

Article

Quantifying Elevation Changes Under Engineering Measures Using Multisource Remote Sensing and Interpretable Machine Learning: A Case Study of the Chinese Loess Plateau

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Highlights

What are the main findings?

- Interpretable machine learning models identify the relative importance and spatial patterns of environmental and anthropogenic factors affecting elevation change.

What are the implications of the main findings?

- The transparent analytical framework supports land management and targeted implementation of erosion control measures on the Loess Plateau.
- This approach bridges remote sensing analytics and geomorphological processes, facilitating large-scale environmental monitoring and sustainable erosion management.



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Abstract

Understanding the effectiveness of engineering measures in mitigating surface erosion is crucial for sustainable land management. However, studies explicitly quantifying the combined effects of large-scale engineering measures and environmental factors remain limited. In this study, multisource remote sensing data were integrated with interpretable machine learning to quantify and analyze the regional influence of erosion control measures. We constructed a comprehensive indicator system encompassing spectral, textural, and topographic variables derived from high-resolution satellite imagery and DEM data. To address model transparency and enhance the interpretability of the results, we employed an interpretable machine learning framework capable of both accurate prediction and explicit attribution of feature importance. The results indicate that the implementation of engineering measures substantially reduces erosion intensity across the study area. Spatial heterogeneity in erosion mitigation effectiveness was closely associated with the distribution patterns of engineering measures and site-specific environmental conditions. Basins with a high proportion of check dams showed average elevation gains of up to 2.5 m compared with those without check dams, and terraces contributed to elevation increases of ~1.9 m in typical loess hilly regions. The interpretable machine learning model achieved $R^2 = 0.62$ at Basin 1 (average area ~100 km²) and $R^2 = 0.73$ at Basin 2 (~600 km²), demonstrating reliable predictive capability. The findings not only validate the role of engineering interventions in erosion mitigation but also provide a transparent analytical framework that connects remote sensing analytics with process-based geomorphological understanding.

Keywords: multisource data; machine learning; Loess Plateau; elevation change

1. Introduction

Earth's surface is the main area for biological survival and human activities. Among its components, surface soil forms the foundation of the Earth's critical zone and is a crucial part of the ecosystem. Stable soil conditions are essential for agricultural production and human habitation. However, global land degradation is often attributed to soil erosion [1,2], which poses a major threat to environmental stability. Soil erosion caused by water runoff has become one of the primary drivers of land degradation [2–4]. On the Loess Plateau, extreme runoff erosion often occurs in the form of gully erosion, leading to severe soil and water loss and threatening global ecological stability [5–7]. Additionally, runoff erosion removes nutrient-rich topsoil, reducing crop yields and causing further land degradation [8]. Sediment-heavy water flow from erosion also poses significant ecological risks to downstream areas [9]. Research suggests that under various future scenarios, the risk of runoff erosion could increase substantially. Without proper management and mitigation, land degradation due to runoff erosion is expected to worsen [10]. The Sustainable Development Goals also set specific targets for land stability, aiming to reduce both the direct and indirect risks associated with land degradation [11].

Soil and water conservation refers to a series of measures aimed at protecting land by reducing soil erosion and conserving water [12,13]. Over the past few decades, various conservation practices have been developed. Among them, engineering measures (EMs) or mechanical measures are particularly effective. EMs involve the construction of various structures or projects that alter local terrain conditions to adjust the soil–water–terrain relationship, thereby controlling runoff and soil erosion, especially gully erosion [13–15]. Terraces and check dams are typical examples of such engineering measures [16–19]. They address erosion caused by concentrated runoff by reducing slope gradients and reinforcing gully floors. One of the key reasons terraces and check dams have become the most widely used soil erosion control measures worldwide is their ability to support agricultural production. These structures provide leveled land, ensuring a stable supply of nutrients and water for farming. They play a significant role in promoting agricultural sustainability and enhancing the economic well-being of society.

Exploring the performance and efficiency of engineering measures is a key research focus in soil and water conservation efforts. Traditional methods typically rely on field data collection [19]. In field experiments, corresponding test sites are usually established, and on-site observations are conducted to determine the efficiency of both individual and collective engineering measures. Hydrological monitoring stations provide a wealth of measured data, including sediment content, flow velocity, and other parameters [20]. This type of data is often highly accurate point data collected at high temporal resolution, facilitating the analysis of continuous time periods. In recent years, the development of Earth observation systems has provided researchers with abundant remote sensing data [21]. Surface erosion is closely linked to changes in surface elevation, and satellite data, particularly digital elevation models (DEMs), can aid in the analysis of elevation changes. The increasing accuracy of topographic data generated by remote sensing now supports detailed research on terrain changes, which provides an opportunity to evaluate the performance of engineering measures in soil and water conservation on a regional scale. However, differences in elevation between periods reflected in the DEMs may result from multiple factors, such as surface erosion, land cover changes, and differences in the reference baselines of the datasets. Therefore, to effectively assess the impacts of

engineering measures using remote sensing data, comprehensively accounting for various environmental factors is essential.

We must highlight that although previous studies have analyzed the performance of engineering measures, several issues still need to be addressed. First, owing to limitations in foundational data, limited research has been conducted on a regional scale. Site-based measured data are characterized by spatial discontinuity and sparsity. While these data are highly accurate at specific measurement locations, they are inadequate for analyzing the performance of engineering measures across large areas. Furthermore, it is important to note that differences in geographical environments can significantly influence the outcomes of such measures. Uncovering these patterns requires macro-level exploration, at least on a regional scale. Climate conditions, topography, and geology influence the effectiveness of soil and water conservation measures. Considering the geographical variability and fundamental characteristics of site data, extending current analytical frameworks to broader-scale studies remains challenging. Finally, different engineering measures within the same region may produce cumulative effects, leading to outcomes that differ from those derived from the analysis of individual measures. Research on this phenomenon requires combined analyses of individual measures with geographic units to explore the synergistic effects of engineering interventions.

In this study, we utilized various types of data obtained mainly from remote sensing satellites to analyze the influence of check dams and terraces on surface erosion in the Loess Plateau region of China. In total, the study considered 50,226 check dams and 125,000 square kilometers of terraces within the research area. The analysis was conducted using Copernicus DEM (COP30) and Shuttle Radar Topography Mission (SRTM) DEMs after the vertical datum was unified. Considering the data resolution, the basin was taken as the basic unit in this study, and the elevation changes within the basin were used to represent surface erosion intensity. Moreover, we examined elevation changes at different scales and their relationships with the distribution of engineering measures. This study also explored the performance differences in these measures under varying precipitation and ecological conditions. Furthermore, interpretable machine learning (IML) models were employed to quantify the relationships between engineering measures, climate factors, geological factors, ecological conditions, human activities, and surface elevation changes. This research contributes to understanding the effectiveness of engineering measures in mitigating hydraulic erosion on a regional scale from a satellite data view. It is important to note that the relationships analyzed in this study are correlations rather than definitive causal links. Establishing causality is inherently difficult because the DEM datasets have limited temporal resolution, the construction time of engineering measures varies across the study area, and natural and anthropogenic processes are deeply intertwined. Therefore, while our framework identifies significant associations, it cannot unambiguously disentangle cause–effect mechanisms.

2. Materials and Methods

2.1. Data

(1) Terrain data

To investigate surface elevation changes, we utilized two DEMs acquired at different times: the Shuttle Radar Topography Mission (SRTM) and the Copernicus Digital Elevation Model with a 30 m resolution (COP30). The SRTM provides elevation data between 60° N and 56° S, captured by the synthetic aperture radar system onboard the space shuttle. The base data were collected in 2000, and SRTM has been validated and widely used across numerous research fields [22]. COP30 [23], provided by the European Union's Copernicus Programme, is a global DEM dataset with no latitudinal limitations and a 30 m spatial

resolution. The base data for generating COP30 were collected after 2010, making it one of the most up-to-date large-scale DEMs available. Although several corrected DEMs derived from SRTM have been developed (e.g., the hydrologically conditioned MERIT DEM), these products are post-processed and may modify certain original elevation signals during the correction process, making them less suitable for temporal differencing with COP30. In contrast, SRTM and COP30 represent two independent datasets collected more than ten years apart, providing a clearer temporal contrast that is more appropriate for analyzing long-term elevation changes.

(2) Engineering measurement data

The terracing data were sourced from the study by Cao et al. [24], who extracted time series spectral and topographic features from Landsat 8 imagery and SRTM DEMs. Using a random forest classifier, they categorized cultivated land from the global land cover dataset Globeland30 into terraced land and nonterraced land. This resulted in the creation of the first 30 m resolution terracing map covering all of China. The accuracy of the map was evaluated using a large number of test samples. The check dam data were derived from the study by Zeng et al. [25], who conducted an in-depth investigation and analysis of the key characteristics of check dams. They obtained Google Earth imagery with a resolution of 0.3 to 1.0 m from the optimal period and used an object-based classification method to produce a vectorized dataset of check dams on the Loess Plateau.

(3) Basin data

The HydroBASINS [26] dataset is a vector layer of subbasin boundaries on a global scale. This product provides a hierarchical and nested subbasin dataset, covering various basin area scales, and serves as a high-quality, standardized global basin delineation resource. For this study, we selected level 8 and level 12 basin data, where the average areas of individual basins are approximately 100 km² and 600 km², respectively. Multiscale research allowed us to analyze the impact of engineering measures at different spatial scales. In this paper, we refer to the level 8 and level 12 data as Basin 1 and Basin 2, respectively. These two levels were selected because they strike a balance between local detail and regional coverage. Level 8 basins provide sufficient resolution to capture the spatial variability of engineering measures, while level 12 basins are suitable for examining broader-scale erosion patterns and cumulative effects. The nested structure of HydroBASINS also facilitates consistent multi-scale comparison, making levels 8 and 12 an appropriate choice for this study.

(4) Environmental data

Changes in surface elevation at the basin scale are influenced not only by engineering measures but also by other environmental factors. We collected relevant environmental data as described below.

