Regional Differences and Thresholds of Ecological Base Flow in the Qinling Mountains and Loess Plateau Region: Postprint

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Abstract

The ecosystem of the Qinling Mountains-Loess Plateau geomorphological continuum is extremely fragile, and river ecological baseflow and its thresholds are crucial for ecosystem conservation. Taking the Qinling Mountains-Loess Plateau as the study area, a system of 22 ecological baseflow influencing factors was constructed, covering six characteristic aspects including climate, vegetation, topography and landform, soil layer structure, watershed morphology, and socioeconomics. Through the construction of a Self-Organizing Map (SOM) neural network and K-means clustering analysis, the Qinling Mountains-Loess Plateau was divided into four sub-regions—the central Loess Plateau, the southern foothills of the Qinling Mountains, the northern foothills of the Qinling Mountains, and the northwestern Loess Plateau—based on the aforementioned influencing factors. The Partial Least Squares Structural Equation Model (PLSSEM) was employed to model and analyze the influencing factors of ecological baseflow in three sub-regions. The results indicate: (1) Ecological baseflow in the central Loess Plateau is primarily influenced by precipitation concentration, that in the southern foothills of the Qinling Mountains is mainly affected by mean annual temperature, and that in the northern foothills of the Qinling Mountains is predominantly influenced by soil moisture content. (2) Significant regional differences exist in ecological baseflow among different sub-regions, with ecological baseflow proportion thresholds of 7.9%, 9.5%, 7.5%, and 4.1% for the central Loess Plateau, southern foothills of the Qinling Mountains, northern foothills of the Qinling Mountains, and northwestern Loess Plateau, respectively. (3) Considering the differential responses of ecological baseflow to environmental changes across sub-regions, a linear regression model capable of calculating and simulating ecological baseflow was established, with model coefficients of determination all greater than 0.87. The research findings not only provide a scientific

basis for the quantitative estimation of ecological baseflow, but also offer references for river health maintenance and sustainable water resource utilization, holding significant theoretical and practical value.

Full Text

Regional Differences and Threshold of Ecological Base Flow in the Qinling Mountains-Loess Plateau Region

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Abstract

The Qinling Mountains-Loess Plateau geological and geomorphological continuum features a fragile ecosystem where river ecological base flow and its thresholds are critical for ecosystem protection. This study examines the Qinling Mountains-Loess Plateau region in China, constructing a system of 22 ecological base flow influencing factors encompassing climate, vegetation, topography, soil structure, watershed morphology, and socioeconomic variables. Using a self-organizing map (SOM) neural network and K-means clustering analysis, the region was divided into four sub-regions: the central Loess Plateau, southern Qinling, northern Qinling, and northwestern Loess Plateau. Partial least squares structural equation modeling (PLS-SEM) was applied to model and analyze ecological base flow influencing factors in three sub-regions. The results indicate that: (1) Ecological base flow is primarily influenced by precipitation concentration in the central Loess Plateau, by annual mean temperature in the southern Qinling, and by soil moisture content in the northern Qinling. (2) Significant regional differences were observed in ecological base flow thresholds, with values of 7.9% for the central Loess Plateau, 9.5% for the southern Qinling, 7.5% for the northern Qinling, and 4.1% for the northwestern Loess Plateau. (3) A linear regression model was developed to calculate and simulate ecological base flow, with determination coefficients exceeding 0.87, accounting for regional differences in environmental response. These findings provide a robust scientific basis for the quantitative estimation of ecological base flow, offer insights into river health maintenance and sustainable water resource utilization, and hold substantial theoretical and practical significance.

Keywords: ecological base flow; cluster analysis; flow threshold; structural

equation; influencing factors

1 Introduction

Ecological base flow refers to the minimum water discharge required to maintain the basic form and ecological functions of a river. Its core purpose is to ensure river connectivity, protect aquatic habitats from irreversible damage, and safeguard the overall health of river ecosystems. Insufficient ecological base flow reduces a river’ s pollutant assimilation and self-purification capacity, lowers groundwater levels, accelerates soil erosion, and deteriorates aquatic habitats, thereby threatening ecological balance and watershed integrity.

