Spatiotemporal Evolution Patterns and Attribution of Precipitation Use Efficiency since the Implementation of the Grain for Green Project: A Case Study of Baoji Region (Postprint)

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Abstract

Based on the vegetation rainfall use efficiency (RUE) model, this study integrates three dimensions of climate, land use/cover, and optical remote sensing to separate human intervention (increase/decrease) factors, monitors the spatiotemporal evolution characteristics of growing season RUE, and further employs the geographical detector method to explore its driving forces. The results show that: (1) After two rounds of the Grain for Green project in the Baoji region, RUE shows an overall increasing trend, with the proportion of pixels exhibiting a significant increasing trend reaching 65.69% especially after the first round (2009–2013). The entire region transformed from being dominated by areas with increased human intervention during the first project implementation period (2001–2008) to being dominated by areas with decreased human intervention; (2) Summer precipitation is most abundant, while spring precipitation is relatively scarce, manifested as the most significant increase rate of summer RUE $[0.07 \cdot (10a)^{-1}]$ and the most significant decrease rate of spring RUE $[-0.06 \cdot (10a)^{-1}]$. Interannually and in summer-autumn, forest land has the highest RUE value, while in spring, urban-rural land has the highest RUE value; (3) The correlation with RUE decreases sequentially for vegetation coverage, relative humidity, sunshine duration, total grain output, maximum wind speed, precipitation, temperature, population density, and afforestation area (at the 95% confidence level), while vegetation type, slope, and aspect show no significant correlation with RUE. Under interactive effects, the correlation with RUE spatial distribution manifests as: climate environmental factors > natural resource factors > human activity factors > geographical environment factors. With increasing slope, RUE shows a trend of first increasing then decreasing, with an inflection point appearing at slopes of $26° \sim 31°$; afforestation area changes synchronously with RUE; vegetation has a significant promoting

effect on RUE, while population density has a significant stress effect on RUE. Additionally, precipitation of 665.51 ~ 679.80 mm shows the greatest effectiveness in improving RUE, concentrated in the east-west horizontal line region of Chencang District.

Full Text

The Evolution Pattern and Attribution of Rainfall Use Efficiency Since the Implementation of the Returning Farmland to Forest (Grassland) Project: A Case Study in Baoji

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Abstract: Based on the Rainfall Use Efficiency (RUE) model, this study integrates climate, land use/cover, and optical remote sensing data to separate human intervention factors (increase/decrease), monitors the spatiotemporal evolution characteristics of RUE during the growing season, and employs the geographical detector method to explore its driving forces. The results show that: (1) After two rounds of the Returning Farmland to Forest (Grassland) project in Baoji, RUE exhibited an overall increasing trend, particularly after the first round (2009-2013), when the proportion of pixel area showing a significant increasing trend reached its highest value at 65.69%. The entire region shifted from being dominated by areas with increased human intervention during the first round (2001-2008) to areas with decreased human intervention. (2) Summer precipitation is the most abundant, while spring rainfall is relatively scarce, manifested as the most significant increasing rate of summer RUE [$0.07 \cdot (10a)^{-1}$] and decreasing rate of spring RUE [$-0.06 \cdot (10a)^{-1}$]. At interannual, summer, and autumn scales, forest land shows the highest RUE values, while urban and rural land shows the highest RUE in spring. (3) The explanatory power of vegetation coverage, relative humidity, sunshine hours, total grain output, maximum wind speed, precipitation, temperature, population density, and afforestation area on RUE decreases sequentially (at 95% confidence level), while vegetation type, slope, and aspect show no significant explanatory power. The interaction effects are expressed as: climate-environmental factors > natural resource factors > human activity factors > geographical environment factors. With increasing slope, RUE shows a trend of first increasing then decreasing, with an inflection point appearing at 26°-31°. Afforestation area and RUE show a synchronous increase-decrease relationship; vegetation demonstrates a significant promoting effect on RUE, while population density shows a significant stress effect. Additionally, precipitation of 665.51-679.80 mm carries the highest risk for increasing RUE, concentrated in the east-west horizontal zone of

Chencang District.