Geological Data: Rock properties form the foundation for surface changes. Lithology describes the geochemical, mineralogical, and physical characteristics of rocks, which play a significant role in basin evolution. Unconsolidated sediments are also important for many Earth surface processes. Therefore, in this study, we utilized two types of geological data: the global lithological map (GLiM) [27] and the global unconsolidated sediment map (GUM) [28].

Geomorphological Data: Landforms are the result of Earth's dynamic processes and also influence subsequent surface processes. This study utilized the geomorphological data published by Iwahashi and Yamazaki [29], which includes a comprehensive range of landform types and offers high accuracy.

Climatic Data: Climatic factors typically include multiple variables, such as precipitation and temperature. Among these, precipitation is a key factor in surface erosion

and is theoretically closely related to topographic changes in the Loess Plateau region. The precipitation data used in this study consisted of annual precipitation records for China from 1982 to 2002 [11]. In addition, to estimate the complex relationships between various climate factors, we used Köppen climate classification data [30], which provides a comprehensive climate assessment based on a combination of environmental factors.

Soil Data: The surface of the Loess Plateau is covered by large areas of soil particles, and the properties and types of soil significantly influence surface erosion. In this study, we incorporated the Harmonized World Soil Database version 2.0 (HWSD v2.0) [31]. This dataset, developed by the Food and Agriculture Organization of the United Nations, provides detailed information on the morphological, chemical, and physical properties of soils at approximately 1 km resolution. We extracted key content data such as sand, silt, clay, and organic carbon, all of which play crucial roles in soil erosion, and calculated the relevant factors for analysis.

Surface Information: Land cover, particularly vegetation cover, has a noticeable effect on surface erosion on the Loess Plateau. Therefore, we incorporated forest canopy height data [32] to reflect surface vegetation conditions. Additionally, land use, which is dominated by anthropogenic activities, also influences surface erosion. We used land use data [33] to capture this influence. Like climate information, factors related to land cover are often interrelated in complex ways. To capture the comprehensive influence of surface factors, we introduced ecological zoning data for the Loess Plateau [34]. This dataset divides the region into zones on the basis of natural conditions, soil and water conservation techniques, and ecological restoration efforts tailored to each area's characteristics.

2.2. Study Area

The Loess Plateau (Figure 1) is the largest and most concentrated loess deposit region in the world [35]. In addition to a few rocky mountains, the area is extensively covered by thick layers of loess, generally ranging from 100 to 200 m in depth. The loess on the surface is loosely textured and permeable. Coupled with the plateau's continental monsoon climate—which is characterized by significant annual temperature fluctuations and concentrated, intense rainfall during the summer—this makes the loess layers highly susceptible to runoff erosion. Geological studies indicate that significant tectonic movements (e.g., faulting and uplift) on the Loess Plateau mainly occurred during the early Cenozoic (Tertiary). For instance, the late Pliocene uplift of the Ordos Block triggered strong river incision and the development of piedmont gullies. During the Quaternary, powerful East Asian monsoons transported large amounts of clastic material, leading to the accumulation of thick aeolian loess deposits. Under semi-arid climatic conditions, these deposits have since been continuously reshaped by fluvial and aeolian processes, producing the characteristic landforms of loess tablelands, ridges, and hills. At the present stage, no significant tectonic activity is observed in this region, and the surface morphology is predominantly controlled by exogenic processes such as weathering and water erosion. Vegetation cover in the Loess Plateau is generally sparse due to long-term soil erosion and water scarcity. Grasslands are widely distributed, but the grasses are typically short, usually less than 0.5 m in height, which reduces their influence on surface elevation measurements at 30 m resolution. In contrast, patches of protected forests are mainly found in the southern and central parts of the Plateau. While these forests may contribute to localized vertical offsets, their areal extent is limited relative to the overall study region. Owing to the influence of natural conditions and anthropogenic activities, the Loess Plateau experiences some of the most severe soil and water erosion issues in China and globally. It is also a major source of sediment for the Yellow River. The area affected by soil and water loss on the Loess Plateau reaches 454,000 km², with water erosion alone accounting for 337,000 km².

Severe erosion not only leads to environmental degradation but also threatens sustainable development in terms of the economy, agriculture, and society. To effectively address soil and water erosion and improve the ecological environment, relevant departments at all levels have implemented extensive soil and water conservation efforts on the Loess Plateau. Among these, terrace and check dams are the primary conservation engineering measures [36]. These interventions have played a significant role in mitigating soil erosion, controlling the rate of land degradation, and improving the overall ecological conditions of the Loess Plateau.

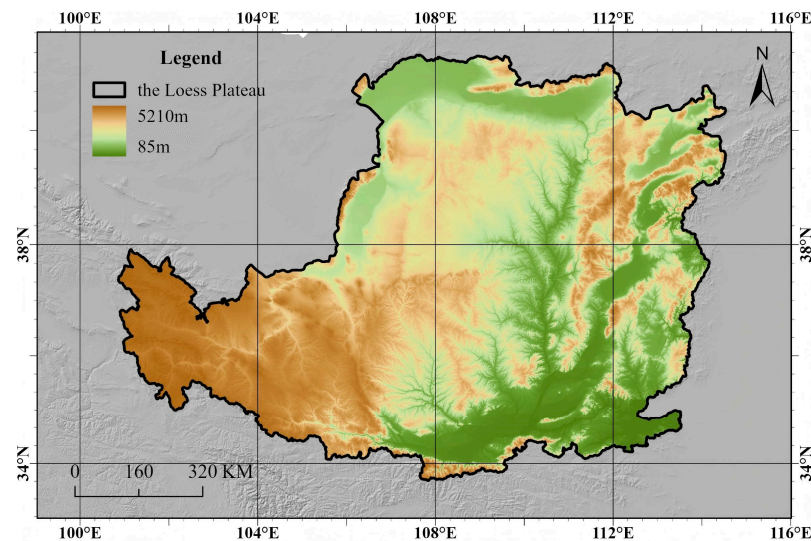


Figure 1. Location and topography of the Loess Plateau.

2.3. Method

In this study, we developed an integrated methodological framework (Figure 2) to quantify the impacts of engineering measures on surface erosion across the Loess Plateau. First, multi-source datasets were compiled, including DEMs, detailed engineering measure inventories, basin boundaries, and environmental covariates such as climate, geology, soils, land cover, and ecological zoning. Then, a random forest (RF) model was constructed to explore the relationships between engineering measures, environmental factors, and elevation change, with Shapley additive explanations (SHAP) applied to interpret feature contributions and enhance model transparency.

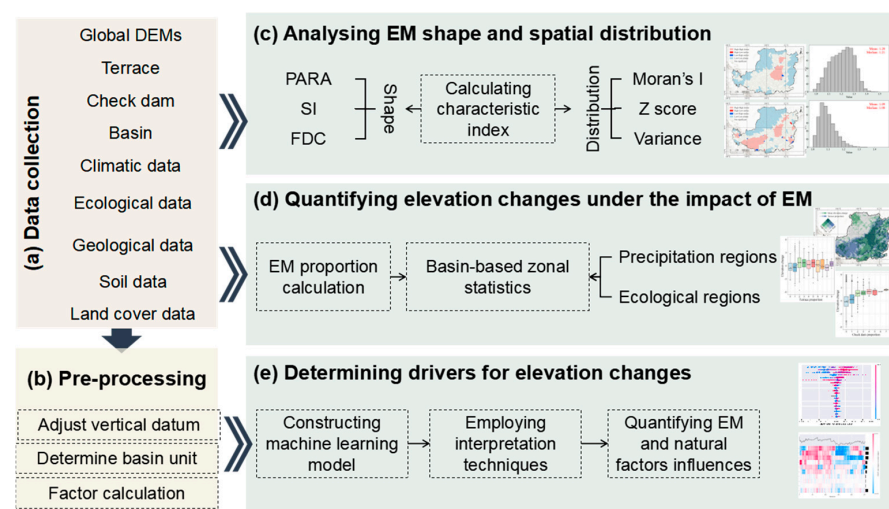


Figure 2. Flowchart of the proposed method.

2.3.1. Data Preprocessing

1. Vertical datum transformation

A flowchart of the proposed method is shown in Figure 2. The vertical datum significantly influences the elevation values stored in the DEMs. In extreme cases, elevation values from the same dataset can differ by several tens of meters depending on the vertical datum used. Therefore, when surface elevation changes are being calculated, unification of the vertical datum is crucial. In this study, the vertical datum for SRTM was EGM96, whereas that for COP30 was EGM2008. Previous research has shown that EGM2008 offers higher accuracy [37,38]. Consequently, we converted the vertical data of both DEMs to EGM2008. After the conversion, we applied bilinear interpolation to resample the SRTM data with 90 m resolution to data with 30 m resolution. The processed SRTM data were then subtracted from the COP30 data. The resulting difference represents the surface elevation change between the SRTM acquisition in February 2000 and the 2011–2015 acquisition period of the COP30 dataset, capturing approximately 15 years of topographic change.

2. Determination of basin units

A basin is widely recognized as a fundamental analysis unit in geomorphological and hydrological studies because it delineates natural drainage boundaries and slope systems, even in areas without higher-order streams. Erosion within a basin is a geomorphological process that is spatially continuous and may be driven by multiple agents, including hydraulic erosion, wind erosion, and mass movements such as landslides. In the context of this study, we focus primarily on water-driven erosion processes, where sediment-laden flow from slopes and upstream areas converges and exits through the basin outlet, but acknowledge that other exogenic processes may also contribute to elevation change. On a basin scale, if soil loss in one area is deposited elsewhere within the basin, the soil and water conditions within the basin are considered to be in balance. This balance results in minimal mean elevation change within the basin and prevents significant downstream impacts on other basins. Given that current regional-scale topographic data typically have a resolution of 30 m, using a basin as the basic research unit allows for more effective data utilization and avoids inappropriate feature extraction. Therefore, this study conducted an analysis based on basin units. Owing to the varying basin scales, the effects of engineering measures may differ accordingly. Analyzing surface changes at different basin scales helps identify relatively stable patterns in the performance of these measures. Thus, in this study, level 8 and level 12 from the HydroBasins dataset were selected as the research units, referred to as Basin 1 and Basin 2, respectively. In the Loess Plateau region, the average basin areas of Basin 1 and Basin 2 are 100 km² and 600 km², respectively.