Current methods for calculating ecological base flow primarily include hydrological approaches, hydraulic methods, hydro-biological analysis, habitat methods, and holistic analysis. Hydraulic methods rely on field-measured hydraulic data and are suitable for small or stable rivers but ignore biological characteristics. Habitat methods determine ecological base flow by analyzing relationships between discharge and habitat indicators but are limited to specific species. Holistic analysis, considered the primary future approach, requires extensive hydrological, ecological, social, and economic data while depending on expert judgment, making it time-consuming and expensive. Hydrological methods, based on flow data, offer simplicity and broad applicability, leading to their adoption in this study.

Ecological base flow exhibits spatial-temporal heterogeneity, quality coexistence, dynamic variability, target specificity, and threshold characteristics. Research on the Wei River Basin demonstrates spatial variability with lower base flow upstream and higher downstream, validating the feasibility of sub-regional classification. Studies show that land use significantly affects runoff, with terraced fields improving base flow guarantee rates, underscoring the critical role of underlying surface conditions. Climate influences vegetation, which indirectly affects runoff, with this influence increasing from north to south across the region.

Despite progress in ecological base flow research, systematic studies addressing different rivers and scales remain limited. This investigation addresses the spatial heterogeneity of the Qinling Mountains-Loess Plateau region by developing a comprehensive control factor system, identifying relationships between primary influencing factors and ecological base flow, and establishing sub-regional thresholds to support water resource management and ecological protection.

1.1 Study Area Overview

The Loess Plateau (32°18 -41°16 N, 100°54 -114°33 E) is located in the interior of the Eurasian continent [Figure 41: see original paper]. The region’ s river systems include tributaries of the Yellow River and Han River. The Qinling Mountains serve as the southern boundary of the Loess Plateau, forming a critical ecological barrier and climate divide between China’ s northern and southern regions. This area, spanning Shaanxi, Shanxi, Gansu, Qinghai, Ningxia, Inner Mongolia, Henan, and Hubei provinces, features significant climatic, topographic, and ecological variations, nurturing rich biodiversity and serving as a vital habitat for numerous rare species.

1.2 Data Sources

Hydrological station data were obtained from regional hydrological yearbooks. Data from Dawukou, Rujigou, Guojiaqiao, Mingshazhou, Quanyanshan, Hanfuwan, Pengyang, Longde, and Jingheyuan stations cover 1980–2020. Zhangjiashan, Huangfuchuan, Wenjiachuan, Suide, Yitang, Lancun, Huaxian, Zhuangtou, Baijiachuan, and Ganguyi stations span 1956–2020. Jingcun and Lucunhe stations cover 1960–2020. Heiyukou, Laoyukou, Qinduzhen, and Maduwang stations span 1970–2020. Chenhe station data cover 1975–2020, while Luolicun, Youshuijie, Chaiping, Nankuanping, Madao, Shengxiancun, Jingziguan, Lianghekou, and Xiangjiaping stations span 1980–2020. All hydrological records exceed 20 years in length.

Climate data, including monthly precipitation, temperature, potential evapotranspiration, soil moisture, leaf area index, surface net solar radiation, and normalized difference vegetation index (NDVI), were sourced from ERA5-Land (https://cds.climate.copernicus.eu) and the National Tibetan Plateau Data Center (https://data.tpdc.ac.cn). Soil texture, net primary productivity (NPP), gross domestic product (GDP), and nighttime light data were obtained from the Chinese Academy of Sciences Resource and Environmental Data Center (www.resdc.cn). Digital elevation model (DEM) data came from the Geospatial Data Cloud (www.gscloud.cn), while land use data were derived from Professor Yang Jie’ s dataset [14]. Table 1 summarizes the control factors and their sources.

Table 1 Control factors system of ecological base flow

Factor	Description	Source
Annual precipitation (P)	Statistics from remote sensing data	ERA5-Land
Precipitation variation coefficient (P_{cv})	Standard deviation/mean of annual precipitation	Calculated from precipitation data
Annual mean temperature (T)	Statistics from remote sensing data	ERA5-Land
Mean humidity index (HI)	Potential evapotranspiration/precipitation	ERA5-Land
Precipitation concentration (P_c)	Calculated from precipitation data	ERA5-Land
Surface net solar radiation (S)	Statistics from remote sensing data	ERA5-Land