Keywords: Returning Farmland to Forest (Grassland); RUE; Human Intervention; Driving Factor; Baoji

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1. Study Area Overview

Baoji is located in western Shaanxi Province (Guanzhong Plain), situated between 106°18 -108°03 E and 33°35 -35°06 N. This region lies in a climate-sensitive zone with fragile habitats and represents one of the earliest pilot areas for the Returning Farmland to Forest (Grassland) project in China. Elevation ranges from 354–3546 m, exhibiting a topographic characteristic of "high in the south and low in the north." Baoji has a warm temperate continental monsoon climate, with annual precipitation of 710–1000 mm concentrated in summer and autumn, showing large interannual and intra-annual variations. The area administers three districts and nine counties. Vegetation types are diverse, with forests and grasslands distributed throughout the region. Along the main tributaries of the Qianhe and Weihe Rivers, the Weibei Tableland and Weihe Plain are dominated by cultivated land and urban-rural land for field crops, vegetables, orchards, and urban greening (Fig. [Figure 1: see original paper]). The forest vegetation coverage rate reaches 36%–42%, concentrated in the Qinling and Guanshan Mountains. As a pilot area for the Returning Farmland to Forest (Grassland) project, Baoji has fully implemented the first round (2001–2008) and second round (2009–2017) of ecological restoration projects.

2.1 Data Collection and Processing

This study involved collecting and processing near-term data for Baoji, including meteorological data, MODIS NDVI, elevation, land cover, soil, and socioeconomic data.

Table 1 Data sources used in this study

2.2 Research Methods

2.2.1 Theil-Sen + Mann-Kendall Trend Analysis

The Theil-Sen+Mann-Kendall trend analysis method is currently the most robust non-parametric statistical method for determining trends in long-term vegetation time series data. The calculation is as follows:

$$\beta = \text{Median}\left(\frac{\text{NDVI}_j - \text{NDVI}_i}{j - i}\right)$$

where NDVI_i and NDVI_j are the NDVI values for time series i and j, respectively. The trend condition is $\beta > 0$ for increasing trends and $\beta < 0$ for decreasing trends. The Mann-Kendall test is used for significance testing (confidence level of 95%).

2.2.2 Rainfall Use Efficiency Estimation

Rainfall Use Efficiency (RUE) characterizes the evolution trend of regional vegetation growth. The calculation formula is:

$$\mathrm{RUE} = \frac{\mathrm{NPP}}{P}$$

where NPP is vegetation net primary productivity and P is annual precipitation. At large scales, MODIS NDVI data can effectively characterize annual vegetation growth conditions. Studies show that NPP has a close correlation with the cumulative NDVI ($\sum \mathrm{NDVI}$). Considering the small study area and limited meteorological stations (6), to improve data accuracy, a fishnet was used to obtain 2000 random points, extracting their longitude, latitude, and elevation. Partial correlation analysis revealed that longitude and latitude showed non-significant relationships with annual precipitation ($P > 0.05$), differing from previous studies showing significant correlations. Based on these results, elevation data was used to correct precipitation through the CoKriging module in ArcGIS software.

2.2.3 Pixel Dichotomy Model

Assuming a single pixel consists of pure vegetation ($\mathrm{NDVI}_{\mathrm{veg}}$) and pure soil ($\mathrm{NDVI}_{\mathrm{soil}}$) components, the weighted average of the two constitutes the mixed pixel vegetation index (NDVI). The area proportion of each component in the pixel represents the weight. The linear pixel dichotomy model is the most widely applicable method for assessing regional vegetation restoration effects using remote sensing data, with estimation results showing extremely significant correlations with ground measurements. By setting confidence intervals, the upper and lower limits of remote sensing data are extracted as $\mathrm{NDVI}_{\mathrm{soil}}$ and $\mathrm{NDVI}_{\mathrm{veg}}$, respectively:

$$\mathrm{FVC} = \frac{\mathrm{NDVI} - \mathrm{NDVI}_{\mathrm{soil}}}{\mathrm{NDVI}_{\mathrm{veg}} - \mathrm{NDVI}_{\mathrm{soil}}}$$

