Forest ecological monitoring of the Shiyang River basin based on Google Earth Engine

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Abstract. The Shiyang River basin is a typical inland arid region and one of the most fragile and sensitive areas of terrestrial ecosystems in China, and it is important to understand its ecological changes in a timely and accurate manner. This article selects the Shiyang River basin forest as the research area and uses Google Earth Engine (GEE) to evaluate and monitor the ecological environment quality of the Shiyang River basin from 1990 to 2020. The geographical detector model (GDM) was also used to analyse the sensitivity of the forest ecological environment to three natural factors: elevation, temperature and altitude. The results showed that the ecological quality of the natural forest is significantly better than that of the man-made forest area, and the ecological quality grade is higher. The forest change area RSEI has a large annual variation in ecological quality and is vulnerable to external factors. Among the influencing natural factors, the sensitive factors of precipitation and altitude are both greater than 84%. The temperature sensitivity of natural forests is stronger than that of man-made forests, ranging from 66% to 92% overall.

1. Introduction
The Shiyang River basin is a typical arid region with an extremely fragile ecological environment. Its forests are an essential part of preventing soil erosion and maintaining ecological stability in the region. One of characteristic features of forest is its highest ecological equivalence [1]. Studying the spatial and temporal patterns and evolution of forest ecology in the dryland is essential for a better understanding of its overall condition and sustainability.

Remote sensing technology is currently a commonly used method to study ecology. A number of remote sensing-based indices have been employed to depict the status of the ecological environment [2]. In order to satisfy the demand for a comprehensive estimation of ecosystems, we propose to use an integrated ecological indicator that combines several rather than one ecological parameter to estimate the ecological condition [3]. Some researchers analyse the total environmental quantity of the area by constructing ecological protection red lines [4], while others study the dynamic monitoring of separate components such as forests [5]. In the Shiyang River basin of China, the ecological research focuses mainly on desert and water resources [6], and the research area is concentrated in the oasis area and artificial (man-made) forest area [7, 8], of which the forest area is understudied.

Google Earth Engine (GEE) has a large historical archive of remote sensing images and can provide users with online cloud services for high-performance computing [9]. With this advantage, GEE has been widely used in remote sensing image fusion [10], multi-temporal image classification [11], and urban change detection [12].
The current research into the Remote Sensing Ecological Index (RSEI) mainly focuses on analysing the spatial and temporal characteristics of ecological environment quality. There is a lack of quantitative research into the influencing factors of ecological environment quality [1]. Therefore, it is necessary to consider the spatial variation of ecological environment quality to provide scientifically-based suggestions for regional ecological construction [13]. The geographical detector model (GDM) is used to detect spatial heterogeneity and reveal the driving force behind it [14], which can detect not only the influence of individual factors on the dependent variable but also the interaction between different influencing factors [15]. At present, it is mostly used in assessment of ecological environment quality [16] and vegetation change [17]. It also has a good analysis effect in desert ecological environment in arid areas [18].

The objective of this study is to establish the ecological environment quality of forest areas in the Shiyang River basin and to analyse the sensitivity of the area under study to the natural factors. To fulfil this objective, the following tasks have been accomplished: 1) Based on the GEE platform, the Landsat image has been used to extract the forest area to construct the RSEI; 2) The monitoring of the temporal and spatial changes of the ecological environment quality of the Shiyang River basin has been carried out for the period from 1990 to 2020; 3) A geographic detector model has been used to analyse the sensitivity of forests to precipitation, temperature and altitude.

2. Research area and methods
The study area is located in the eastern part of the Hexi Corridor in Gansu, to the west of the Wushiling Mountains and to the north of the Qilian Mountains, at 36°29′-39°27′N, 101°42′-104°15′E, and is one of the three major inland river basins in the Hexi Corridor (figure 1). The whole basin altitude is 1,203-5,232 m. It includes 8 rivers: Dajing, Gulang, Huangyang, Zhaomu, Jinta, Xiying, Dongdahe, and Xidahe. The basin's total area is about 41,600 km², and the terrain is high in the south and low in the north, sloping from southwest to northeast. The climate is a temperate continental arid climate with four distinct seasons and low precipitation.

![Figure 1. Location map of the Shiyang River basin.](image-url)
The remote sensing images were obtained from the GEE platform with radiation- and atmospherically-corrected Landsat 5 surface reflectance data for 1990, 1991 and Landsat 8 surface reflectance data for 2019 and 2020 (www.usgs.gov). The DEM data were obtained from USGS Global Multi-resolution Terrain Elevation Data 2010 (www.usgs.gov). Temperature and precipitation data were obtained from the China Meteorological Data Network (http://data.cma.cn/). GEE as the world's advanced petabyte-scale scientific analysis platform for geographic data [9] enables fast computation of large regional remote sensing indices in the cloud. The calculation and normalization of the component indices for each year are completed on the GEE platform according to the formulae [20] proposed for each component based on Landsat images.