Factor	Description	Source
NDVI	Statistics from remote sensing data	ERA5-Land
Forest and grassland proportion (FG)	Calculated from land use data	Land use dataset
NPP	Statistics from remote sensing data	Resource and Environmental Data Center
Leaf area index (LI)	Statistics from remote sensing data	ERA5-Land
Clay proportion (Clay)	Calculated from soil texture data	Soil texture dataset
Silt proportion (Silt)	Calculated from soil texture data	Soil texture dataset
Sand proportion (Sand)	Calculated from soil texture data	Soil texture dataset
Soil moisture content (SM)	Statistics from remote sensing data	ERA5-Land
Mean catchment elevation (E)	Statistics from remote sensing data	DEM
Relief degree (R)	Statistics from remote sensing data	DEM
Watershed area (A)	Calculated from DEM	DEM
Watershed shape coefficient (K)	Perimeter/area of equivalent circle	Calculated from DEM
River network density (D)	Statistics from remote sensing data	DEM
Nighttime light (NL)	Statistics from remote sensing data	Resource and Environmental Data Center
GDP	Statistics from remote sensing data	Resource and Environmental Data Center

1.3 Methodology

1.3.1 Q90 Method The Q90 method, recommended in China' s official standard "Specification for Calculation of Ecological Flow for Rivers and Lakes" (SLT712-2021) [15], is widely used for ecological base flow assessment. This approach extracts annual minimum flows, ranks them in descending order, and calculates the frequency of occurrence (P) for each year using the formula:

$$P = \frac{r}{n+1} \times 100\%$$

where n is the total sample size and r is the rank of each sample. A Pearson Type III distribution curve is then fitted, and the discharge corresponding to 90% frequency is defined as the ecological base flow.

1.3.2 Self-Organizing Map (SOM) The self-organizing map, proposed by Kohonen [17], is an artificial neural network that extracts patterns and identifies clusters in large multivariate datasets. SOM maps multidimensional input data onto a two-dimensional space where similar inputs occupy proximal nodes. Map size (number of output neurons) is critical for SOM performance. The empirical rule $m = 5\sqrt{n}$ provides an initial estimate, where n is the sample size and m is the number of neurons. To optimize map size, node counts around this estimate are tested, with quantization error (QE) evaluating map quality:

$$QE = \frac{1}{n}\sum_{i=1}^{n}\|x_i - m_c\|$$

where x_i represents sample data and m_c is the nearest map unit.

1.3.3 K-means Clustering K-means clustering [20] partitions data into k clusters by minimizing within-group variance. The Davies-Bouldin Index (DBI) determines the optimal cluster number:

$$DBI = \frac{1}{k}\sum_{i=1}^{k}\max_{j\neq i}\left(\frac{c_i + c_j}{\|c_i - c_j\|}\right)$$

where c_i and c_j are centroids of clusters i and j, and c_i represents mean distance from data points to cluster centroid. Additionally, the within-group sum of squares (WGSS) identifies the optimal cluster number at its inflection point:

$$WGSS = \sum_{l=1}^{k}\sum_{x\in G_l}(x - \bar{x}_l)^2$$

where G_l is the lth cluster and $\bar{x}_l$ is its mean.

1.3.4 Partial Least Squares Structural Equation Modeling (PLS-SEM) PLS-SEM estimates path models with latent variables [21], comprising internal and external components. The internal model shows relationships among latent variables, with path coefficients resulting from regressing each latent variable on its direct predecessors. The external model represents relationships between latent variables and their observed indicators:

$$Observed\ variable = a \times Latent\ variable + e$$

where a quantifies regression coefficients and e represents random measurement error. PLS-SEM better reveals relationship strength and direction while avoiding parameter estimation biases common in regression analysis [22].

1.3.5 Ecological Base Flow Proportion Threshold Calculation Following Liu et al. [12], the ecological base flow proportion threshold represents its fluctuation range under changing environments:

$$T_i = \frac{BM_{avg,i} + BM_{p50,i}}{2}$$

where T_i is the threshold for sub-region i, and $BM_{avg,i}$ and $BM_{p50,i}$ are the mean and median proportions of ecological base flow to multi-year average natural runoff, respectively.