2.2.4 Geographical Detector

The geographical detector method explores spatial differentiation and identifies driving factors. Its advantage is overcoming the arbitrariness and subjectivity in data discretization by obtaining optimal results through unsupervised classification. The method quantitatively analyzes and detects the explanatory power of influencing factors on RUE spatial distribution and their interactions. The calculation principle is:

$$q = 1 - \frac{1}{N\sigma^2}\sum_{h=1}^{L} N_h \sigma_h^2$$

where q and σ^2 are indicators of spatial differentiation and variance of the dependent variable explained by independent variables; h and L are variable strata and number of strata, $h = 1, 2, 3, \cdots, L$; and N is the total sample size. The q value characterizes the correlation of spatial differentiation, ranging between [0,1]. A larger (smaller) value indicates stronger (weaker) correlation and greater (lesser) influence. When $q = 1$ (or 0), the spatial differentiation is completely controlled by this factor (or has no influence).

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3. Results and Analysis

3.1 Determination of Human Intervention Factors

The spatial distribution of NDVI during the growing season in Baoji is consistent with RUE distribution, showing a south-high, north-low pattern that increases from northwest to southeast, with the Weihe River as the boundary. Statistics were compiled for NDVI values of cultivated land, forest land, grassland, water bodies, urban-rural land, and unused land. Since the second round, the highest mean NDVI values for cultivated land, forest land, grassland, and unused land were observed, representing the highest values across all three periods, followed by the post-first-round period.

After the first round, water bodies and urban-rural land showed the highest mean NDVI values, followed by the first-round period. Forest land NDVI values were intermediate across all periods but highest among all land use types, concentrated in the area east of Hongya River in the southeast of Taibai County, accounting for 32.81% of the area. The abundant water supply from the Taibai and Xushui Rivers, combined with snowmelt from the Qinling Mountains, contributes to vegetation cover restoration in this region. Overall, the ecological restoration effects of the Returning Farmland to Forest (Grassland) project in Baoji show that forest land has the highest values, while low-value areas appear in water bodies, urban-rural land, and cultivated land, mostly concentrated along the Weihe and Qianhe Rivers and east of the Qianhe River, accounting for 31.57% of pixels. This region is densely populated, where urban expansion leads to an inverse relationship between built-up area and vegetation area. Additionally, seasonal characteristics of crops, vegetables, and economic plants cause the lowest vegetation cover in this area.

Based on NDVI value changes across the three periods and using the Sen+M-K trend analysis method for classification, pixel areas and proportions were extracted (Table). Values with $\beta < 0.8$ and $\beta > 1.2$ were defined as human intervention decrease and increase areas, respectively.

3.2 Spatiotemporal Evolution Characteristics of RUE

Compared with the first-round period, high-value areas along the southern Weihe River coast and in central and southern Fengxian and Taibai decreased during the post-first-round period. High-value areas in the western region at the intersection of the Weihe and Qianhe Rivers increased, with the proportion decreasing to 12.3%. This result corresponds to the area with the highest vegetation cover values being human intervention decrease areas. The main reason is that in arid and semi-arid regions affected by urbanization, precipitation is no longer the only water source for vegetation growth along the drought-prone Weihe and Qianhe Rivers. Additionally, Linyou, a hilly and gully region with high-density vegetation cover, has a pleasant climate with warm winters and cool summers, resulting in smaller impacts on vegetation cover changes from RUE.

