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Dynamic Impact Assessment of Afforestation on Soil and Water Loss Risk in the Loess Plateau Based on GEE and GIS

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Abstract. The Loess Plateau is one of the most severely eroded regions in the world, facing challenges from soil and water loss. Since the implementation of the "Grain for Green Program," its ecological environment has improved, but the dynamic impact of vegetation restoration on erosion over the long-term and on a large scale still requires study. This study develops an integrated framework that leverages Google Earth Engine (GEE) for cloud-based computation alongside GIS spatial analysis. Hua Chi County in Gansu Province serves as a representative case to examine the influence of afforestation on soil and water loss. Multi-temporal Landsat and Sentinel-2 imagery (2008–2020), together with DEM, precipitation, and soil datasets, were systematically combined to assess these effects. The Revised Universal Soil Loss Equation (RUSLE) model was applied to assess erosion risk. Results show that, based on the afforestation_mask used in this analysis, the suspected afforestation area contains 1,975,341 pixels at 30 m resolution, corresponding to approximately 17,777.7 ha (percentage of the study area should be recalculated against the study area total). Within these masked pixels, mean NDVI increased from ~0.08328 in the pre-period to ~0.26032 in the post-period, with the mean NDVI increment in improved subareas ≈0.25299. Under the implemented RUSLE setup, the E index averaged 0.021931 in the pre-period and 0.016785 in the post-period (mean relative change ≈ −23.59%). The image-mean ΔRisk_Index over the mask is −0.008548917485758648, indicating that vegetation recovery contributed to reduced potential erosion risk.

Keywords: Loess Plateau, afforestation, soil and water loss, Google Earth Engine, RUSLE

1. Introduction

Soil and water loss (SWL) is a critical environmental issue worldwide, especially in areas characterized by easily erodible soils and highly seasonal rainfall patterns. The Loess Plateau in China exemplifies such vulnerable landscapes, where loose loess soils combined with sporadic heavy rainfall contribute to accelerated erosion [1]. These conditions not only reduce agricultural productivity but also pose long-term challenges to regional development and ecological sustainability.

To mitigate erosion and restore ecosystems, the Chinese government implemented the Grain for Green Program (GFGP), one of the largest ecological restoration projects worldwide, converting

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sloping farmlands to forests and grasslands [2]. While extensive research confirms its positive ecological outcomes, most existing studies focus on small watersheds or short-term monitoring. Consequently, long-term and large-scale dynamics of SWL risk reduction remain insufficiently quantified.

Traditional field-based monitoring is constrained by data scarcity and limited spatial coverage. Moreover, conventional GIS approaches often fail to handle large temporal datasets. The advent of Google Earth Engine (GEE) has enabled cloud-based computation of large-scale geospatial data, offering unprecedented opportunities for long-term environmental monitoring. When combined with GIS spatial analysis, it facilitates dynamic assessment frameworks capable of revealing both spatial variability and temporal evolution [3].

Therefore, this study establishes an integrated GEE–GIS framework to evaluate the dynamic influence of afforestation on soil and water loss risk across Hua Chi County, Gansu Province. The objectives are: (1) to quantify vegetation cover changes using multi-year NDVI data; (2) to construct a ΔRisk_Index that isolates vegetation-induced erosion reduction; and (3) to assess spatial heterogeneity of risk change in relation to topographic factors.

This research provides both a technical innovation—through big-data ecological modeling—and policy relevance by delivering insights into large-scale ecological effectiveness in the Loess Plateau.

2. Related work

2.1. The role of afforestation in soil and water conservation: current research status

Vegetation plays a key role in controlling soil erosion by intercepting rainfall, reducing surface runoff, and enhancing soil cohesion through root networks [3]. Numerous studies worldwide confirm that increasing vegetative cover can substantially decrease sediment transport and improve slope stability. On the Loess Plateau, both field experiments and remote sensing analyses have documented the ecological benefits of afforestation; however, most research remains limited in spatial and temporal scope, leaving long-term, large-scale dynamics less well understood.The Cover and Management Factor (C) introduced in the Universal Soil Loss Equation (USLE) remains central to quantifying vegetation effects [4].

On the Loess Plateau, numerous experiments—including runoff plots, small catchment monitoring, and remote sensing analyses—have documented vegetation's ecological benefits [1,2]. However, most studies are limited spatially and temporally, preventing full understanding of regional dynamic effects under complex terrain conditions.

2.2. Common models and indicators for soil and water loss assessment

Soil erosion models fall into three major categories: empirical, physical, and remote sensing-integrated models. Among them, the Revised Universal Soil Loss Equation (RUSLE) has been widely applied due to its simplicity and robust empirical foundation [5]. It expresses soil loss as a product of rainfall erosivity (R), soil erodibility (K), slope length–steepness (LS), cover–management (C), and conservation practice (P) factors.