2 Results

2.1 Sub-region Division and Control Factor Characteristics

2.1.1 Sub-region Division This study selected 25 hydrological stations across the Qinling Mountains-Loess Plateau region. After normalizing 22 control factors, SOM mapped them onto 25 neurons [Figure 2: see original paper]. Factors including annual precipitation, mean temperature, humidity index, precipitation concentration, surface net solar radiation, NDVI, forest/grassland proportion, NPP, leaf area index, clay proportion, mean humidity index, soil moisture, and relief degree showed similar patterns, indicating strong correlations. Conversely, mean catchment elevation exhibited opposite trends. Population and nighttime light showed correlated patterns, reflecting socioeconomic interrelationships. Watershed shape coefficient and river network density also correlated, representing watershed morphology factors. Precipitation variation coefficient, forest/grassland proportion, and watershed area displayed similar color distributions, leading us to group them as "other" variables. Sand and silt proportions showed clear complementarity, distinct from clay distribution. These dimensionally processed data served as K-means clustering inputs.

The WGSS scree plot [Figure 3: see original paper] identified four as the optimal cluster number. Considering cluster spatial distribution and river system integrity, the study area was divided into four sub-regions [Figure 4: see original paper]: central Loess Plateau (7 samples), southern Qinling (6 samples), northern Qinling (7 samples), and northwestern Loess Plateau (5 samples, concentrated in Ningxia' s irrigated plain area). The sub-regions form irregular belts along latitudinal lines. The southern Qinling exhibits the highest temperature, humidity, and vegetation cover, with abundant water and heat resources, predominantly clay soils, high shallow soil moisture, large relief, and lower mean elevation. However, its socioeconomic development and surface net solar radiation rank lowest, with relatively uniform annual precipitation distribution.

2.1.2 Control Factor Characteristics by Sub-region Cluster centers [Figure 5: see original paper] represent sub-regional averages. The central Loess Plateau features sandy soils, large inter-annual precipitation variability, and sparse river networks. The northern Qinling, a transitional zone, shows moderate levels for many factors with high mean catchment elevation and dense population. The northwestern Loess Plateau exhibits concentrated precipitation during flood seasons (low overall), high surface net solar radiation, flat terrain, and developed socioeconomic conditions.

2.2 Ecological Base Flow Spatial Distribution and Thresholds

2.2.1 Spatial Distribution Characteristics Ecological base flow varies substantially across hydrological stations, ranging from below 0.1 $m^3 \cdot s^{-1}$ at Huangfuchuan and Longde to near 3.32-7.66 $m^3 \cdot s^{-1}$ at Lanzhou and Xiangjiaping [Figure 6: see original paper]. In the central Loess Plateau, eastern rivers show low base flow. The humid southern Qinling displays relatively uniform base flow across stations. The northern Qinling shows lower values than its southern counterpart, with Hanfuwan, Jingheyuan, Pengyang, Heiyukou, and Longde stations averaging around 0.1 $m^3 \cdot s^{-1}$. Mainstream and headwater stations generally exhibit higher ecological base flow.

Compared to the Montana method' s recommended 10%-30% of average annual flow, 19 of 25 stations fall within this range. The Q90 method emphasizes low-flow periods. In the central Loess Plateau, Lanzhou' s higher dry-season flows produce elevated base flow proportions, while eastern stations mostly range 10%-30%. The central Loess Plateau and northern Qinling show "short and fat" violin plot distributions [Figure 7: see original paper], with most stations concentrated near 10%. Southern Qinling stations, mostly in the Yangtze River basin, show more uniform distribution.

2.2.2 Sub-regional Ecological Base Flow Proportion Thresholds Ecological base flow exhibits clear spatial patterns, with thresholds reflecting sub-regional levels and inter-regional differences. All sub-regions show means exceeding medians, indicating right-skewed distributions with values above 50% of sample points below average, highlighting uneven water resource distribution .

Table 2 Sub-regional ecological base flow proportion thresholds

Sub-region	Threshold
Central Loess Plateau	7.9%
Southern Qinling	9.5%
Northern Qinling	7.5%
Northwestern Loess Plateau	4.1%

These thresholds help protect river ecosystems by preventing excessive water withdrawal and flow reduction, playing a crucial role in water resource management and environmental protection.

2.3 Influencing Factors of Ecological Base Flow

PLS-SEM models were constructed for three sub-regions [Figure 8: see original paper]. Due to numerous climate factors, they were grouped into latent variables, with an "other" variable added to improve model precision.

In the central Loess Plateau, the model explains 90.5% of base flow proportion variation. Climate, vegetation, and "other" factors show significant positive correlations with base flow proportion, while climate and vegetation also exhibit negative correlations. Watershed morphology and socioeconomic factors show weak positive correlations.