Overall, the influence of precipitation on vegetation growth is less than that of human intervention after the first round. Human intervention increase areas in Baoji decreased from 68.48% to 19.1%, while human intervention decrease areas increased from 98.93% to 92.66% across the three periods. During the first-round period, these were mainly distributed in the western region at the Weihe-Qianhe intersection and along the southern Weihe coast, with central and southern Fengxian and Taibai also showing RUE high-value areas. Compared with the first-round period, the post-first-round period added new high-value areas at the confluence of Qishui and Hengshui Rivers, increasing to 21.09%. The highest RUE values for forest land and grassland ranged between 0.58 $g \cdot m^{-2} \cdot mm^{-1}$. Longxian, Linyou, Chencang District, Fengxian, and Taibai are key construction areas for the Returning Farmland to Forest (Grassland) project, featuring Guanshan Pasture, Beishan, Wushan, and typical ecological forest areas that represent RUE high-value zones. Soil water retention capacity increases with improved vegetation cover.

Under human intervention conditions, to study the response relationship between project implementation and RUE in Baoji, the Sen+M-K trend method was applied. Referencing Mou Le et al., RUE change trends were classified as: significant decrease ($\beta \leq -1.96$), slight decrease ($-1.96 < \beta \leq -0.8$), basically unchanged ($-0.8 < \beta \leq 0.8$), slight increase ($0.8 < \beta \leq 1.96$), and significant increase ($\beta > 1.96$). Overall, the high increase trend was most evident after the first round, with pixel proportion reaching 39.33% and 65.69% for slight and significant increase areas, respectively, which is 30.3% and 45.88% higher than in the second round. Comparing human intervention across periods shows a shift from 99.85% human intervention increase in the first round to 86.07% in the post-first-round period, then to 81.23% human intervention decrease in the second round. The proportion of significantly improved vegetation area from the project implementation across the three periods was 63.29%, 39.33%, and

0.01%, respectively, showing good synchronization between RUE change trends and cumulative afforestation area.

Since project implementation, interannual RUE in Baoji shows a decreasing trend [$0.03 \cdot (10a)^{-1}$], while summer RUE shows an increasing trend [$0.07 \cdot (10a)^{-1}$] and spring RUE shows a decreasing trend [$-0.06 \cdot (10a)^{-1}$]. The variation trends differ across seasons (Fig. [Figure 4: see original paper]). Overall, interannual and summer RUE show consistent trends: decreasing (2001–2008), increasing (2009–2013), then increasing (2014–2017), while spring shows an increasing (2001–2008), increasing (2009–2013), then decreasing (2014–2017) trend. Calculating precipitation relative variability and comparing it with national precipitation anomaly percentage maps reveals Baoji' s drought-flood conditions: interannual 24.94% (normal), summer 23.91% (normal), autumn 30.27% (normal), and spring 27.12% (normal).

Across the three periods, human intervention increase and decrease areas show annual precipitation ranging from 376.85 mm to 1201.81 mm. Summer precipitation is highest in both human intervention increase (1065.22 mm) and decrease (703.6 mm) areas, with the most significant increasing rate of summer RUE and decreasing rate of spring RUE. This indicates that spring rainfall is relatively scarce while summer rainfall is abundant in Baoji. Since the early 21st century, summer precipitation in China has increased significantly, with the vulnerable northwestern arid zone increasing at a rate of $mm \cdot (10a)^{-1}$, consistent with Baoji' s trend.

Statistical analysis of RUE values under different land use/cover types shows that forest land has the highest RUE values across interannual, summer, and autumn scales, while urban-rural land has the highest RUE in spring. At interannual and seasonal scales, higher RUE values appear in forest land, with the largest fluctuations in autumn, followed by interannual variation.

Table 3 RUE driving force evaluation index system

3.3 Quantitative Attribution of Vegetation Rainfall Use Efficiency Since Project Implementation

3.3.1 Analysis of Dominant Driving Factors and High-Risk Range Identification

Based on both natural and human perspectives, an index system was constructed with natural resource factors, climate-environmental factors, geographical environment factors, and human activity factors as primary indicators. Secondary indicators include vegetation coverage (X_1), afforestation area (X_2), precipitation (X_3), relative humidity (X_4), sunshine hours (X_5), maximum wind speed (X_6), temperature (X_7), slope (X_8), aspect (X_9), vegetation type (X_{10}), population density (X_{11}), and total grain output (X_{12}). For natural resource factors, Fractional Vegetation Cover (FVC) was used to reflect vegetation coverage, representing the proportion of vegetation projection area per unit area, improved based on NDVI. For human activity factors, population density was represented by the ratio of population per unit area to total population.