2.1. Image synthesis and classification
In order to use the image information of the same season in the study area to the full and to overcome the influence of atmosphere clouds, the study adopts the image synthesis method of minimum cloudiness at the image element level to obtain clean images of the same seasonal phase. In this study, we select the summer Landsat data of two consequent years and compute the input Landsat-5 and Landsat-8 surface reflectance datasets that fit the temporal and spatial scales using the Landsat cloud mask algorithm in the GEE platform, remove the cloudy image elements, and replace the images with minimum clouds in the target year with cloud-free images. The random forest module of the GEE platform is used to classify the image features, increase the arbitrary number of 30% training samples as the accuracy verification group, and output the composite feature classification image. It is divided into four parts: forest increase area, constant forest area, forest decrease area, and man-made forest area.

2.2. Calculation and normalization of component indexes
The calculation of ecological indexes was based on the Remote Sensing Ecological Index (RSEI) method proposed by Hanqiu Xu [18]. Four important indicators of the natural ecological environment were used as the evaluation indicators of the proposed ecological index, i.e. greenness, humidity, heat, and dryness. The four remote sensing indexes, namely, the Normalized Difference Vegetation Index (NDVI), Normalized Difference Bareness Index (NDBSI), Wetness (WET), and Land Surface Temperature (LST), represent greenness, dryness, humidity, and heat to construct the RSEI. The first principal component was extracted by using Eigen Analysis on the GEE platform, and the RSEI was calculated for the period 1990-2020 (table 1).

In order to analyse the spatial variation of RSEI in the study area, it was divided into five classes with the interval of 0.2: ecological index 'Poor' (0.0–0.2), ecological index 'Fair' (0.2–0.4), ecological index 'Moderate' (0.4–0.6), ecological index 'Good' (0.6–0.8), ecological index 'Excellent' (0.8–1.0) with the reference to a related study [20]. These classes of ecological indices are also numbered as 1-5 for convenience.

2.3. Spatial data exploration geographical detector model
Geographical detector model is one of the methods used for spatial data exploration. The spatial distribution of geographical objects has apparent differences and is influenced by physical geographic environmental factors and human socio-economic factors. The principle of this method is that it is possible to test the spatial heterogeneity of a single variable and detect the possible causal relationship between two variables by testing the consistency of their spatial distribution. The most important feature of this approach is that it has almost no assumptions, which can effectively overcome the limitations of traditional mathematical statistical models in dealing with such problems [14]. This study uses risk detection and factor detection to detect the interrelationship between ecological land change and various influencing factors in the Shiyang River basin.
Table 1. Remote sensing ecological index composition.

| Element      | Formula                                                                 |
|--------------|-------------------------------------------------------------------------|
| Greenness    | \( NDVI = (\rho_{NIR} - \rho_b) \times (\rho_{NIR} + \rho_b)^{-1} \)     |
| Humidity     | \( WET = C_1 \rho_b + C_2 \rho_G + C_3 \rho_R + C_4 \rho_{NIR} + C_5 \rho_{SWIR1} + C_6 \rho_{SWIR2} \) |
| Heat         | \( L = \text{gain} \times \text{DN} + \text{base} \)                       |
|             | \( P_v = NDVI - NDVI_{\text{Soil}} \times NDVI_{\text{Vegetation}} - NDVI_{\text{Soil}}^{-1} \) |
|             | \( \epsilon_{\text{surface}} = 0.9625 + 0.0614P_v - 0.0461P_v^2 \)        |
|             | \( \epsilon_{\text{building}} = 0.9589 + 0.086P_v - 0.0671P_v^2 \)          |
|             | \( B(TS) = [L \times (1 - \epsilon)]L_{\text{down}} \times T^{-1} \times \epsilon \) |
|             | \( LST = K_2 \times \ln[K_1 \times B(TS)^{-1} + 1]^{-1} - 273 \)            |
| Dryness      | \( NDPSI = (IBI + SI) \times 2^{-1} \)                                     |
|             | \( IBI = IBI_{\text{min}} \times IBI_{\text{max}} \)                        |
|             | \( IBI_{\text{min}} = 2\rho_{SWIR1} \times (\rho_{SWIR1} + \rho_{NIR})^{-1} - \rho_{NIR}(\rho_{NIR} + \rho_b) - \rho_G(\rho_{NIR} + \rho_{SWIR1})^{-1} \) |
|             | \( IBI_{\text{max}} = 2\rho_{SWIR1} \times (\rho_{SWIR1} + \rho_{NIR})^{-1} + \rho_{NIR}(\rho_{NIR} + \rho_b) + \rho_G(\rho_{NIR} + \rho_{SWIR1})^{-1} \) |
|             | \( SI = \left[(\rho_{SWIR1} + \rho_{NIR}) - (\rho_{NIR} + \rho_b)\right] \times \left[(\rho_{SWIR1} + \rho_{NIR}) + (\rho_{NIR} + \rho_b)\right]^{-1} \) |
| RSEI        | \( RSEI = \text{RESI}_0 - \text{RSEI}_{0-\text{min}} \times \text{RSEI}_{0-\text{max}} - \text{RSEI}_{0-\text{min}}^{-1} \) |
| \( q \)     | \( q = 1 - \frac{\sum_{h=1}^{L} N_h \sigma_h^2}{N \sigma^2} = 1 - \frac{\text{SSW}}{\text{SST}} \) |

