moisture and LAI and the coupling of precipitation and LAI remained the most robust explanatory. At the ecozone level, the contrast between wet and dry years was characterized by a distinct reordering of top-ranked interaction pairs rather than a uniform regional shift. In R1, R3, and R5 ecozones, the interaction

Fig. 7 Interaction strength and type between ETa drivers in XJ (a) and its five ecozones (b–f) during 2001–2022

Bivariate enhancement Nonlinear enhancement

transitioned from temperature- and precipitation-linked couplings in the wet year to wind speed-mediated interactions in the dry year. Conversely, in R2 and R4 ecozones, a persistent dominance of vegetation-mediated regulation exhibited, with the coupling of VPD and LAI and the coupling of net radiation and LAI becoming more prominent during the dry year. These results underscore that the sensitivity of ETa to the interaction of driver is highly context-dependent, varying significantly with local hydrothermal conditions.

Cross-method validation revealed moderate-to-high consistency between GeoDe-

Fig. 8: Contributions of GeoDetector to intra-annual ETa drivers for XJ (a) and its five ecozones (b–f) in 2003 (the wet year)

Figure 8: Fig. 8: Contributions of GeoDetector to intra-annual ETa drivers for XJ (a) and its five ecozones (b–f) in 2003 (the wet year)

Fig. 9. Interaction strength and type between ETa driver in XJ (a) and its five ecozones (b–f) in 2003 (the wet year). Green triangles indicate bivariate enhancement; red triangles indicate nonlinear enhancement.

Figure 9: Fig. 9. Interaction strength and type between ETa driver in XJ (a) and its five ecozones (b–f) in 2003 (the wet year). Green triangles indicate bivariate enhancement; red triangles indicate nonlinear enhancement.

tector and RF model in identifying ETa drivers during the growing season (April–September), with ρ and directional agreement peaking across most ecozones (Figs. 10 and S4). Although intermittent divergences occurred during the shoulder seasons (e.g., in R3 and R5 ecozones), the overall convergence between the two independent methods underscores the robustness of the identified hydro-climatic controls.

Monthly comparisons further confirmed a mechanistic transition in ETa regulation between the extreme years. In the wet year, both methods identified soil moisture and LAI as the dominant drivers across XJ, with net radiation and precipitation contributing substantially in R2 and R3 ecozones. Conversely, in the dry year, while soil moisture remained a critical baseline control, the

relative importance of VPD and temperature significantly increased, particularly in R1 and R2 ecozones. These findings demonstrate that ETa dynamics are governed by a shifting hierarchy of hydrological factors, vegetation state, and atmospheric demand, with the wet-dry contrast manifesting as a seasonal reordering of these multi-driver controls rather than a uniform regional shift.

Fig. 8 Contributions of GeoDetector to intra-annual ETa drivers for XJ (a) and its five ecozones (b–f) in 2003 (the wet year)

5 Discussion

Using the PML_V2 ET dataset, this study systematically analyzed the spatiotemporal evolution and driving mechanisms of ETa in XJ. Multi-scale validation has demonstrated that, compared with other satellite-based ET products such as Advanced Very High Resolution Radiometer (AVHRR) and MODIS, PML_V2 provides superior accuracy and robustness for representing ET variability over China, particularly in regions with complex terrain (Ma and Zhang, 2022). In terms of spatial patterns, ETa in XJ exhibited pronounced geomorphological differentiation, with a clear "high in north, low in south; high in west, low in east" gradient and a "high in mountains, low in basins"

Fig. 10

Figure 10: Fig. 10

Fig. 9 Interaction strength and type between ETa driver in XJ (a) and its five ecozones (b–f) in 2003 (the wet year)

structure. The temporal analysis indicated an overall increasing trend in regional ETa, consistent with previous findings by Yao et al. (2020). However, the regional response is highly heterogeneous: the R1, R3 and R5 ecozones showed significant wetting and increasing ETa, whereas the two major basin deserts R2 and R4 ecozones exhibited drying tendencies, in line with observations that mountain ETa has generally increased while ETa in basin deserts has decreased (Liu, 2022; Shi et al., 2024; Jie et al., 2026). Attribution analysis further revealed that water supply was, overall, the primary driver of ETa in XJ (Yang et al., 2023; Zhu et al., 2023). Yet no single factor can reproduce the complex spatial pattern on its own. This study integrated Mann-Kendall test, GeoDetector, and RF model to evaluate ETa dynamics during representative wet (2003) and dry (2022) years. Our results demonstrated that the dominant interaction governing ETa remained broadly stable at the regional scale, with moisture–vegetation coupling interactions consistently maintaining their central importance. These findings revealed a primarily moisture-limited regime modulated by vegetation dynamics, whereas the hierarchy of leading interactions underwent distinct reordering at ecozone level. This refined analysis of pairwise interactions and scenario-dependent mechanistic shifts clarified how ET responds to climate