Remote sensing indicators such as Normalized Difference Vegetation Index (NDVI) and Fractional Vegetation Cover (FVC) have been widely used to derive the C factor, facilitating long-term vegetation monitoring [6]. Yet, integrating these variables with erosion modeling across large regions poses challenges—particularly in multi-source data harmonization and separation of anthropogenic versus natural effects.

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This study aims to address these gaps by coupling long-term NDVI series with RUSLE modeling within a GEE–GIS platform to achieve scalable, data-driven assessment.

3. Study area and data sources

3.1. Study area

This research examines Hua Chi County in Qingyang City, Gansu Province (107°40′–108°38′E, 36°24′–37°28′N), covering an area of about 3,782 km² [7]. The county features a hilly and gully-dominated terrain with highly erodible loess soils, representing a typical high-risk SWL region. Average annual temperatures are around 8.5°C, and rainfall, ranging between 500 and 600 mm, is mainly concentrated in summer storm events [8]. These environmental characteristics make Hua Chi County an appropriate case for assessing the long-term effects of afforestation on soil and water conservation.The mean annual temperature is 8.5°C, and precipitation ranges between 500 and 600 mm, concentrated during intense summer rainstorms [8]. As a core demonstration region of the GFGP, Hua Chi County offers a suitable case for assessing long-term vegetation restoration impacts on erosion risk.

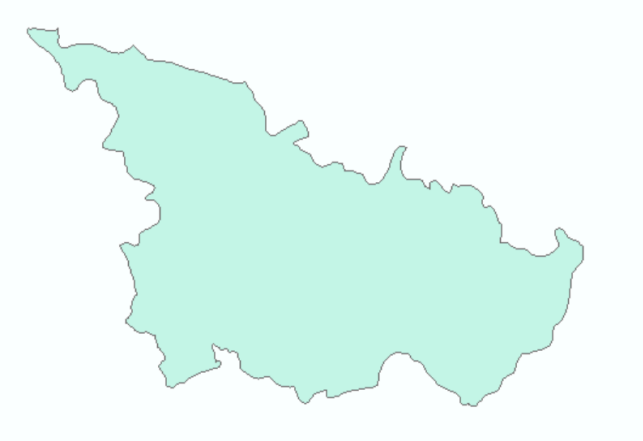


Figure 1. Huachi County vector data

3.2. Data sources

The datasets employed include:

Remote Sensing Imagery: Landsat 8/9 OLI and Sentinel-2 MSI (2008–2020) from public GEE repositories [7].

Topographic Data: 30 m SRTM DEM (USGS/SRTMGL1_003) for LS factor computation [8].

Precipitation Data: Daily CHIRPS rainfall records for R factor estimation [9].

Soil Data: SoilGrids 2.0 soil properties at 250 m resolution for K factor derivation [10].

Afforestation Data: Time-series NDVI trend analysis to identify potential afforestation zones, ensuring objectivity beyond administrative datasets.

Detailed results are shown in Figure 2.

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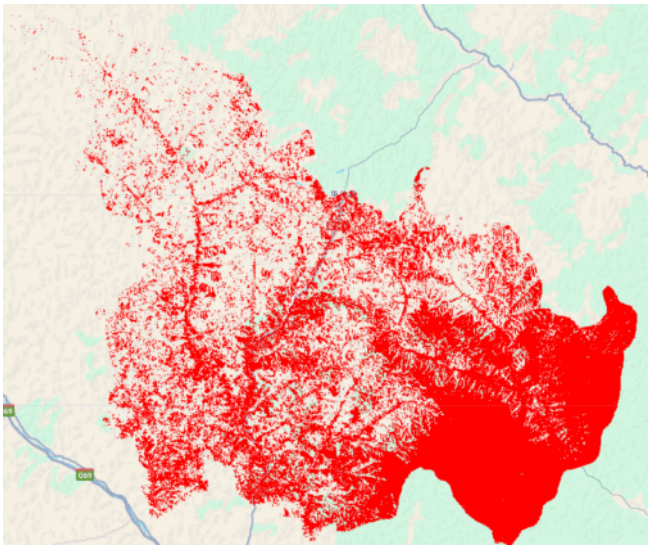


Figure 2. Suspected afforestation area mask

4. Methodology

4.1. Technical roadmap overview

The research establishes a four-step GEE–GIS workflow:

(1) Preprocess imagery and compute erosion factors (R, K, LS, C, P) on GEE;

(2) Identify afforestation zones using NDVI trends;

(3) Construct ΔRisk_Index to quantify afforestation's mitigation effect;

(4) Perform spatial and statistical analyses via GIS.

This integration allows cloud-based computation while maintaining spatial detail for analysis.