Where, \( h = 1, \ldots, L \) is the stratification (Strata) of the variable \( Y \) or factor \( X \), that is, classification or division; \( N_h \) and \( N \) are the number of units in the layer \( h \) and the whole area respectively; \( \sigma_h^2 \) and \( \sigma^2 \) are the layers \( h \) and the variance of the \( Y \) value of the whole area. SSW and SST are the Within Sum of Squares and the Total Sum of Squares, respectively. The value range of \( q \) is \([0, 1]\), the larger is the value, the more obvious is the spatial differentiation of \( Y \); if the stratification is generated by the independent variable \( X \), the larger is the value of \( q \), the greater is the explanatory power of the independent variable \( X \) on the attribute \( Y \), otherwise, it is weaker.

3. Results and discussion

The forest was mainly concentrated in the southern mountainous area, and the man-made forest was scattered around Jinchang and Wuwei. The forest decreased from 4,836.04 to 3,728.82 ha in 1990 by 1,107.22 accounting for 22.89%. The elevation of the increasing part ranges from 1,289 to 4,570 m with an average elevation of 2,932 m. The elevation range of the unchanged area is between 1,414 to 4,243 m, with an average elevation of 3,128 m. The decreasing area has an elevation range of 1,308-4,334 m with an average elevation of 2,827 m. Man-made forest area has the lowest elevation of 1,257-1,894 m with an average elevation of 1,545 m.

The low quality data with high cloudiness were removed from 1990-2020, and the average RSEI was extracted once every two years for the four types of the regions, where the 15th value was the average between the three years of 2018-2020. The trend graph in figure 2 shows that the RSEI values of man-made forest areas have a smooth trend, and the overall RSEI values of man-made forests are lower than those of the three natural forest areas. In the natural forest, part of the ecological index of forest increase experienced two significant decreases and two significant increases and maintained higher values in the later period. The constant forest region had a stable trend of the RSEI values with minor variation. The forest decrease region had the most frequent fluctuations, with three significant
decreases and four significant increases in the RSEI values. The RSEI values significantly rise four times.

Figure 2. RSEI trends for the forest increasing areas, forest constant areas, forest decreasing areas and man-made forest areas over 1990-2020 based on the sampling size of 15 average values.

The four different types of the RSEI rank indices of the latest year were extracted for each of the four different types of areas (figure 3). The forest constant areas have the best ecological quality, and the Ecological Index 'Excellent' is more than 95%. The percentage of Ecological Index 'Excellent' in the forest increase areas is more than 90%, and the percentage of Ecological Index 'Excellent' in the forest decrease areas is better overall, 70%. However, when compared with the forest constant and forest increase areas, the Ecological Index 'Good' accounted for more areas, and the Ecological Index 'Moderate' areas were found. The man-made forest areas had the lower RSEI and the Ecological Index 'Poor'. The Ecological Index 'Fair' areas accounted for more than 70%.

Figure 3. The remote sensing ecological index grade map of the four forest areas, where the 1-5 points represent the Ecological Index 'Poor Ecological Index 'Fair', Ecological Index 'Moderate', Ecological Index 'Good', Ecological Index 'Excellent'.

To further analyse the change characteristics of the ecological index in the study area, the ecological index of the two-time phases was compared and classified in three levels: decreasing, unchanging and increasing, resulting in a spatial change map of the ecological index in the study area (figure 4). The ecological indices of the study area were mainly constant and increasing, with slight decreases in some areas. A forest increase was concentrated in the low elevation area between 1,280 to 2000 m, and the increase was concentrated above 2,500 m. The constant area was between 2500 to 4500 m. The ecological index of the constant forest area is mostly unchanged. The ecological index increases in the area between 2000 to 3000 m, and the areas where the ecological index decreases are scattered and small in size. There is no obvious geographical feature in the area of the ecological index change in the forest area.