Fig. 10 Comparison of the contribution of GeoDetector and Random Forest (RF) models to ETa drivers for XJ (a1 and b1) and its five ecozones (a2–a6 and b2–b6) in 2003 (the wet year) and 2022 (the dry year). +, positive association; –, negative association; ±, no significant directional association; , P*<0.05 level; , positive accumulated local effect (ALE); , negative ALE.

forcing across heterogeneous topography, providing a robust, process-based foundation for future hydrological research.

Based on the quantitative identification of dominant drivers, this study elucidated how regional hydrothermal conditions, vegetation physiological regulation, and aerodynamic characteristics jointly shaped the spatial heterogeneity of ETa in XJ. Overall, the high sensitivity of ETa to temporal fluctuations in precipitation and soil moisture is consistent with global evidence of water-controlled ET variability in drylands (Jung et al., 2010). However, along elevational and topographical gradients, the governing mechanism transitioned along a continuum from energy limitation in mountainous regions to water limitation in the basins. Three distinct response regimes emerged across the ecozones: water–energy–vegetation co-driven regime (R1 and R3 ecozones), dynamically enhanced regime (R2 ecozone), and extreme water constraint and anthropogenic modification (R4 and R5 ecozones). In R1 and R3 ecozones, the strong coupling between mid-latitude westerlies and orography—including orographic precipitation and the "mountain water-tower" effect (Sorg et al., 2012; Yao et al., 2012) combined with seasonal snowmelt buffering, effectively alleviates growing-season water stress (Zhang et al., 2018). Under these conditions, abundant net radiation and relatively high LAI shifted ETa from a strictly water-limited regime toward one constrained primarily by energy availability and growing-season length (i.e., an energy-limited regime) (Nemani et al., 2003). R2 ecozone represented a typical moisture transition zone. Within the basin, natural precipitation and reanalysis-derived soil

moisture exhibited subtle spatial gradients, whereas the oasis–desert mosaic produced a pronounced spatial contrast in LAI. Consequently, LAI statistically integrated the long-term effects of water availability, irrigation, and land-management intensity, emerging as the dominant contributor to ETa. The phenomenon is consistent with eddy-covariance evidence from other arid regions (Hoek van Dijke et al., 2020). Additionally, ETa in R2 ecozone showed high sensitivity to wind speed, primarily due to pressure-gradient forcing and flow channeling associated with the mountain–basin topography. Strong wind fields reduced aerodynamic resistance and enhanced turbulent exchange, thereby amplifying the positive dynamic control of wind on evapotranspiration under non-extreme water-limited conditions (McVicar et al., 2012). In contrast, R4 and R5 ecozones illustrated a severe decoupling between precipitation and evaporation. In R4 ecozone, the spatial pattern of ETa was tightly governed by lateral hydrological inputs from irrigation and river leakage, reflecting the profound redistribution of water resources superimposed on the natural cycle (Jaramillo and Destouni, 2015). In R5 ecozone, low temperatures and sparse precipitation led to a pronounced water–energy co-limitation, where thermal constraints limited potential evapotranspiration while scarce rainfall further restricted ETa (Ma and Zhang, 2022).