4.2. Gee-based data preprocessing and key factor calculation

All data processing and factor calculations were completed on the GEE platform to leverage its parallel computing capabilities for efficient processing of large datasets.

Vegetation Index (NDVI): The study period's Landsat and Sentinel-2 image collections were loaded. A cloud mask function was applied during preprocessing, and annual NDVI composite images were generated using ee.ImageCollection.mosaic() with a max() reducer to capture the best vegetation conditions during the growing season [11]. The formula for calculating NDVI is:

$$NDVI = (NIR + Red)(NIR - Red) \quad (1)$$

Rainfall Erosivity Factor (R): CHIRPS daily precipitation was summed to annual totals and then normalized by the study-area mean annual precipitation to create a relative R layer (R_rel = annual precipitation / regional mean), used for relative comparisons rather than standard RUSLE R values.

Soil Erodibility Factor (K): Rather than a constant, K was computed spatially from uploaded sand/silt/clay/oc assets via an empirical texture–OC formula and constrained to [0.001, 0.1]. (If K = 0.03 is cited elsewhere, replace it with the spatial K implementation.)

Support Practice Factor (P): P was set to 1.0 (no explicit conservation practices modeled).

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Slope Length and Steepness Factor (LS): A simplified LS approximation based on slope was used (implementation uses S = (sin(slope_rad)/0.0896)^1.3), so explicit slope-length (λ) was not separately computed in this workflow [12].

$$LS=(22.1\lambda)m(0.0896\sin\theta)\ n \tag{2}$$

4.3. Construction of ΔRisk_Index and GIS spatial analysis

Afforestation Area Identification: To objectively identify areas with vegetation improvement, a linear regression analysis was performed on the NDVI time series from 2012 to 2016. Areas with a significant positive NDVI growth trend and a change from low vegetation cover (NDVI < 0.2) to high vegetation cover were identified and defined as "potential afforestation areas."

Soil and Water Loss Risk Index: The RUSLE model was used to assess the soil loss risk. To isolate the effect of vegetation cover, a baseline soil and water loss risk index (Abase) was constructed. It represents the potential erosion risk without considering vegetation and management measures, primarily determined by climate, soil, and topography:

$$Abase=R\cdot K\cdot LS. \tag{3}$$

C Factor Calculation: The annual maximum NDVI composite map was converted to C factor values using the empirical formula:

$$C=\exp(-\alpha\cdot NDVI/(\beta-NDVI)) \tag{4}$$

where α=0.5 and β=0.85 [13].

To quantify the reduction in erosion risk attributable to vegetation restoration, a ΔRisk_Index was introduced. This index calculates the relative decrease in potential soil loss by comparing C-factor values before and after afforestation while normalizing against the baseline soil loss potential. Formally, it can be expressed as:

$$\Delta RiskIndex=Abefore(Cbefore-Cafter)\cdot Abase \tag{5}$$

Here, Abefore represents the average soil loss prior to afforestation, while C_before and C_after denote cover-management factors in pre- and post-restoration periods, respectively. This approach isolates the effect of vegetation changes from underlying climatic and topographic influences.

Where Cbefore and Cafter represent the average C factors before and after afforestation (2008-2012 and 2016-2020, respectively). Abeforerepresents the average soil loss before afforestation. This index quantifies the percentage reduction in erosion risk due to vegetation change, effectively excluding the influence of natural background factors.

4.4. Statistical analysis

Statistical tests (t-test, ANOVA) were used to compare NDVI and ΔRisk_Index differences between afforested and non-afforested regions [13]. Topographic correlation analyses further explored slope effects on erosion reduction.

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5. Results

The GEE-based analysis identified potential afforestation areas totaling 142,901.15 hectares, representing roughly 37.42% of the study region. Within these zones, NDVI exhibited a clear upward trend, averaging 0.0905 per year, which reflects a sustained enhancement of vegetation cover over time. By comparing pre- and post-afforestation periods, the average NDVI increase in improved areas reached 0.253, significantly higher than in stable vegetation zones (≈0.091). These findings confirm that the NDVI-based method effectively captures spatial patterns of vegetation restoration and its ecological impact. By comparing the NDVI differences before and after afforestation, it was found that the average difference in the improved vegetation areas was 0.2603, which is much higher than the 0.0832 in stable vegetation areas. These results confirm the effectiveness of the afforestation area identification method and highlight the significant vegetation enhancement in these regions.