On the basis of the above, we defined the mean elevation change of basins (MECB), which reflects the overall elevation change within the basin and serves as an indicator of soil and water loss. This metric was defined as the average of all elevation changes within a basin. A positive value indicates an increase in average elevation (reflecting a gain in material), and a negative number indicates a net decrease in elevation (reflecting a loss of material). This indicator was used in the subsequent analysis and modeling of the relationship between engineering measures and erosion.

3. Factor calculation

In addition to the MECB, we computed 25 feature factors (Table 1) on the basis of topographic data, basin data, environmental data, and engineering measures. These factors were selected to capture the multidimensional relationships between different variables and the effectiveness of soil and water conservation measures.

Table 1. Environmental factors related to surface erosion.

Data Type	Dataset	Factors
Terrain data	COP30 [23] and SRTM DEM [22]	MECB
	SRTM DEM [22]	Mean LS factor in the Universal Soil Loss Equation (USLE) [39]
Engineering measure data	Check dam [25]	Variation in check dam volume Sum of check dam volume Number of check dams Area proportion of check dams in basins
	Terrace [24]	Area proportion of terraces in basins
Basin data	HydroBASINS L8 and L12 [29]	W-L ratio Basin area
Geological data	Global Lithological Map (GLiM) [27]	Variety of lithological types Major lithological types in basins
	Global Unconsolidated Sediment Map (GUM) [28]	Variety of unconsolidated sediment types Major unconsolidated sediment type in basins
Climatic data	Precipitation [40]	Mean precipitation in 1982–2022
	Köppen climate type [30]	Mean R factor Major climate types in basins
Geomorphological data	Landform type [29]	Variety of landform types Major landform types in basins
Soil data	HWSD 2.0 [31]	Mean sand content Mean silt content Mean clay content Mean organ carbon content Mean K factor in USLE [39]
Surface information	forest canopy height [32]	Mean forest height
	Land use data [33]	Mean P factor in USLE [39]
	Ecological type [34]	Major ecological types in basins

2.3.2. Analysis of EM Shapes and Spatial Distribution

To illustrate the characteristics of check dams and terraces, we developed a feature set that quantifies the shapes and spatial distribution of these engineering measures. The descriptions and calculation methods for these indices are shown in Table 2.

Table 2. Metrics for characterizing engineering shapes and spatial distribution.

Type	Name	Formula	Description
Shape indices	Perimeter-Area Ratio (PARA)	$PARA = \frac{P_{ij}}{A_{ij}}$ P_{ij} indicates the unit perimeter; A_{ij} indicates the unit area.	PARA is a commonly used metric for quantifying shape complexity.
	Shape Index (SI)	$SI = \frac{0.25 * P_{ij}}{\sqrt{A_{ij}}}$ P_{ij} indicates the unit perimeter; A_{ij} indicates the unit area.	SI is the most basic measure for assessing patch shape complexity, addressing numerical scaling issues inherent in perimeter-to-area ratios by normalization against a square standard. The patch shape is square when SI equals 1; the SI increases as shape complexity rises.
	Fractal Dimension Index (FRAC)	$FRAC = \frac{2 * \ln(0.25 * P_{ij})}{\ln(A_{ij})}$ P_{ij} indicates the unit perimeter; A_{ij} indicates the unit area.	The FRAC is one of the most commonly employed metrics, reflecting the complexity of shapes across a range of spatial scales and overcoming the issue of nonnormalized values inherent in perimeter-to-area ratios. For shapes with extremely simple perimeters, the FRAC approaches 1, whereas for those with highly convoluted, plane-filling perimeters, the FRAC approaches 2. A larger FRAC indicates higher patch complexity.

Table 2. Cont.

Type	Name	Formula	Description
Spatial distribution indices	Global Moran's I	$I_g = \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^n \sum_{j=1}^n w_{ij} \sum_{i=1}^n (x_i - \bar{x})^2} x_j$ x_j represents the attribute value of the j-th basin; $\bar{x}$ denotes the average attribute value across all basins; w_{ij} represents the spatial weight matrix between basins, where each element defines the spatial relationship or interaction; s is the sum of all elements in the spatial weight matrix; n represents the total number of basins.	The Global Moran's I index is used to determine whether a spatial phenomenon exhibits spatial autocorrelation within a region. Its value ranges from -1 to 1. Positive values indicate positive spatial autocorrelation, meaning that similar attribute values are clustered in space. Negative values indicate negative spatial autocorrelation, implying that neighboring locations tend to have dissimilar values. Values close to 0 suggest the absence of spatial autocorrelation, meaning the spatial distribution of the data is random.
	Local Moran's I	$I_l = \frac{(x_i - \bar{x})}{s^2} \sum_{j=1}^n w_{ij} (x_j - \bar{x}) x_i$ where the notations are the same as for Global Moran's I	The Local Moran's I is an extension of the Global Moran's I, allowing for the identification of statistically significant hotspots, cold spots, and spatial outliers. By conducting spatial clustering using the Local Moran's I, a Local Indicators of Spatial Association (LISA) cluster map can be generated. This map categorizes spatial clustering into five types: high-high (H-H), high-low (H-L), low-high (L-H), low-low (L-L), and nonsignificant clusters. Utilizing the Local Moran's I, we can effectively display the spatial distribution of the study objects.

2.3.3. Quantifying Elevation Changes Under the Impact of EMs

In basin-based analysis, we need to consider both the area of EMs and the relative relationship between the EMs and the scale of the basin. The latter has a more pronounced effect on soil and water conservation in basins. Therefore, in this section, we use the proportion of the EM area within each basin as the primary criterion for classification. The calculation of the EM proportion (EMP) is as follows:

$$EMP_i = \frac{\sum Area_i}{Area_{basin}} \quad (1)$$

i represents the type of EM (e.g., check dams and terraces). In this section, we use the MECB of all locations within each basin as the quantitative indicator for assessing the elevation changes in the basin. Using the two-level basins as the fundamental units, we employed a zonal statistical approach to discuss the elevation changes under varying precipitation and ecological conditions.

2.3.4. Determining the Factors Influencing Elevation Changes

Changes in surface elevation at the basin scale are influenced by both environmental factors and EM attributes. We introduce IML to analyze the driving forces of various factors. IML goes beyond conventional machine learning by not only making predictions but also seeking to elucidate the reasoning behind those predictions [41,42]. It has been widely applied in the geosciences, particularly for predictive modeling [43,44]. The specific steps are as follows. (1) Data Preparation: We established a dataset containing both environmental and EM factors. The sources of these foundational data have been previously discussed. The EM factors include the area of check dams and terraces, the proportion of area occupied by check dams and terraces, the total volume of check dams within each basin, the total number of check dams, and the diversity of check dam grades. The areas of check dams and terraces and the volume of check dams were directly obtained from the dataset, while the proportions of check dam and terrace areas were calculated using the EMP. Furthermore, check dams have different grades, and the combination of these grades plays a varied role in controlling soil and water loss [36]. We calculated the variation in the volume of check dams within each basin as an indicator of the diversity of check dam grades. All the factors were stored in the attribute tables of the shapefiles for Basins 1 and 2. (2) Prediction

Model Construction: We constructed an RF model to explore the relationships between environmental and EM factors and elevation changes at the basin scale. We selected the RF model for this study because it is well suited to capture nonlinear relationships and complex interactions among diverse environmental and engineering variables. Compared with linear models or single-decision-tree approaches, RF offers higher robustness to noise and multicollinearity, and performs reliably with mixed data types and large feature sets. The fitting and training of the RF model was conducted exclusively on basins where soil and water conservation projects exist. (3) **Interpretable Value Calculation:** After model training, we calculated the SHAP value [45] to reflect the impact intensity and influence pattern of each factor. The SHAP value is a common metric in IML and provides detailed insight into each feature's contribution to instance-level model predictions [46], which can be further aggregated to provide a global perspective of the dataset. This combination ensures that the model achieves high predictive accuracy while also yielding transparent and consistent explanations, making it particularly appropriate for geomorphological applications where both accuracy and interpretability are crucial [47]. SHAP values were calculated using the TreeSHAP algorithm, which provides consistent and locally accurate feature attributions for tree-based ensemble models. The method estimates the marginal contribution of each predictor by averaging its impact across all possible feature coalitions, thereby assigning a fair contribution score to each feature. In this study, SHAP values were first computed at the instance level for each basin and then aggregated to obtain global importance rankings of predictors. These values enabled us not only to identify the most influential environmental and engineering factors but also to interpret the direction (positive or negative) and intensity of their impacts on elevation change.

3. Results

3.1. Characteristics of Engineering Measures

The shape characteristics of the EMs are shown in Figure 3. Overall, the shape indicators of the check dams more closely resemble a normal distribution, indicating higher homogeneity than that of the terraces. The PARA of check dams is significantly greater than that of terraces, which suggests that terraces tend to have longer boundaries at similar scales. However, this does not necessarily imply that the shape of terraces is more complex. The SI, which addresses the numerical scaling issues of the PARA, reveals that check dams have greater overall shape complexity, although terraces exhibit greater variability in shape and are prone to extreme values, as shown in Figure 3e. Additionally, the FRAC value for check dams is significantly greater than that for terraces. Check dams are typically located in valley bottom areas and are constrained by the surrounding slopes. Owing to the effects of hydraulic erosion, the valleys in the Loess Plateau often exhibit distinct fractal patterns, which may explain the similar fractal characteristics observed in the check dams.

