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Studies of Disaster Response and Ecosystem Behaviour in Xiaojiang Fault Zone by Use of Multi-Source Remote Sensing

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Abstract. The unexpectedness and destructive character of geophysical disasters represent a two-fold danger to regional safety and ecosystems. Conventional monitoring tools, including GNSS sites and ground surveys, are limited in scope and slow, making them incapable of fulfilling the requirements of full-chain disaster evaluation. In this research, the authors focus on the Dongchuan segment of the Xiaojiang Fault Zone, which integrates InSAR, LiDAR, and UAV remote sensing to develop a reproducible, integrated technical system for deformation monitoring, disaster identification, and ecological response. With the help of this framework, it would be possible to identify disaster risks repeatedly, quantify disaster-related losses, and conduct ecological assessments throughout the process. It was found that three high-risk landslide hazard areas, totalling 1.2 km², were located within the active fault segment. Simulated post-disaster surface damage was 0.8 km², of which landslides covered 62 per cent of the area. The average landslide volume was 2.3×10^4 m³, and the terrain's roughness increased by 42%. Mean RSEI had reduced to 0.45. NDVI declined with distance to the landslide ($R^2 = 0.68$), and the rate of alteration in runoff paths was 35%. This paper standardised a multi-source remote sensing application workflow, confirmed the effectiveness of collaborative monitoring, and provided data support and reproducibility for disaster prevention and mitigation and ecological restoration in Southwest China.

Keywords: Multi-source remote sensing, Geophysical hazards, Crustal deformation, Ecological response, Xiajiang Fault Zone

1. Introduction

Disasters related to geophysics (i.e., earthquakes and landslides) result from the interaction between crustal motion and surface environmental conditions. Their unpredictable and dangerous character poses a direct threat to human life and assets, and, in addition, causes a series of ecological problems, such as vegetation degradation and landscape alteration [1]. Southwest China, at the Xiaojiang Fault Zone, lies at the boundary of a tectonic plate, where the rate of crustal deformation is 5-15 mm/year, and therefore a geophysical disaster hotspot worldwide. The region is an ecological barrier of the upper Yangtze River basin, whose ecological security is vulnerable to disaster chain reactions, thus requiring accurate disaster monitoring and evaluation of the ecological responses [2].

Traditional monitoring techniques (GNSS stations, ground surveys) have serious technical drawbacks: the GNSS stations are widely spaced, do not cover the entire area of interest, and cannot

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detect small crustal deformation features; ground surveys are slow and labour intensive, severely limited by environmental factors like topography and climate, which is why they cannot be timely and cannot react quickly to the disaster process [3]. Such constraints prevent conventional approaches to help the entire disaster prevention and mitigation chain- pre-disaster warning, during-disaster response, post-disaster assessment - and effective technical support to emergency decision-making. The new technical paradigm of the field is presented by the development of multi-source remote sensing technologies that can complement each other: InSAR is capable of millimeter-level continuous crustal deformation monitoring and accurately measuring the precursor deformation before disasters [4]; LiDAR can generate highly accurate terrain maps and can form the basis of landslide quantification analysis [5]; UAV remote sensing provides great spatial and temporal resolution enabling prompt access to detailed post-disaster surface data [4]. Nevertheless, the current studies tend to focus on either single-technology applications or single disaster types, with no multi-technology collaborative disaster ecology evaluation model being developed. Moreover, the detailed experimental procedures and model computation steps are not defined, so the research results cannot be replicated [6].

As such, this paper combines InSAR, LiDAR and UAV multi-source remote sensing technologies according to the geophysical principles. It is based on the representative study area of the Dongchuan segment of the Xiaojiang Fault Zone, and is designed for conducting a disaster-monitoring and ecological-response study, with an integrated technical system for disaster monitoring that can be replicated by others (deformation monitoring-disaster identification-ecological response). Each stage includes a detailed description of the operations involved, the parameters used, and the substitutions made in the formulas, ensuring that every stage can be repeated in hazard identification, disaster quantification, and ecological response analysis. The methodology presented here provides a precise aid to regional disaster prevention and mitigation, with methodological guidelines for the standardisation of multi-source remote sensing solutions in geophysical disaster research.

2. Data and methods

2.1. Overview of the study area

Xiaojiang Fault Zone - Dongchuan portion (103°15′–103°30′E, 26°00′–26°15′N) is located on the border of the provinces of Sichuan and Yunnan. It has an intricate geological structure and high levels of crustal activity, with an average annual deformation rate of more than 5 mm, making it a high-rate region of geophysical risks, including earthquakes and landslides. The region is part of the subtropical evergreen broadleaf forest ecoregion, characterised by high vegetation cover. It is an important ecological barrier in the upper Yangtze River basin, and its environment is sensitive and fragile, making it a typical dual-sensitivity zone of geophysical hazards and ecological vulnerability. This is why it is a perfect example of multi-source remote sensing collaborative monitoring research.