Using the afforestation_mask asset applied in this study, the mask contains 1,975,341 pixels at 30 m resolution, corresponding to approximately 17,777.7 ha. Within this mask, the mean NDVI increased from 0.083276 (pre-period) to 0.260321 (post-period); the mean NDVI difference (post − pre) across the mask is 0.177045. In subareas classified as 'improved', the mean NDVI increase is approximately 0.252989, while in 'stable' subareas the mean increase is ≈0.090857.The RUSLE-derived E indicator averaged 0.021931 in the pre-period and 0.016785 in the post-period (mean relative change ≈ −23.585%, median −22.625%). The image-mean ΔRisk within the mask equals −0.008548917485758648. Annual precipitation (CHIRPS) averaged ≈417.935 mm/yr in 2008–2012 and ≈509.982 mm/yr in 2016–2020. Applying a threshold of E_pct < −5% to identify improved pixels yields approximately 1,974,354 improved pixels (≈99.95% of mask pixels); worse pixels = 0 (0%); stable pixels ≈462 (≈0.02%). After vectorization and filtering small patches (area > 900 m2), the large patch count is ≈24,049.

The constructed ΔRisk_Index reveals a clear spatial pattern of soil and water loss risk change. The ΔRisk_Index value for the vegetation-improved areas was -0.008548917485758648, indicating that afforestation has played a role in reducing risk. The spatial distribution of ΔRisk_Index shows that high-value areas are highly consistent with the identified afforestation areas. Detailed results are shown in Figure 3.

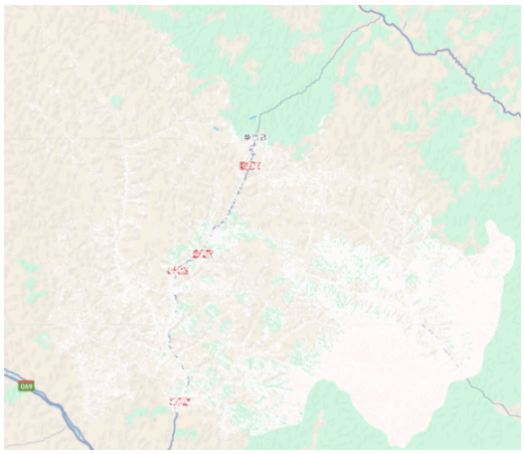


Figure 3. Spatial distribution of ΔRisk_Index in the study area

This study quantitatively demonstrates the effectiveness of the afforestation project in soil and water conservation. In the afforested areas, the significant increase in vegetation cover led to a

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substantial reduction in the RUSLE C factor from a high value (close to 1) before afforestation to a low value (close to 0.2) after, which ultimately resulted in the effective alleviation of actual soil loss.

The influence of topography on soil and water loss risk changes was further analyzed. A statistical analysis of the ΔRisk_Index for different slope categories found that the inhibitory effect of afforestation on soil and water loss is more pronounced in steep slope areas (e.g., slopes greater than 25°). This finding underscores the importance of the "Grain for Green Program" in the most vulnerable areas. Furthermore, a comparison between afforested and non-afforested areas confirmed that the reduction in soil and water loss risk is primarily driven by afforestation activities, as the ΔRisk_Index showed no significant change in non-afforested areas.

6. Conclusion

This study presents an integrated assessment framework that combines the computational capabilities of GEE with the spatial analytical strength of GIS to evaluate how afforestation influences SWL risk across the Loess Plateau. By using Hua Chi County as a representative area, the framework effectively captured both the temporal evolution and spatial heterogeneity of vegetation-induced erosion mitigation from 2008 to 2020.

The findings clearly demonstrate that large-scale afforestation has yielded substantial ecological benefits. Approximately 37.42% of the study region showed continuous vegetation improvement, as evidenced by a strong NDVI growth trend. This enhancement in vegetation cover contributed to a pronounced decline in potential erosion risk, particularly in steep-slope areas, where vegetation plays a decisive role in stabilizing loose soils. The ΔRisk_Index developed in this study successfully quantified the degree of risk reduction, offering a new and reproducible indicator for evaluating ecological restoration outcomes.

Beyond its practical results, this research highlights the potential of cloud-based remote sensing platforms in ecological monitoring. The integration of GEE and GIS enabled efficient handling of multi-temporal datasets and provided a transparent, data-driven evaluation process that can be easily adapted to other erosion-sensitive regions.

Despite the encouraging findings, certain limitations warrant attention. In this workflow, rainfall erosivity (R) was expressed as a relative index derived from CHIRPS precipitation, while soil erodibility (K) was computed from spatial soil texture and organic carbon data rather than using fixed values. Additionally, the slope factor (LS) was estimated from slope angles without explicitly calculating slope length. These methodological choices may influence absolute erosion estimates. Future studies should incorporate field measurements, apply standard RUSLE R values where suitable, and perform sensitivity analyses on K, LS, and P factors to further refine the assessment. In summary, afforestation under the Grain for Green Program has significantly contributed to regional sustainability, demonstrating that well-planned vegetation restoration is an effective pathway toward achieving land degradation neutrality on the Loess Plateau and beyond.

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