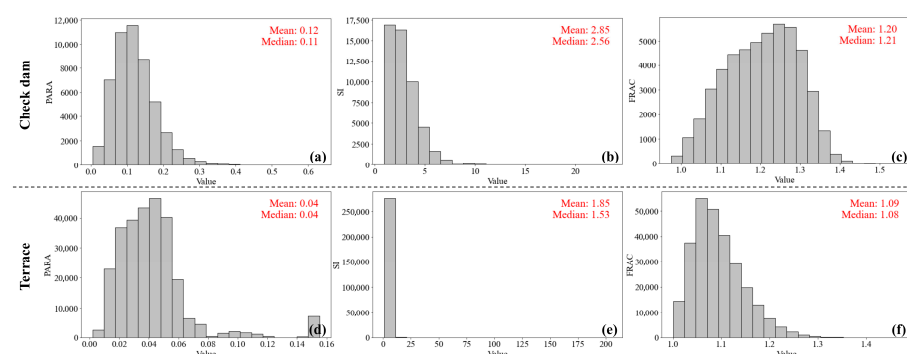


Figure 3. Characteristics of engineering measures of check dams and terraces, respectively: (a,d) PARA; (b,e) SI; (c,f) FRAC.

The spatial distribution characteristics of check dams and terraces are shown in Figure 4. Overall, at both scales of analysis, check dams and terraces exhibit significant clustering patterns. Check dams are concentrated in the central region and the left bank of the Yellow River, which is the core area of the hilly and gully region. This area features favorable conditions for gully development, including thick loess deposits, steep underlying topography, and high precipitation. The terraces show two distinct clusters of distribution, located in the central and southwestern parts of the Loess Plateau. As previously mentioned, the central region of the Loess Plateau is a key area for hydraulic erosion, and the construction of terraces serves as a method to mitigate the effects of this erosion. The southwestern region has a large population, and the terraces provide additional arable land, which is beneficial for food production.

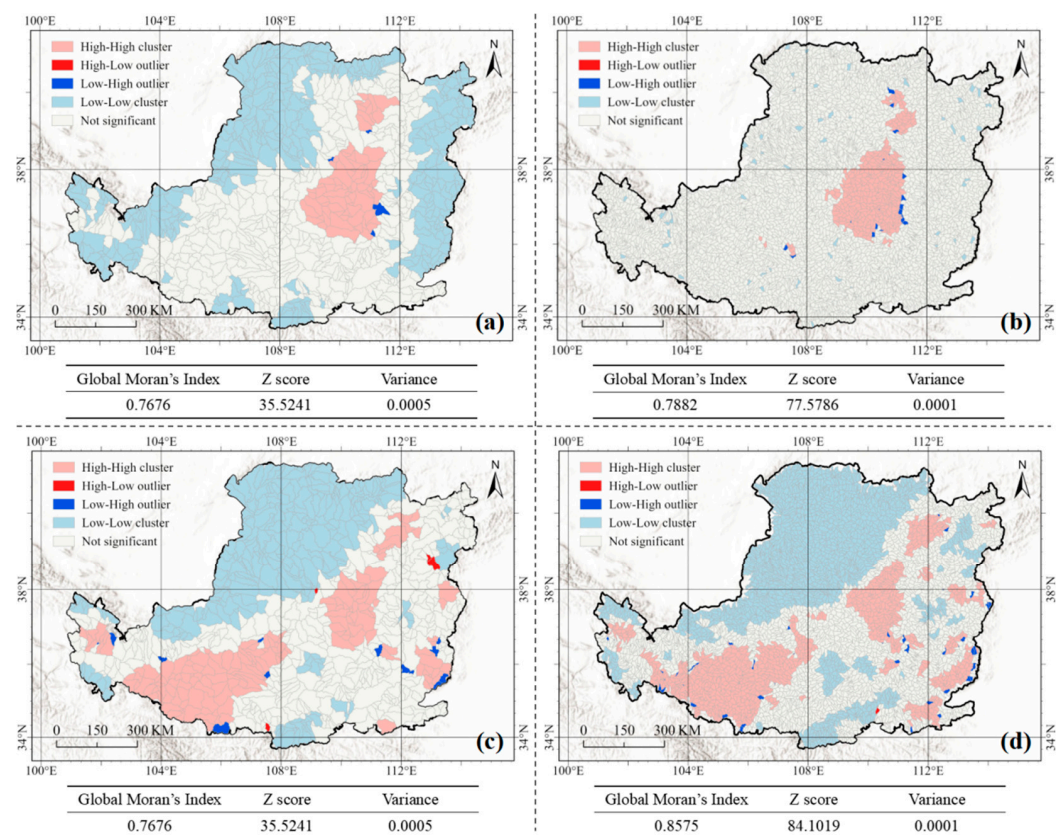


Figure 4. Spatial distribution characteristics of check dams and terraces. (a,c) Basin 1-based spatial clusters on the basis of local Moran's I values of check dams and terraces, respectively. (b,d) Basin 2-based spatial clusters on the basis of local Moran's I values for check dams and terraces, respectively.

3.2. Influence of Engineering Measures on Elevation Changes

To assess whether the elevation changes obtained from the SRTM and Copernicus DEMs were influenced by systematic biases, we conducted an independent validation using ground-based datasets from four representative catchments on the Loess Plateau (Suide, Ansai, Changwu, and Wangmaogou). The first-period data for all four sites were produced by professional surveying departments in 2002, while the second-period data were obtained through UAV photogrammetry and field measurement conducted in 2020 (Suide and Wangmaogou), 2021 (Ansai), and 2023 (Changwu). Although these datasets do not perfectly match the acquisition years of the SRTM (2000) and COP30 (2011–2015), their time spans broadly overlap with the two global DEMs, providing a reasonable basis for validation. All UAV-derived DEMs were resampled to 30 m resolution to ensure consistency with the spatial resolution of the global DEMs. Following the same workflow as in the

main analysis, we calculated the mean elevation change within each basin. The results show that while the absolute magnitude of elevation change differs by more than 10% in some cases, the overall trends are consistent in terms of both the direction (positive or negative change) and the spatial distribution of erosion versus deposition. The largest discrepancy was found in the Changwu catchment, which experienced substantial human disturbances after 2020, leading to localized changes not captured in the Copernicus DEM. These validation results suggest that the elevation changes observed in our analysis are not artifacts of DEM biases but instead reflect real geomorphic processes at the basin scale. As shown in Figure 5, the spatial distribution characteristics of the influence of check dams and terraces on elevation changes at different analytical scales are quite similar. In both Basin 1 and Basin 2, the central region of the Loess Plateau exhibits a high–high clustering pattern. From the box plots, we observe that an increase in check dam proportion is accompanied by a positive elevation change, indicating an increase in the average elevation within the basin. At both analytical scales, when the check dam proportion changed from type 1 to type 2, the MECB increased by approximately 200%. This suggests a potential threshold effect where check dams significantly influence elevation changes. However, the results for terraces are not consistent with those observed for check dams. Overall, when the terrace proportion ranges from 0.1 to 0.8, there is a noticeable positive elevation effect, contributing to a height increase of approximately 10% to 50%. However, when the proportion of terraces continues to increase beyond this range, a negative elevation change occurs, indicating a decrease in the mean basin elevation. In terms of the spatial distribution, this negative trend is primarily observed in the southwestern region, where a low–high clustering pattern is formed.

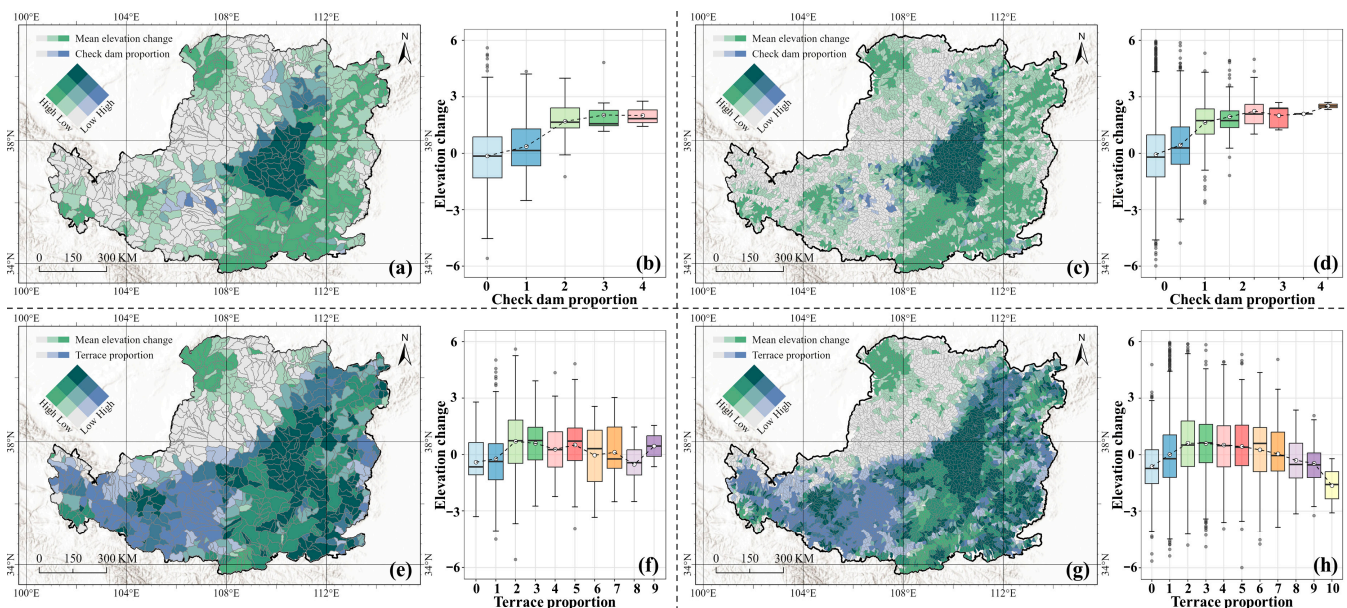


Figure 5. The elevation changes and the proportion of engineering measures at the basin scale. (a,e) Basin 1 results for check dams and terraces, respectively; (b,f) Elevation changes in areas with different proportions of check dams and terraces in Basin 1; (c,g) Basin 2 results for check dams and terraces, respectively; (d,h) Elevation changes in areas with different proportions of check dams and terraces in Basin 2.