Ecological detector results (Table , 95% confidence level) show significant differences in correlations between RUE spatial distribution and vegetation coverage, afforestation area, slope, aspect, vegetation type, and population density. Using ArcGIS software and the natural breaks classification method, the 12 driving factors were reclassified into 5 levels (categorical variables). To obtain higher data precision, 2000 geographic coordinate points were created using a fishnet, extracting values for 7 numerical and 5 categorical driving factors, matching raster and point data.

When $q = 0.17$, relative humidity, slope, aspect, vegetation type, and population density show significant differences in correlation with RUE spatial distribution. This not only highly corresponds with the strong correlation between vegetation growth and RUE mentioned earlier but also indicates different influence mechanisms of vegetation type, slope, and aspect on RUE spatial distribution compared to the highest q value factor (vegetation coverage). Additionally, temperature, sunshine hours, maximum wind speed, vegetation coverage, relative humidity, precipitation, and population density show significant annual fluctuations in q values (Fig.).

Risk detector results (95% confidence level) compare mean RUE values within the risk ranges of 12 driving factors. The factors with the highest mean RUE values are: afforestation area of 22462.87 hm^2, population density of 679.80 people$\cdot$ km^{-2}, and vegetation coverage of 0.58, which pose the highest risk for increasing RUE. Overlaying multi-year precipitation distribution maps reveals that precipitation of 665.51–679.80 mm carries the highest risk for increasing RUE, concentrated in the east-west horizontal zone of Chencang District. Comparing mean RUE values across different slope zones shows that RUE first increases then decreases with slope, with an inflection point at 26°–31°, representing a high-risk zone for increasing RUE.

3.3.2 Interaction Effects of RUE Driving Factors

The interaction of driving factor pairs enhances the correlation with RUE spatial distribution (Table). The synergistic effect of population density with other factors is strongest, representing significant controlling factors for RUE. Overall, the top interactions in correlation are: vegetation coverage ∩ temperature, vegetation coverage ∩ relative humidity, vegetation coverage ∩ precipitation, and temperature ∩ relative humidity. These four driving factors have large internal differences in areas with significant spatial differentiation. Due to regular patterns between slope and aspect, their interactions with other factors show weaker correlations, particularly slope ∩ population density and aspect ∩ total grain output. However, ecological detection results show significant differences between slope/aspect and total grain output regarding RUE spatial distribution, indicating similar mechanisms. Similarly, temperature ∩ total grain output, relative humidity ∩ total grain output, vegetation coverage ∩ total grain output, and population density ∩ total grain output show strong and similar correlations with RUE spatial distribution, suggesting consistent spatial distribution patterns. However, ecological detection shows no significant differences between these four factors and total grain output, indicating similar mechanisms and strong interaction correlations.

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4. Discussion

4.1 Contribution Rates of Climate Change and Human Activities to RUE Variation

The method for determining human intervention factors in this study involves uncertainty. Based on the first-round, post-first-round, and second-round periods, vegetation cover change trends were obtained using the Sen+M-K method, and human intervention increase/decrease areas were determined by integrating these with actual conditions. During this determination process, the Sen+M-K trend showed large deviations, with the proportion of significantly improved vegetation area decreasing from 63.29% in the first round to 39.33% post-first-round, then to 0.01% in the second round. Human intervention shifted from 99.85% increase → 86.07% increase → 81.23% decrease. The decreasing precipitation at each stage highlights vegetation degradation, especially in arid/semi-arid regions. Implementing the Returning Farmland to Forest (Grassland) project according to local conditions, based on water-land resource matching, can effectively improve regional RUE.