In the southern Qinling, the model explains 98.0% of variation. Climate and topography show negative correlations, while vegetation and "other" factors show positive correlations.

In the northern Qinling, the model explains 85.3% of variation. Topography, "other" factors, vegetation, soil structure, and watershed morphology show negative correlations, while climate and socioeconomic factors show positive correlations.

2.4 Ecological Base Flow Proportion Threshold Simulation

Linear regression equations were established between ecological base flow proportion and primary control factors for the central Loess Plateau, southern Qinling, and northern Qinling, representing dynamic thresholds that adjust with factor changes. Control factors were selected based on large path coefficients from PLS-SEM internal models, with final models determined by maximizing R^2.

Central Loess Plateau Model ($R^2 = 0.871$):

$$BM = 11.408 - 18.929 \times LI + 0.013 \times R + 0.082 \times NPP - 2.197 \times T$$

All coefficients are significant ($P < 0.05$), with leaf area index, relief degree, NPP, and annual mean temperature as controls.

Southern Qinling Model ($R^2 = 0.871$):

$$BM = -413.001 - 242.51 \times FG + 0.004 \times A + 754.283 \times NDVI$$

All coefficients are significant ($P < 0.01$), with forest/grassland proportion, watershed area, and NDVI as controls.

Northern Qinling Model ($R^2 = 0.871$):

$$BM = -14.393 + 8.825 \times P - 18.159 \times K + 0.027 \times NPP + 1.521 \times Silt$$

All coefficients are significant ($P < 0.05$), with annual precipitation, watershed shape coefficient, NPP, and silt proportion as controls.

These equations capture spatial heterogeneity in ecological base flow and provide reference for estimation and regulation.

3 Discussion

This study investigated spatial heterogeneity and influencing factors of ecological base flow in the Qinling Mountains-Loess Plateau region. A control factor system with 22 elements was constructed, examining climate, vegetation, topography, soil structure, watershed morphology, and socioeconomic influences. The region was divided into four sub-regions using SOM and K-means clustering.

Key findings reveal regional differences in controlling factors: precipitation concentration dominates in the central Loess Plateau, annual mean temperature in the southern Qinling, and soil moisture in the northern Qinling. These align with Li et al. [27], who highlighted climate' s important role. Soil characteristics, particularly moisture, critically affect base flow maintenance [28]. Climate influences base flow indirectly through vegetation, with this effect strengthening from north to south [29].

Soil type differences indicate that sandy soils benefit base flow more than clay soils. Sandy soils' good permeability facilitates groundwater formation and river recharge [32], while high clay content negatively impacts base flow [33]. In the central Loess Plateau, vegetation increase negatively affects base flow, while in the water-rich southern Qinling, it has positive effects. This suggests vegetation competition reduces base flow in water-scarce regions [31], whereas in humid areas, vegetation helps soil retain precipitation [34].

The linear regression models achieved $R^2 > 0.87$, demonstrating strong explanatory power. However, limitations exist: results may not generalize to other regions, some factors (e.g., groundwater conditions) were not considered, and prediction errors may occur despite high R^2 values.

4 Conclusions

1) Based on control factor systems and river network distribution, the Qinling Mountains-Loess Plateau was divided into four sub-regions with irregular latitudinal belts. Ecological base flow varies significantly among rivers, with higher values at mainstream and headwater stations. Spatial variation is greater in the central Loess Plateau and northern Qinling, while more uniform in the southern Qinling.

2) Ecological base flow proportion thresholds are 7.9% for the central Loess Plateau, 9.5% for the southern Qinling, 7.5% for the northern Qinling, and 4.1% for the northwestern Loess Plateau.

3) The main controlling factors are precipitation concentration in the central Loess Plateau, annual mean temperature in the southern Qinling, and soil moisture content in the northern Qinling. Climate indirectly affects base flow through vegetation, with influence strengthening from north to south. Sandy soils better support base flow than clay soils. Vegetation impacts differ regionally—negative in the central Loess Plateau and northern Qinling, positive in the southern Qinling.

4) Linear regression models for simulating ecological base flow proportion achieved determination coefficients exceeding 0.87, providing flexible threshold calculation tools that account for regional environmental responses.

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