In addition, we analyzed the proportions of positive and negative elevation changes within each basin. As shown in Figure 6, we calculated the ratio of positive elevation changes within basins and visualized the spatial distribution of this indicator. A higher value indicates that a greater proportion of the basin area experienced elevation gain. The

results from both basins exhibited strong consistency. Overall, the proportions of positive and negative elevation changes within basins displayed a clear spatial clustering pattern. Regions dominated by positive elevation change (i.e., a positive elevation change ratio greater than 0.5) are mainly found in the eastern part of the study area, along the lower reaches of the Yellow River. In these regions, the basins are generally located downstream, where the density of check dams is also relatively high. This spatial overlap suggests that engineering measures (EMs) such as check dams can effectively reduce elevation loss across multiple locations within a basin. Notably, check dams often create large new depositional areas, resulting in a net increase in elevation. However, in the northwestern part of the plateau, where EMs are also relatively concentrated, the proportions of positive and negative elevation changes tend to be more balanced. This may be because these basins are located in the upper and middle reaches of the Yellow River, where lower-order streams are less developed and EMs are less effective compared to the downstream regions. In contrast, regions dominated by negative elevation change (i.e., a positive elevation change ratio less than 0.5) are mainly distributed in the northwest, which also corresponds to areas with the lowest density of engineering measures. The spatial distribution of these two patterns shows a strong correlation.

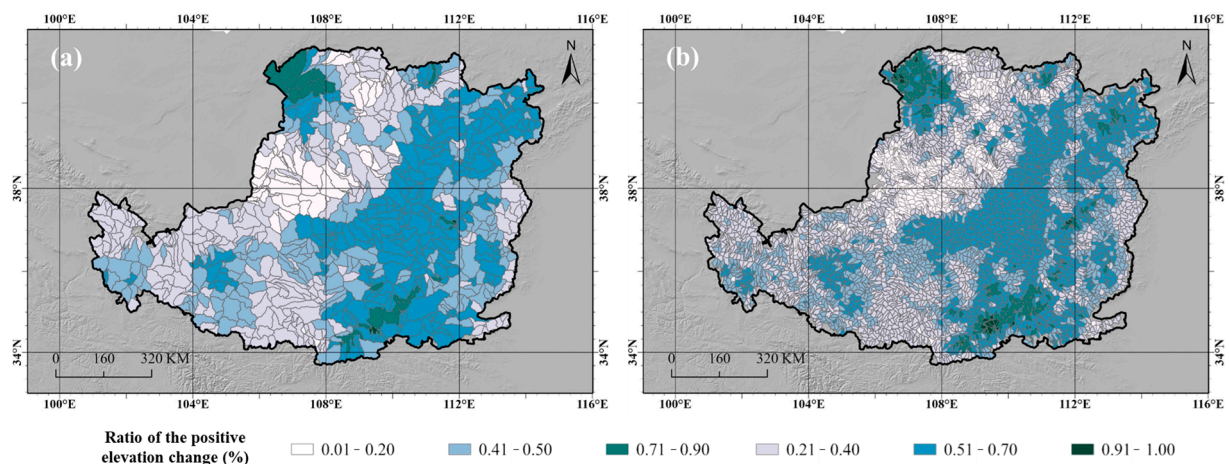


Figure 6. The ratio of the positive elevation change. (a,b) Results in Basin 1 and 2.

3.2.1. Role of Engineering Measures Under Different Precipitation Conditions

Typically, an increase in precipitation leads to intensified surface erosion, resulting in a negative change in average elevation within basins. However, as shown in Figure 7b,c, we observed that regions 3, 4, 5, and 6, which experience greater precipitation, exhibit positive changes in the MECB. Region 6 is located on the southern Loess Plateau, where urban areas and mountains with only minimal loess cover exist. Despite high rainfall, this region does not exhibit significant decreases in elevation. The changes in regions 3, 4, and 5 highlight the mitigating effects of EMs on surface erosion. From the detailed box plots (Figure 7d3–d5), it is clear that regions 3, 4, and 5 contain a large number of soil and water conservation measures, and within these areas, as EMP increases, the MECB increases, transforming the basin into a depositional mode. As detailed in Figure 7d1–e7, the MECB tends to increase in both Basins 1 and 2 as the check dam proportion increases. In areas with check dams, the average elevation gain compared with regions without check dams can reach 2.5 m. This finding indicates that in basins with a high proportion of check dams, eroded soil does not leave the basin but accumulates in certain areas, and this accumulation is strongly correlated with the proportion of check dam coverage. However, the influence of terraces is more complex. In both Basins 1 and 2, as the proportion of terraced areas increases, the MECB fluctuates. In areas with lower precipitation (Regions 1–3), terrace

proportion is positively correlated with elevation change. In Regions 5 and 6, compared with Region 1, the mean MECB increased by approximately 2 m. In Regions 4–6, the effect of terraces in mitigating elevation reduction was less pronounced.

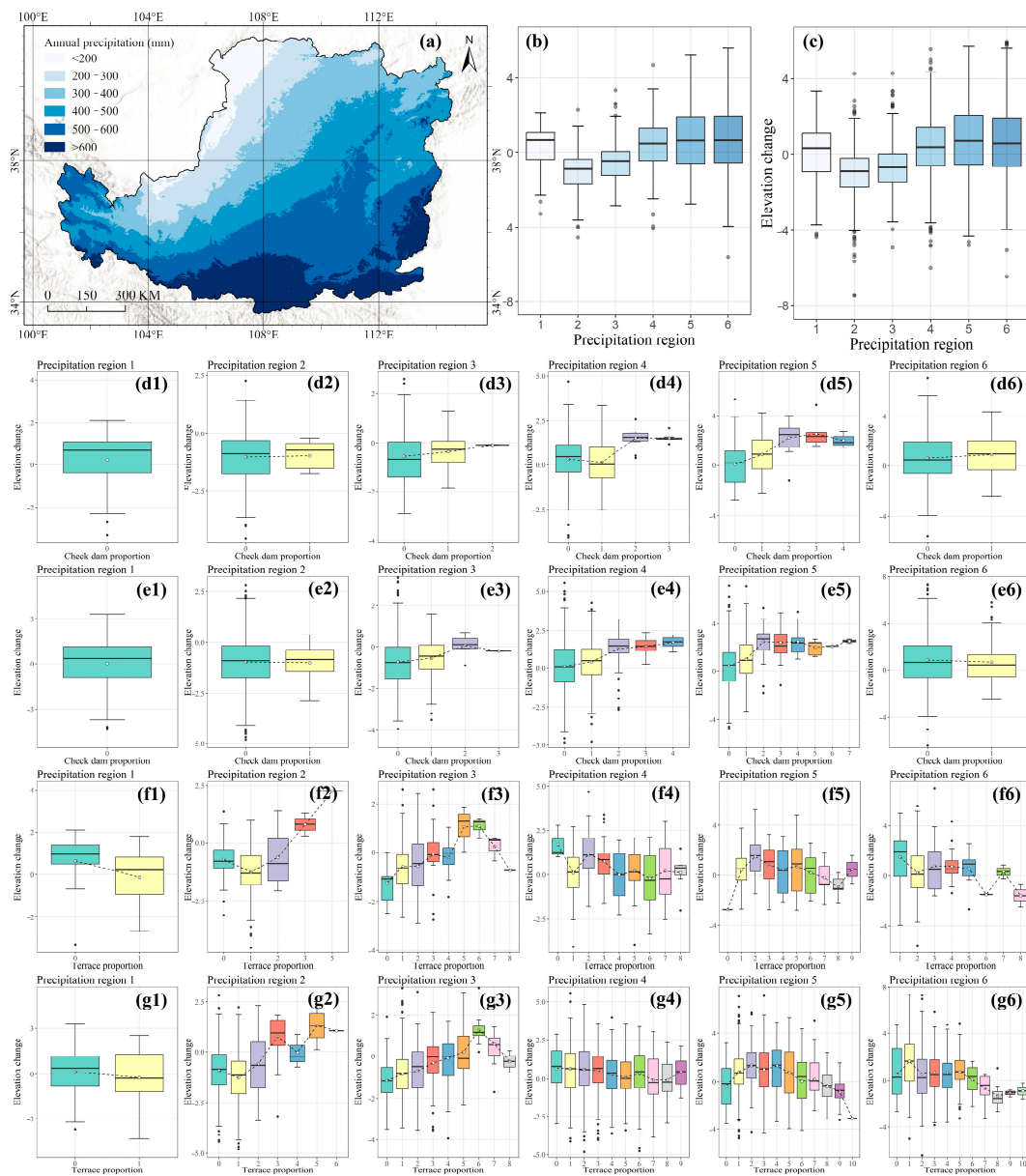


Figure 7. Changes in the mean elevation of basins in regions with different levels of precipitation influenced by EMs. (a) shows the results of the precipitation partition. (b,c) show the overall elevation changes at the scale of Basins 1 and 2, respectively. (d1–e6) are the results of elevation changes influenced by the check dam proportion at the scale of Basins 1 and 2, respectively. (f1–g6) are the results of elevation changes influenced by terrace proportion at the scale of Basins 1 and 2, respectively. In (b,c), classes 1 to 7 of the *x*-axis represent the seven regions in a, respectively. For Figures (d1–e7), the *x*-axis values from 0 to 7 represent check dam proportion values of 0, 0–0.01, 0.01–0.02, 0.02–0.03, 0.03–0.04, 0.04–0.05, and 0.05–0.06, respectively. Similarly, for Figures (f1–g6), the *x*-axis values from 0 to 10 represent terrace proportion values of 0, 0–0.1, 0.1–0.2, 0.2–0.3, 0.3–0.4, 0.4–0.5, 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, and greater than 0.9, respectively. The dashed lines in Figures (d1–g6) represent the average values under different conditions.

3.2.2. Roles of Engineering Measures Under Different Ecological Conditions

In different ecological regions, varying influences of the EMs on elevation changes can be observed. In A1 and A2 (ecological regions 1 and 2), the relationship between elevation

change and the EMP is unstable, with the mean trendline fluctuating. However, in B1 and B2 (ecological regions 3 and 4), which are the most typical loess hilly regions, the influence of EMs on increasing elevation is more evident. Specifically, in Region 4 (B2 in Figure 8), at the Basin 2 scale, areas with check dams and terraces showed MECB increases of approximately 2.2 m and 1.9 m, respectively, compared with regions without EMs. In contrast, in ecological regions 5 and 6, the relationship between EMs and elevation change is negative, a phenomenon similar to the results of the precipitation analysis.