Figure 4. Ecological index spatial change map on the territory of the Shiyang River basin.

The results of the detection of the three influencing factors affecting the spatial differentiation characteristics of the ecological environment quality of the Shiyang River basin are shown in figure 5. The q-values of the three influencing factors of temperature, precipitation and elevation all exceed 60%, indicating that they all have significant effects on the ecological environment quality of the Shiyang River basin. The explanatory power of precipitation, elevation and air temperature is from high to low. Precipitation data had the highest explanatory power of more than 90%, indicating that precipitation was the most influential factor affecting ecological quality. Precipitation had large q-values in all four divisions, with stable values in the montane forest area and slightly lower in the man-made forest area.
The q-values of elevation and temperature differed greatly in the four regions, but both had the same trend in the four areas. The q-values of elevation and air temperature were more prominent in the areas of the mountainous forest increase and decrease, indicating that they had a more decisive influence in the changing regions. The q-values of the three parts of the mountain forest region are larger than those of the man-made forest region, indicating that the ecological environment in the natural forest region is more susceptible to natural factors. The q-values of the man-made forest region are relatively lower, and all q-values in 2020 are lower than those in 1990, indicating that the man-made forest region is less influenced by natural environmental factors, and the influence also gradually decreases. The q-values of the two changing regions in the mountain forest are higher than those of the constant regions, and the natural factors have a greater influence on the changes of the mountain forest.

![Figure 5. Comparison of temperature, precipitation, and elevation sensitivity as ecological impact factors for four forest types.](image)

Forests in the Shiyang River basin are primarily concentrated in the upper reaches of the mountainous region at the elevations of 2000-4000 m, which plays a vital role in the ecology of the basin. When compared with temperature and elevation, precipitation is the main climatic factor affecting the interannual variation of vegetation [21]. From 1990 to 2020, the forest increase component was 3,256.64 km², and the forest decrease component was 4,404.17 km², and the overall forest area decreased by 22.89%. According to the RSEI multi-year curve, the largest part of the forest area is the constant forest area, which accounts for 62.23%.

The average elevation of the region is the highest, and the RSEI multi-year mean curve is smooth, and the increasing and decreasing trends during this period remain approximately the same as in the rest of the forest area, but with a low degree of variability. The average value of RSEI is not significantly correlated with the percentage of ecological rank, indicating that the area covered by high ecological rank areas is large, but the absolute value is not high. Among the natural forests, the constant forest areas are the most ecologically stable and less sensitive to precipitation, temperature and elevation and have the best overall ecological environment.

The forest increase area and forest decrease area account for 8.39% and 29.37% of the natural forest area, and both areas are mostly located in the low elevation area of 1,300-2,500 m and the high elevation.
area above 4,000 m in the mountainous region. The both RSEI multi-year mean curves have large fluctuations. The RSEI multi-year mean curve of the forest increase area has the greatest degree of change, and after two large falls and rises, it is maintained in the higher value range. In the less forested areas, the values were significantly lower than those in the forest increase areas after several rises and falls. The same trend is observed in the ecological classification. These two areas are also the most sensitive to precipitation, temperature, and elevation, and climate change can lead to changes in vegetation in the mountainous areas within a short period of time.

The ecological quality of the man-made forest is significantly lower than that of the natural forest. Still, it remains stable throughout the year and is less sensitive to external conditions such as precipitation, temperature and elevation. This is consistent with the nature of man-made forest itself, and human intervention is the most important factor affecting the area and ecological quality of the man-made forest.

4. Conclusions
This study analyses the spatial and temporal characteristics of RSEI of the forest ecosystem quality of the Shiyang River basin from 1990 to 2020 using the GEE platform and the factors influencing the ecosystem quality of four forest areas in the region such as precipitation, temperature and elevation. The results show that the constant forest area is stable and has a high annual mean value of RSEI, while the man-made forest is equally stable but has a low value. The annual average RSEI values of the forest increase area and forest decrease area fluctuate greatly. The ecological quality of the natural forest areas is higher than that of the constant forest area, forest growth area, and forest decrease area. The artificial forest’s ecological quality is significantly lower than that of the natural forest. The forest ecology in this area is most sensitive to changes in precipitation, elevation and temperature. The ecological performance of the man-made forest is different from that of the natural forest. The man-made forest is ecologically stable but have lower ecological quality and is less sensitive to precipitation, elevation and temperature. The adequate protection of the natural forest change area focuses on preserving its forest ecosystem in the future.

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