These contrasting hydrothermal constraint regimes not only shaped the spatial patterns of ETa but also determined the divergent sensitivity and response trajectories of different ecozones to regional climate change. Since 2001, northwestern China has undergone a pronounced "warming and wetting" trend (Yao et al., 2022b), yet the pathways followed by various ecozones diverged significantly under their respective environmental constraints. In R1 and R3 ecozones, regional moistening effectively alleviated pre-existing water stress, pushing ecosystems beyond critical water-limitation thresholds, which promoted vegetation greening and a synergistically positive response of ETa to warming (Piao et al., 2020). Conversely, in R4 and R5 ecozones, the severe water-limited regime rendered ETa largely insensitive to additional thermal input. Although precipitation showed marginal increases, the warming-driven elevation in VPD and potential evapotranspiration (PET) far outpaced these moisture gains. This supply–demand imbalance precluded the translation of enhanced energy into higher ETa, instead intensifying the trend toward aridification (Huang et al., 2016). In essence, the spatiotemporal evolution of ETa in XJ encapsulates a nonlinear outcome of macroclimatic forcing (input) filtered through distinct land-surface hydrothermal constraints. This finding provides critical empirical evidence from a complex mountain-basin system for the conceptual framework of water-energy limitation transitions in global drylands (Denissen et al., 2022), underscoring the necessity of explicitly accounting for land-surface "filtering" effects when projecting future hydrological dynamics.

While this study offered a new perspective on ETa controls in XJ, the precision of certain findings was inherently constrained by dataset accuracy and methodological assumptions. The primary source of uncertainty arose from biases in the underlying datasets. As the PML_V2 product relies heavily on MODIS optical parameters, cloud, and snow cover in northwestern mountains and aerosol loading along southern desert margins may have caused local data gaps or quality degradation, potentially leading to ETa underestimations (Li et al., 2016; Zhang et al., 2019). Additionally, the relatively coarse resolution of ERA5-Land reanalysis hampered the representation of micro-meteorological gradients in oasis-desert ecotones, while the lack of explicit irrigation data may have amplified attribution biases in fine-scale hydrothermal processes (Jiang et al., 2021).

Beyond data constraints, the internal assumptions of the statistical methods imposed interpretive bounds. On one hand, the discretization of continuous variables in GeoDetector inevitably entailed information loss and in the presence of strong collinearity (e.g., precipitation and soil moisture), may have introduced attribution redundancy (Song et al., 2020). On the other hand, while RF is adept at capturing high-dimensional nonlinearity, tree-based importance measures cannot fully disentangle direct and indirect effects under pronounced multicollinearity. Fundamentally, the interactions revealed by both methods represent statistical associations that still require corroboration from flux-based physical observations (e.g., eddy-covariance measurements) (Belgiu and Drăguţ, 2016; Reichstein et al., 2019).

Despite these limitations, the integrated use of GeoDetector and RF model in a cross-validation framework provided a pragmatic balance between interpreting nonlinear responses and capturing spatial differentiation. The high level of agreement between the two methods bolstered the robustness of our conclusions. Looking ahead, the integration of high-resolution remote sensing products and improved land-surface models with site-scale process observations will be essential for mechanistically disentangling natural and anthropogenic controls and refining our understanding of the water cycle in arid regions.

6 Conclusions

This study systematically quantified the spatiotemporal dynamics of ETa across the arid mountain-basin system in XJ during 2001-2022. The multi-year mean ETa was 193.15 mm/a, exhibiting a pronounced "high in mountains and low in basins" pattern, with the highest values observed in the Tianshan Mountains and the lowest in the Tarim Desert. Interannual trends were spatially heterogeneous, characterized by increases in mountainous areas and stabilization or declines in hyper-arid basins.

Integrated GeoDetector and RF analyses demonstrated that hydrological factors governed spatial ETa variability, collectively explaining 40% of the variance. Notably, pairwise interactions significantly enhanced explanatory power, with vegetation–atmosphere/energy couplings prevailing across most ecozones. The contrast between wet and dry years revealed a spatially divergent reconfiguration of dominant interaction regimes. Specifically, the hyper-arid Tarim Basin pivoted from hydrothermal control during the wet year to a vegetation–moisture stress coupling under drought conditions; conversely, the alpine regions shifted from hydrothermal synchrony to moisture–aerodynamic regulation.

These findings highlight that ETa in arid regions is governed not by individual driver but by region-specific, nonlinear interaction regimes that reconfigure under hydroclimatic extremes. This combined methodological framework strengthens the mechanistic prediction of ETa controls and provides a process-based foundation for zonal water-ecosystem management. Ultimately, the necessity of incorporating interactive driver dynamics when projecting water cycles in arid regions under a changing climate is underscored.

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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Author contributions

Conceptualization, methodology, software, formal analysis, investigation, data curation, visualization, and writing - original draft preparation: MA Zhenrong; Writing - review and editing: WANG Yongdong; ZHOU Zhibin, CHEN Yusen; Supervision: CHEN Yushen. All authors approved the manuscript.