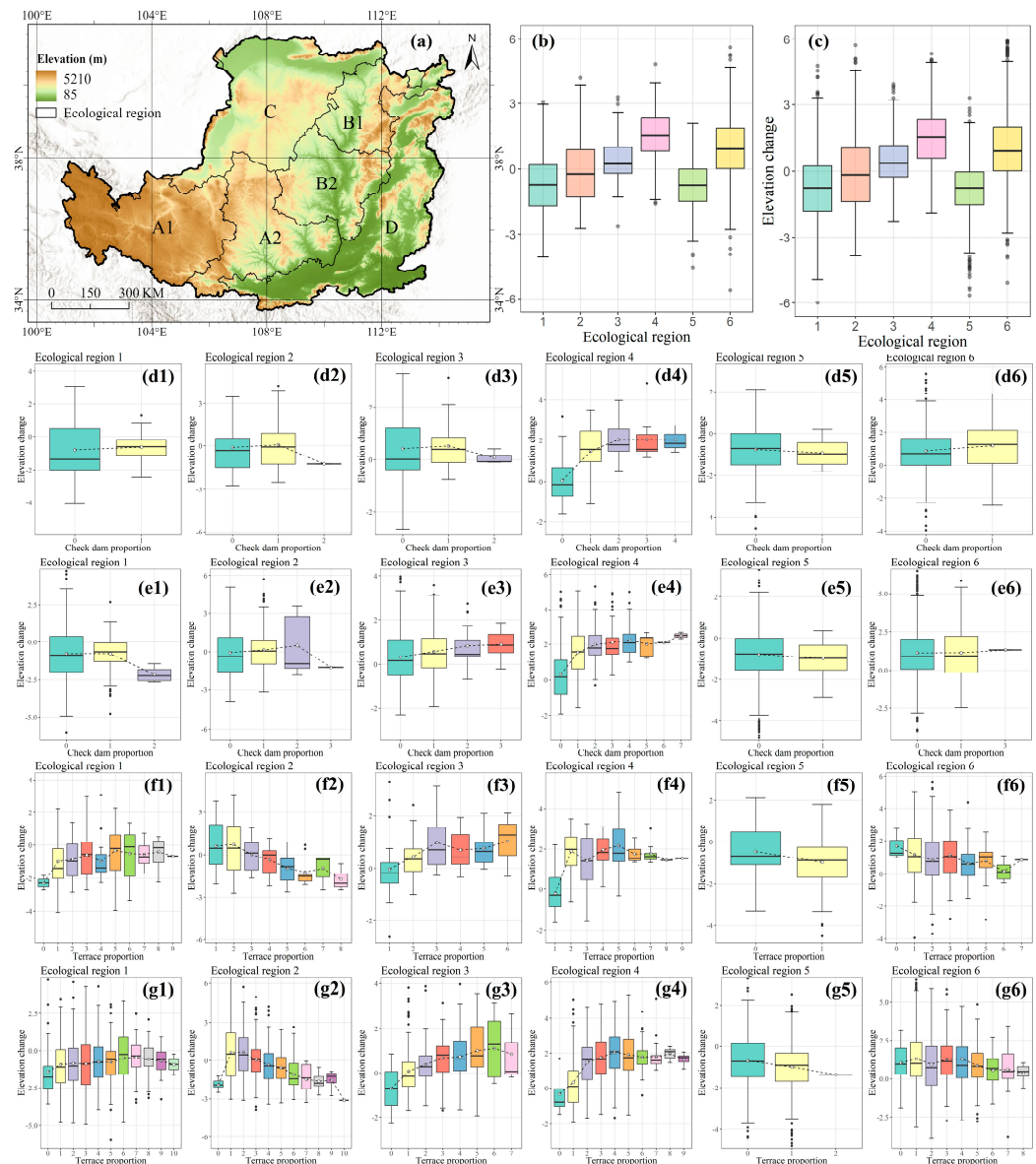


Figure 8. Changes in the mean elevation of basins in regions with different ecological conditions influenced by EMs. (a) is the result of ecological partitioning. (b,c) show the overall elevation changes at the scale of Basins 1 and 2, respectively. (d1–e6) are the results of elevation changes influenced by the check dam proportion at the scale of Basins 1 and 2, respectively. (f1–g6) are the results of elevation changes influenced by terrace proportion at the scale of Basins 1 and 2, respectively. In (b,c), labels 1–6 of the x-axis represent A1, A2, B1, B2, C and D, respectively. For Figures (d1–e7), the x-axis values from 0 to 7 represent check dam proportion values of 0, 0–0.01, 0.01–0.02, 0.02–0.03, 0.03–0.04, 0.04–0.05, and 0.05–0.06, respectively. Similarly, for Figures (f1–g6), the x-axis values from 0 to 10 represent terrace proportion values of 0, 0–0.1, 0.1–0.2, 0.2–0.3, 0.3–0.4, 0.4–0.5, 0.5–0.6, 0.6–0.7, 0.7–0.8, 0.8–0.9, and greater than 0.9, respectively. The dashed lines in Figures (d1–g6) represent the average values under different conditions.

3.3. Driving Factors of Elevation Changes

The results are presented as normalized values. As shown in Figure 9, the R-square values for the model reached 0.62 and 0.73 at the Basin 1 and Basin 2 scales, respectively. Considering the complexity of the relationship between surface change and environmental influences, we believe that the results at both scales are reliable.

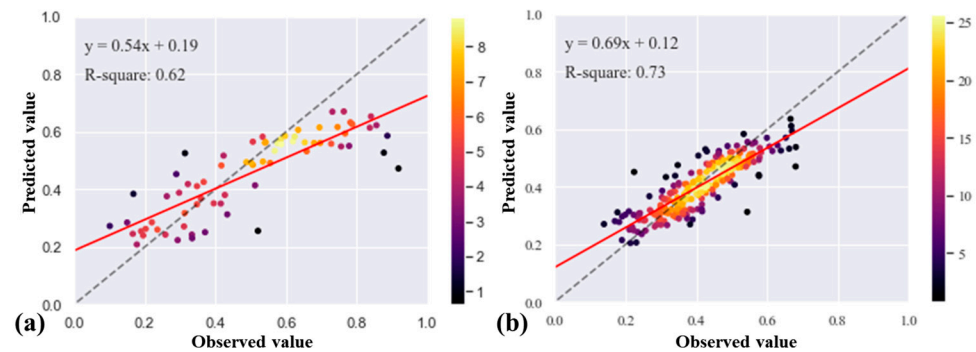


Figure 9. Comparison of predicted results and reference data. (a,b) Results at the scale of Basin 1 and Basin 2, respectively.

The importance of the top 20 factors in Basins 1 and 2 is shown in Figure 10a,b, respectively. At the Basin 1 scale, forest canopy height emerged as the top predictor, highlighting the substantial role of afforestation projects on the Loess Plateau. Taller forests enhance rainfall interception, reduce the kinetic energy of raindrops, and strengthen root cohesion, thereby mitigating surface erosion. At the same time, seasonal differences in canopy density may lead to variations in DEM elevation retrieval, partially amplifying the importance of this factor. Other natural factors also played important roles. The rainfall erosivity factor (R) and soil erodibility factor (K) consistently contributed to elevation change predictions, confirming their expected roles in driving hydraulic erosion. Lithology and landform types influenced the spatial heterogeneity of erosion responses, as basins underlain by loose sediments or steep terrain were more sensitive to erosion processes.

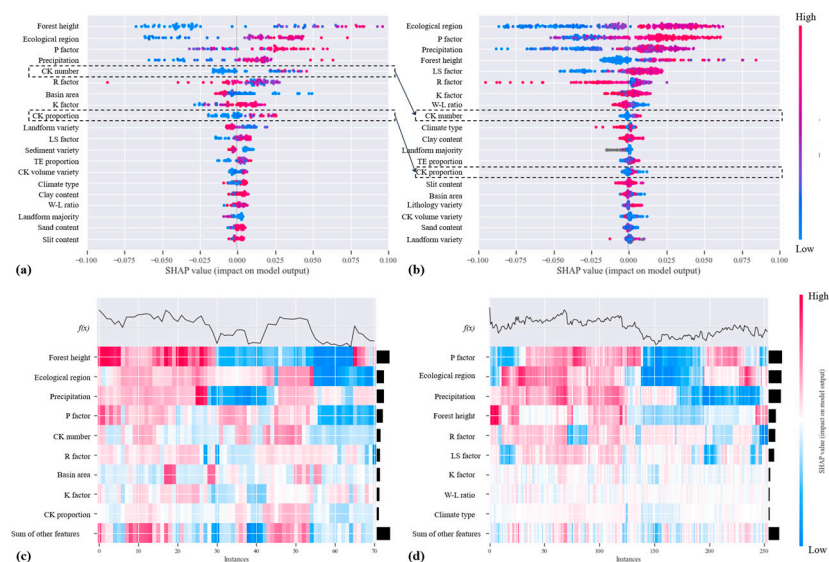


Figure 10. SHAP-based feature importance analysis. (a,b) Influence patterns and importance of different factors at the Basin 1 and Basin 2 scales. The black boxes highlight the number and proportion of check dams with significant changes in importance. The arrows indicate that the ranking of these two factors changes with the variation in watershed scale. (c,d) Importance of different factors under varying elevation change conditions.

Check dam indicators, particularly the diversity of check dam volumes, were ranked highly at the Basin 1 scale. This result suggests that a system composed of multiple check dams with varying sediment-retention capacities is more effective in controlling erosion than a uniform system, as it promotes both localized sediment deposition and broader-scale erosion reduction. At the Basin 2 scale, however, the absolute number of check dams became more important than their diversity, reflecting the fact that at larger catchment extents, the cumulative quantity of structures dominates over fine-scale heterogeneity. Terrace proportion also showed significant contributions in both scales, but with nonlinear effects. Moderate terrace coverage (0.1–0.8 of basin area) was associated with positive elevation changes, supporting slope stabilization and reduced soil loss. Beyond this threshold, SHAP values indicated a negative effect, likely because over-terracing can destabilize slopes, increase maintenance burdens, and lead to reduced effectiveness in controlling erosion. This finding underscores the need to optimize terrace coverage rather than maximize it.