4.2 Spatiotemporal Evolution of RUE Since Project Implementation

Since project implementation, Baoji' s RUE has shown an interannual decreasing trend [$0.03 \cdot (10a)^{-1}$], summer increasing trend [$0.07 \cdot (10a)^{-1}$], and spring decreasing trend [$-0.06 \cdot (10a)^{-1}$]. The maximum RUE anomaly appeared in autumn 2013 (780.24 mm), and the minimum in 2001 (376.85 mm). Forest land shows the highest RUE values each year. Autumn RUE fluctuates most, followed by interannual variation. The spatial distribution of RUE high-value areas corresponds to key project areas: Guanshan Grassland (southwest Longxian), Wushan (Xinjie Town, Chencang District), Qianhu National Wetland Park (across Chengguan Town, Shigou Township, and Koujiahe Township in Qianyang), and Anshuzhuang Forest Park (Qishan, Linyou). Tourism development has driven changes from "basically unchanged and significantly improved" in the first round to "improved" post-first-round, then to "basically unchanged and decreased" in the second round, with large trend deviations. Corresponding human intervention shifted from 99.85% increase → 86.07% increase → 81.23% decrease. Decreasing precipitation highlights vegetation degradation, particularly in arid/semi-arid regions. Implementing ecological restoration projects according to local water-land matching conditions can effectively improve RUE.

4.3 Discussion on RUE Driving Forces Since Project Implementation

Dominant driving factor detection shows the explanatory power ranking for RUE spatial distribution: natural resource factors > climate-environmental factors > human activity factors > geographical environment factors. In interaction effects, the ranking becomes: climate-environmental factors > natural resource factors > human activity factors > geographical environment factors. Ecological detection shows no significant differences for geographical environment factors, indicating weak explanatory power as single factors but enhanced correlation when interacting with human activity factors.

Baoji features complex topography with the Qinling Mountains and Weihe Plain, showing obvious vertical differentiation of heat. On sunny slopes, solar altitude angle increases with surface slope until direct solar radiation, then decreases. On shady slopes, solar altitude angle decreases with increasing slope. Table shows that slopes >31° on shady slopes represent maximum RUE risk areas where solar altitude angle is minimal and ground solar radiation is lowest. However, sunny slopes with lower elevation and gentler terrain have frequent human activities and higher population density (10.84–679.80 people $\cdot$ km^{-2}). In this Loess Plateau border region, implementing Returning Farmland to Forest (Grassland) policies on slopes >14.70° promotes RUE improvement through artificial vegetation. Therefore, vegetation coverage of 22462.87 hm^2 represents a high-risk area for RUE improvement. In recent years, rapid urbanization (along Weihe River and east of Qishan) and tourism-driven economic development (in Fengxian and Longxian) have increased RUE through project implementation, promoting vegetation growth and ecological restoration. Thus, moderate urban construction and industrial development, with reasonable control of vegetation degradation caused by human activities, are necessary prerequisites for sustainable ecological restoration.

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5. Conclusions

(1) Since implementing the Returning Farmland to Forest (Grassland) project, Baoji' s RUE shows an interannual decreasing trend [0.03 $\cdot$ (10a)$^{-1}$], summer increasing trend [0.07 $\cdot$ (10a)$^{-1}$], and spring decreasing trend [-0.06 $\cdot$ (10a)$^{-1}$]. Maximum RUE values appear on forest land each year, with autumn showing the largest fluctuations. (2) The explanatory power of driving factors on RUE spatial distribution decreases as: vegetation coverage, relative humidity, sunshine hours, total grain output, maximum wind speed, precipitation, temperature, population density, and afforestation area. Vegetation type, slope, and aspect show no significant explanatory power. (3) Interaction effects rank as: climate-environmental factors >

natural resource factors > human activity factors > geographical environment factors. With increasing slope, RUE first increases then decreases, with an inflection point at 26°–31°. Afforestation area and RUE show synchronous change trends; vegetation significantly promotes RUE, while population density significantly stresses RUE. Precipitation of 665.51–679.80 mm carries the highest risk for increasing RUE, concentrated in Chencang District' s east-west horizontal zone.

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