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Appendix

Table S1 Predictive performance metrics of Random Forest (RF) model for actual evaporation (ETa) across Xinjiang (XJ) and its five ecozones (R1–R5)

Region and ecozone	Period	No. of model	R^2_{val}	R^2_{OOB}	Average sample size
XJ	Annual (2003–2022)	20	0.779 ± 0.052	0.781 ± 0.051	100,000
XJ	Monthly (2003, 2022)	24	0.790 ± 0.072	0.792 ± 0.075	100,000
R1 (Altay Mountains)	Annual (2003–2022)	20	0.898 ± 0.013	0.888 ± 0.014	100,000
R1 (Altay Mountains)	Monthly (2003, 2022)	24	0.868 ± 0.105	0.860 ± 0.097	100,000
R2 (Junggar Basin)	Annual (2003–2022)	20	0.868 ± 0.022	0.890 ± 0.018	100,000
R2 (Junggar Basin)	Monthly (2003, 2022)	24	0.870 ± 0.057	0.878 ± 0.056	100,000
R3 (Tianshan Mountains)	Annual (2003–2022)	20	0.868 ± 0.039	0.872 ± 0.039	100,000
R3 (Tianshan Mountains)	Monthly (2003, 2022)	24	0.865 ± 0.050	0.860 ± 0.049	100,000
R4 (Tarim Basin)	Annual (2003–2022)	20	0.708 ± 0.049	0.700 ± 0.050	100,000

Fig. S1

Figure 11: Fig. S1

Region and ecozone	Period	No. of model	R^2_{val}	R^2_{OOB}	Average sample size
R4 (Tarim Basin)	Monthly (2003, 2022)	24	0.765 ± 0.113	0.767 ± 0.105	100,000
R5 (Kunlun Mountains)	Annual (2003–2022)	20	0.763 ± 0.078	0.761 ± 0.081	100,000
R5 (Kunlun Mountains)	Monthly (2003, 2022)	24	0.786 ± 0.106	0.786 ± 0.106	100,000

Note: R^2_{val}, independent testing set; R^2_{OOB}, internal out-of-bag R^2. Mean±SD.

Fig. S1 Contribution of permutation importance (PI) from Random Forest (RF) model to actual evaporation (ETa) drivers for Xinjiang (XJ; a) and its ecozones (b–f) during 2001–2022. P, precipitation; SM, soil moisture; Rn, net radiation; T, temperature; LAI, leaf area index; VPD, vapor pressure deficit.

Table S2 Consistency between RF and GeoDetector for ETa drivers across XJ and its five ecozones during 2001–2022

Region and ecozone	ρ	ALE vs. risk-detector
XJ	0.54 [0.36, 0.71]	71 [57, 71]
R1	0.64 [0.51, 0.75]	67 [60, 75]
R2	0.45 [0.37, 0.71]	80 [76, 100]
R3	0.48 [0.37, 0.71]	69 [67, 83]
R4	0.41 [0.29, 0.54]	83 [67, 96]
R5	0.43 [0.29, 0.53]	75 [53, 79]

Note: ρ, Spearman' s rank correlation. ALE, accumulated local effects. The numbers in square bracket mean the median values at 25^{th} and 75^{th} percentiles.

(a) XJ

(b) R1

(c) R2

Fig. S3. Pairwise interactions between ETa drivers in XJ (a) and its five ecozones (b-f) in 2022 (the dry year).

Figure 12: Fig. S3. Pairwise interactions between ETa drivers in XJ (a) and its five ecozones (b-f) in 2022 (the dry year).

Fig. S4

Figure 13: Fig. S4

(d) R3

(e) R4

(f) R5

Fig. S2 Contributions of GeoDetector to intra-annual ETa drivers for XJ (a) and its five ecozones (b–f) in 2022 (the dry year)

Bivariate enhancement Nonlinear enhancement

Fig. S3 Pairwise interactions between ETa drivers in XJ (a) and its five ecozones (b–f) in 2022 (the dry year)

Fig. S4 Consistency between GeoDetector and RF model in the strength (ρ; Spearman' s rank correlation) and direction (agreement rate) of monthly ETa drivers for XJ (a1 and b1) and its five ecozones (a2–a6 and b2–b6) in 2003 (the wet year) and 2022 (the dry year)

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