Collectively, these SHAP-derived insights highlight that engineering measures exert significant but context-dependent influences on elevation change. Their effectiveness is strongly moderated by vegetation cover, precipitation regimes, and geomorphic settings. At finer spatial scales, the structure and diversity of engineering interventions (e.g., check dam systems) are critical, whereas at broader scales, overall abundance and distribution patterns dominate.

4. Discussion

4.1. EM Efficiency from the Remote Sensing Perspective

Satellite remote sensing offers a new perspective for regional soil and water conservation research. With the support of abundant data and advanced algorithms, it enables in-depth studies of surface processes at the regional scale. The results indicate that while EMs clearly inhibit erosion, their influence remains lower than that of natural environmental factors. These findings affirm the positive role of EMs, demonstrating that their construction helps mitigate land degradation. However, it is important to recognize that building EMs involves significant costs, and the appropriate scale must be clearly identified before construction. For example, a check dam system, which involves the combination of multiple dams with varying sediment-trapping capacities, has been proven effective at significantly reducing surface erosion [20]. In our Basin 1 analysis, we also found that the diversity of check dam capacity (which can be seen as the complexity of the dam system within a basin) had a significant influence. These results suggest that when addressing land degradation caused by surface erosion, it is crucial to consider the rational construction of check dam systems. At relatively smaller scales (such as Basin 2), however, the proportion of EMs or the number of structures tends to have a more pronounced effect on reducing soil erosion. EMs need to be combined with geographic scale analysis to ensure more reasonable and effective EM construction. This approach would not only increase the efficiency of reducing soil erosion but also allow for better cost management. In this process, satellite remote sensing holds vast potential for application.

Moreover, it should be noted that the relationships identified between elevation changes and influencing factors are correlations and not definitive causal relationships. For example, many check dams were constructed before the 21st century, and these dams are responsible for reduced elevation loss. However, in some basins with numerous check dams, significant elevation loss still occurs, possibly because the dams were constructed in recent years, and their impact is not yet reflected in the DEM data. In such cases, elevation loss may actually be the reason for the construction of additional dams. In future research, incorporating more detailed information (such as the year of check dam construction) could lead to deeper and more comprehensive analyses.

4.2. Limitations and Future Work

In most cases, studies on the influence of EMs are conducted on a small scale. These studies typically rely on site-specific observational data, making it difficult to carry out research on a larger scale. However, the quality of remote sensing data, in terms of accuracy and resolution, has significantly improved over the past few decades. In this study, satellite remote sensing data were used to perform research that traditionally could be conducted only over small areas, offering a viable analytical approach for investigating surface erosion and land degradation. It is important to note, however, that there are uncertainties when satellite-based DEMs are used. First, satellite-acquired DEMs are typically collected over a specific time period (such as several months for global coverage), which means that elevation differences across regions may be influenced by seasonal vegetation changes. Additionally, while we standardized the elevation references of the two DEMs, the inherent errors in the data still introduce limitations in the precision of the elevation changes derived from the DEMs. Nevertheless, since the two datasets used in this study were collected more than a decade apart, these errors are likely to have a minimal effect compared with the observed elevation changes. Meanwhile, the elevation change analysis relies on DEMs collected about a decade apart, which means that very recently constructed engineering measures are not yet reflected in the datasets. This indicates that the elevation loss might be the reason for dam construction in some cases, rather than the result of a lack of dams. For instance, in some sub-basins where erosion has historically been extremely severe, rapid elevation loss may have prompted the urgent construction of multiple check dams in recent decades. In such cases, the elevation decrease recorded in the DEM data predates the dam construction, meaning that the correlation we observe reflects a response to erosion rather than the preventive effect of the dams themselves. While this limits our ability to evaluate the most recent interventions, it should be noted that large-scale engineering projects constructed in the most recent years account for only a small proportion of the total. For studies focusing on short-term elevation changes, however, more detailed validation should be conducted when satellite-derived DEMs are used.

This study is subject to several limitations primarily related to the use of global DEM products and the inherent uncertainties in multi-temporal elevation change detection. Although we unified the vertical and horizontal reference systems of SRTM and Copernicus DEM, we did not perform further vertical registration or correction using ground control points due to the absence of high-density, region-wide, and temporally consistent GCP data. As a result, residual errors—such as small vertical biases, co-registration inaccuracies, and the effects of vegetation and surface changes unrelated to geomorphic processes—may remain. These uncertainties could introduce noise into the elevation change estimates, especially at fine spatial scales or in densely vegetated areas.

Additionally, this study focuses on changes over a period of approximately ten years, which is suitable for long-term research on hydraulic erosion. With respect to short-term changes, several potentially useful data sources have emerged, such as InSAR or the DCM released by the DLR. In any case, the combination of remote sensing data with surface erosion and land degradation research presents a vast field of potential applications and deserves increased attention from researchers. Another source of uncertainty arises from vegetation dynamics. While trees generally do not cause rapid vertical changes, grasses and shrubs can grow quickly and colonize disturbed surfaces within a few years, potentially leading to vertical offsets of up to ± 2 m in DEM differencing. In the Loess Plateau, however, vegetation is mostly sparse, and grass height is relatively low (< 0.5 m), so the aggregate impact on basin-scale elevation change is minor. Nevertheless, in the southern and central regions where patches of protected forest are present, vegetation growth may introduce localized offsetting effects that partially mask true erosion signals. This limitation highlights

the need for more detailed vegetation-structure data (e.g., LiDAR or multi-temporal high-resolution UAV surveys) in future studies to better constrain the role of vegetation in elevation change analyses.

5. Conclusions

This study highlights the potential of integrating multisource remote sensing data with interpretable machine learning to quantitatively assess the impacts of engineering measures on surface erosion mitigation across the Loess Plateau. By combining spectral, textural, and topographic indicators, the proposed framework effectively captured erosion-related surface features and revealed the contributions of engineering measures relative to environmental drivers. The results demonstrate that engineering interventions substantially decrease erosion intensity. In basins with a high proportion of check dams, the mean elevation increased by approximately 2.5 m compared with basins without such measures, whereas terraces in loess hilly regions produced mean elevation gains of ~1.9 m. At smaller scales, the number and proportion of engineering measures were more influential, while at medium scales, the systematic construction and diversity of check dam systems became more critical. These findings provide quantitative evidence for the effectiveness of engineering measures and emphasize the importance of considering spatial scale and ecological context in land management strategies. The interpretable modeling approach ($R^2 = 0.62$ at Basin 1 and $R^2 = 0.73$ at Basin 2) enhances transparency and reliability, offering a valuable reference for large-scale environmental monitoring and sustainable erosion control planning. This work highlights the importance of fusing remote sensing observations with domain-specific knowledge to support large-scale environmental monitoring, land management, and sustainable erosion control strategies.

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References

1. Lal, R. Soil degradation by erosion. *Land Degrad. Dev.* **2001**, *12*, 519–539. [\[CrossRef\]](#)
2. Borrelli, P.; Robinson, D.A.; Panagos, P.; Lugato, E.; Yang, J.E.; Alewell, C.; Wuepper, D.; Montanarella, L.; Ballabio, C. Land use and climate change impacts on global soil erosion by water (2015–2070). *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 21994–22001. [\[CrossRef\]](#) [\[PubMed\]](#)
3. Du, X.; Jian, J.; Du, C.; Stewart, R.D. Conservation management decreases surface runoff and soil erosion. *Int. Soil Water Conserv. Res.* **2022**, *10*, 188–196. [\[CrossRef\]](#)
4. Ran, Q.; Su, D.; Li, P.; He, Z. Experimental study of the impact of rainfall characteristics on runoff generation and soil erosion. *J. Hydrol.* **2012**, *424*, 99–111. [\[CrossRef\]](#)
5. Li, Z.; Zhang, Y.; Zhu, Q.; Yang, S.; Li, H.; Ma, H. A gully erosion assessment model for the Chinese Loess Plateau based on changes in gully length and area. *Catena* **2017**, *148*, 195–203. [\[CrossRef\]](#)
6. Wang, J.; Zhang, Y.; Deng, J.; Yu, S.; Zhao, Y. Long-term gully erosion and its response to human intervention in the tableland region of the Chinese loess plateau. *Remote Sens.* **2021**, *13*, 5053. [\[CrossRef\]](#)
7. Alewell, C.; Rengeval, B.; Ballabio, C.; Robinson, D.A.; Panagos, P.; Borrelli, P. Global phosphorus shortage will be aggravated by soil erosion. *Nat. Commun.* **2020**, *11*, 4546. [\[CrossRef\]](#)

8. Mishra, P.K.; Rai, A.; Abdelrahman, K.; Rai, S.C.; Tiwari, A. Land degradation, overland flow, soil erosion, and nutrient loss in the Eastern Himalayas, India. *Land* **2022**, *11*, 179. [\[CrossRef\]](#)
9. Cantón, Y.; Solé-Benet, A.; de Vente, J.; Boix-Fayos, C.; Calvo-Cases, A.; Asensio, C.; Puigdefábregas, J. A review of runoff generation and soil erosion across scales in semiarid south-eastern Spain. *J. Arid Environ.* **2011**, *75*, 1254–1261. [\[CrossRef\]](#)
10. Borrelli, P.; Robinson, D.A.; Fleischer, L.R.; Lugato, E.; Ballabio, C.; Alewell, C.; Meusburger, K.; Modugno, S.; Schütt, B.; Ferro, V. An assessment of the global impact of 21st century land use change on soil erosion. *Nat. Commun.* **2017**, *8*, 2013. [\[CrossRef\]](#)
11. Quine, T.A.; Van Oost, K. Insights into the future of soil erosion. *Proc. Natl. Acad. Sci. USA* **2020**, *117*, 23205–23207. [\[CrossRef\]](#)
12. Singh, R. *Soil and Water Conservation Structures Design*; Springer Nature: Singapore, 2023; Volume 123.
13. Fang, N.; Zeng, Y.; Ran, L.; Wang, Z.; Lu, X.; Wang, Z.; Yang, X.; Jian, J.; Yu, Q.; Ni, L. Substantial role of check dams in sediment trapping and carbon sequestration on the Chinese Loess Plateau. *Commun. Earth Environ.* **2023**, *4*, 65. [\[CrossRef\]](#)
14. Chauhan, C.; Singh, M.; Vinayak, A.B.; Uday, K.V. Quantification of the effectiveness of mitigation measures on erosion potential of soil with image analysis. *J. Soils Sediments* **2024**, *24*, 98–110. [\[CrossRef\]](#)
15. Ediş, S.; Timur, Ö.B.; Tuttu, G.; Aytaş, İ.; Göl, C.; Özcan, A.U. Assessing the impact of engineering measures and vegetation restoration on soil erosion: A case study in Osmancık, Türkiye. *Sustainability* **2023**, *15*, 12001. [\[CrossRef\]](#)
16. Dorren, L.; Rey, F. A review of the effect of terracing on erosion. In *Briefing Papers of the 2nd SCAPE Workshop*; SCAPE: New York, NY, USA, 2004; pp. 97–108.
17. Arnáez, J.; Lana-Renault, N.; Lasanta, T.; Ruiz-Flaño, P.; Castroviejo, J. Effects of farming terraces on hydrological and geomorphological processes. A review. *Catena* **2015**, *128*, 122–134. [\[CrossRef\]](#)
18. Bussi, G.; Rodríguez-Lloveras, X.; Francés, F.; Benito, G.; Sánchez-Moya, Y.; Sopeña, A. Sediment yield model implementation based on check dam infill stratigraphy in a semiarid Mediterranean catchment. *Hydrol. Earth Syst. Sci.* **2013**, *17*, 3339–3354. [\[CrossRef\]](#)
19. Li, S.; Xiong, L.; Hu, G.; Dang, W.; Tang, G.; Strobl, J. Extracting check dam areas from high-resolution imagery based on the integration of object-based image analysis and deep learning. *Land Degrad. Dev.* **2021**, *32*, 2303–2317. [\[CrossRef\]](#)
20. Haidong, G.; Mengdie, W.; Xinjing, H. Check dams in the Yellow River basin: Sediment reduction efficiency and future development. *Land Degrad. Dev.* **2024**, *35*, 4042–4054. [\[CrossRef\]](#)
21. Li, D.; Tong, Q.; Li, R.; Gong, J.; Zhang, L. Current issues in high-resolution earth observation technology. *Sci. China Earth Sci.* **2012**, *55*, 1043–1051. [\[CrossRef\]](#)
22. NASA JPL. *Shuttle Radar Topography Mission Global 1 Arc Second*; NASA Land Processes Distributed Active Archive Center: Sioux Falls, SD, USA, 2013. [\[CrossRef\]](#)
23. Airbus Defence and Space GmbH. *Copernicus DEM: Copernicus Digital Elevation Model: Product Handbook*; RFP/RFI-No.: AO/1-9422/18/I-LG; Airbus Defence and Space GmbH: Taufkirchen, Germany, 2020; pp. 1–3.
24. Cao, B.; Yu, L.; Naipal, V.; Ciais, P.; Li, W.; Zhao, Y.; Wei, W.; Chen, D.; Liu, Z.; Gong, P. A 30-meter terrace mapping in China using Landsat 8 imagery and digital elevation model based on the Google Earth Engine. *Earth Syst. Sci. Data Discuss.* **2020**, *13*, 2437–2456. [\[CrossRef\]](#)
25. Zeng, Y.; Jing, T.; Xu, B.; Yang, X.; Jian, J.; Zong, R.; Wang, B.; Dai, W.; Deng, L.; Fang, N. Vectorized dataset of silted land formed by check dams on the Chinese Loess Plateau. *Sci. Data* **2024**, *11*, 348. [\[CrossRef\]](#)
26. Lehner, B.; Grill, G. Global river hydrography and network routing: Baseline data and new approaches to study the world's large river systems. *Hydrol. Process.* **2013**, *27*, 2171–2186. [\[CrossRef\]](#)
27. Hartmann, J.; Moosdorf, N. The new global lithological map database GLiM: A representation of rock properties at the Earth surface. *Geochem. Geophys. Geosystems* **2012**, *13*, Q12004. [\[CrossRef\]](#)
28. Börker, J.; Hartmann, J.; Amann, T.; Romero-Mujalli, G. Terrestrial sediments of the earth: Development of a global unconsolidated sediments map database (GUM). *Geochem. Geophys. Geosyst.* **2018**, *19*, 997–1024. [\[CrossRef\]](#)
29. Iwahashi, J.; Yamazaki, D. Global polygons for terrain classification divided into uniform slopes and basins. *Prog. Earth Planet. Sci.* **2022**, *9*, 33. [\[CrossRef\]](#)
30. Peel, M.C.; Finlayson, B.L.; McMahon, T.A. Updated world map of the Köppen-Geiger climate classification. *Hydrol. Earth Syst. Sci.* **2007**, *11*, 1633–1644. [\[CrossRef\]](#)
31. Nachtergaele, F.; van Velthuisen, H.; Verelst, L.; Wiberg, D.; Henry, M.; Chiozza, F.; Yigini, Y.; Aksoy, E.; Batjes, N.; Boateng, E. *Harmonized World Soil Database Version 2.0*; FAO: Rome, Italy, 2023.
32. Potapov, P.; Li, X.; Hernandez-Serna, A.; Tyukavina, A.; Hansen, M.C.; Kommareddy, A.; Pickens, A.; Turubanova, S.; Tang, H.; Silva, C.E. Mapping global forest canopy height through integration of GEDI and Landsat data. *Remote Sens. Environ.* **2021**, *253*, 112165. [\[CrossRef\]](#)
33. Xu, X.; Liu, J.; Zhang, S.; Li, R.; Yan, C.; Wu, S. China's Multi-Period Land Use Land Cover Remote Sensing Monitoring Dataset (CNLUCC). In *Resource and Environment Science Data*; Chinese Academy of Sciences: Beijing, China, 2018. [\[CrossRef\]](#)
34. Yang, Y.; Wang, B.; Wang, G.; Li, Z. Ecological regionalization and overview of the Loess Plateau. *Acta Ecol. Sin.* **2019**, *39*, 7389–7397. [\[CrossRef\]](#)

35. Zhao, G.; Mu, X.; Wen, Z.; Wang, F.; Gao, P. Soil erosion, conservation, and eco-environment changes in the Loess Plateau of China. *Land Degrad. Dev.* **2013**, *24*, 499–510. [\[CrossRef\]](#)
36. Fu, B. Soil erosion and its control in the Loess Plateau of China. *Soil Use Manag.* **1989**, *5*, 76–82. [\[CrossRef\]](#)
37. Hirt, C.; Featherstone, W.; Marti, U. Combining EGM2008 and SRTM/DTM2006.0 residual terrain model data to improve quasigeoid computations in mountainous areas devoid of gravity data. *J. Geod.* **2010**, *84*, 557–567. [\[CrossRef\]](#)
38. Fang, K.; Cai, T. An algorithm for strapdown airborne gravity disturbance vector measurement based on high-precision navigation and EGM2008. *Sensors* **2024**, *24*, 5899. [\[CrossRef\]](#)
39. Desmet, P.J.; Govers, G. A GIS procedure for automatically calculating the USLE LS factor on topographically complex landscape units. *J. Soil Water Conserv.* **1996**, *51*, 427–433. [\[CrossRef\]](#)
40. Peng, S. 1-km monthly precipitation dataset for China (1901–2017). *Earth Syst. Sci. Data* **2024**, *11*, 1931–1946. [\[CrossRef\]](#)
41. Rachunok, B.; Verma, A.; Fletcher, S. Predicting and understanding residential water use with interpretable machine learning. *Environ. Res. Lett.* **2024**, *19*, 014069. [\[CrossRef\]](#)
42. Nikraftar, Z.; Parizi, E.; Saber, M.; Boueshagh, M.; Tavakoli, M.; Esmaili Mahmoudabadi, A.; Ekradi, M.H.; Mbuva, R.; Hosseini, S.M. An Interpretable Machine Learning Framework for Unraveling the Dynamics of Surface Soil Moisture Drivers. *Remote Sens.* **2025**, *17*, 2505. [\[CrossRef\]](#)
43. Sonnewald, M.; Lguensat, R.; Jones, D.C.; Dueben, P.D.; Brajard, J.; Balaji, V. Bridging observations, theory and numerical simulation of the ocean using machine learning. *Environ. Res. Lett.* **2021**, *16*, 073008. [\[CrossRef\]](#)
44. Temenos, A.; Temenos, N.; Kaselimi, M.; Doulamis, A.; Doulamis, N. Interpretable deep learning framework for land use and land cover classification in remote sensing using SHAP. *IEEE Geosci. Remote Sens. Lett.* **2023**, *20*, 8500105. [\[CrossRef\]](#)
45. Mosca, E.; Szigeti, F.; Tragianni, S.; Gallagher, D.; Groh, G. SHAP-based explanation methods: A review for NLP interpretability. In Proceedings of the 29th International Conference on Computational Linguistics, Gyeongju, Republic of Korea, 12–17 October 2022; pp. 4593–4603.
46. Lundberg, S.M.; Erion, G.; Chen, H.; DeGrave, A.; Prutkin, J.M.; Nair, B.; Katz, R.; Himmelfarb, J.; Bansal, N.; Lee, S.-I. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2020**, *2*, 56–67. [\[CrossRef\]](#) [\[PubMed\]](#)
47. Xiao, X.; Zou, Y.; Huang, J.; Luo, X.; Yang, L.; Li, M.; Yang, P.; Ji, X.; Li, Y. An interpretable model for landslide susceptibility assessment based on Optuna hyperparameter optimization and Random Forest. *Geomat. Nat. Hazards Risk* **2024**, *15*, 2347421. [\[CrossRef\]](#)

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