2.2. Data sources and preprocessing

Every piece of information used in this research was subjected to standardised preprocessing, which included detailed records of the preprocessing software, operational procedures, and essential parameters that would allow the process to be reproduced. The accuracy of the preprocessed data is sufficient to support further analysis. The chosen Sentinel-1 IW-mode imagery (orbit number 148)

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was the one obtained in 2023-2024. The baseline in space-time was set to 12 days in time and 100 meters in space. GAMMA software was used to perform the data preprocessing operations, namely image registration, interferogram generation, terrain phase removal, atmospheric correction, and phase detangling. The error of image registration was limited to 0.1 pixels. Terrain phase removal was done based on SRTM 30m resolution DEM data, atmospheric correction was done based on ERA5 atmospheric grid data, and phase disentanglement was done through the minimum cost flow method. This eventually enabled the extraction of the fields of crustal deformation rates for the study area [6]. The study used 1-meter-resolution point cloud data collected by the RIEGL VQ-1560i airborne LiDAR. Preprocessing was done with CloudCompare software, involving statistical filtering to reduce noise (neighbouring point count: 15; standard deviation threshold: 2.0) > Bouguer filtering to differentiate ground and non-ground points > resampling of rasters to obtain a 2-meter resolution Digital Elevation Model (DEM) to extract terrain parameters and conduct landslide quantification analysis [5]. To obtain 0.1m resolution multispectral images of the study area, a DJI M300 RTK UAV (Zenmuse P1 camera) was used. Image mosaic was finished with Pix4Dmapper (forward overlap: 80%, side overlap: 70%). -> orthorectification -> band processes to create orthoimages and compute the Normalised Difference Vegetation Index (NDVI) with the formula

$$NDVI = (NIR - R) / (NIR + R) \quad (1)$$

NIR is the near-infrared band, and R is the red band [7].

To test the accuracy of the InSAR deformation rate field, GNSS deformation monitoring data applied by the China Earthquake Administration were used. The soil type data at a scale of 1:1,000,000, based on the HWSD database, were clipped and reclassified in ArcGIS to aid in determining the spatial distribution of disaster hazards. The same WGS84/UTM Zone 47N projection was used to project both datasets before their application.

2.3. Research methods

The study develops a combined analytical framework that integrates the concepts of deformation monitoring, disaster identification, and ecological response. All methods define the model equations, variable substitutions, and computational procedures to ensure reproducible experimental procedures and verifiable outcomes. In hazard identification, InSAR data were initially applied to determine the crustal deformation rate field of the study area. Then, terrain factors (slope gradient and aspect) were calculated based on the LiDAR DEM by using ArcGIS surface analysis tools (slope gradient calculated using a 3x3 neighbourhood; aspect categorised as 0°–90° and 270°–360° as sunny slopes, and 90°–270° as shaded slopes). Core input factors were deformation rate, slope gradient, and aspect. These were loaded into SPSS software to create a binary logistic regression model. Its formula is

$$P = 1/(1 + e \hat{} (-(\beta 0 + \beta 1X1 + \beta 2X2 + \beta 3X3))) \quad (2)$$

where P denotes the probability of landslide occurrence (P > = 0.7 refers to high-risk areas), β0 is the model constant term, β1–β3 are the regression coefficients of the respective factors, and X1-X3 are the deformation rate, slope gradient, and slope aspect, respectively.

The object-oriented division of multispectral UAV imagery was used during the disaster-quantification stage to identify post-disaster surface damage, which was classified into landslide bodies, bare ground, and vegetation-damage zones. A DEM differential model was used to estimate

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landslide volume with pre- and post-disaster LiDAR DEMs, where V= $\sum(Ai \times hi)$, V being landslide volume, Ai being each grid area (4m² in the present case), and hi being the difference in elevation between pre- and post-disaster grid cells. At the same time, the Terrain Roughness Index (TRI) was used to measure the changes in the surface morphology, which was computed as

$$TRI = \sqrt{1/8 \sum (hj - h0)^2} \tag{3}$$

where h0 is the elevation of the middle grid cell. Hj is the elevation of the eight surrounding neighbour grid cells.

The construction of the Remote Sensing Ecological Index (RSEI) involved using ecological response analysis to assess ecological quality before and after disasters. It is a combination of four indicators: greenness (NDVI), humidity index, aridity index (NDBSI), and heat index (LST). Each indicator was normalised (0-1) and then reduced by principal component analysis (PCA). The RSEI value was taken to be the first principal component and computed as

$$RSEI = PCA(F(NDVI), F(WET), F(NDBSI), F(LST)) \tag{4}$$

where F(·) is the normalisation function of each indicator.

3. Results

The present chapter will conclude the assessment of crustal deformation monitoring, hazard identification, disaster quantification, and ecological response analysis for the Dongchuan section of the Xiaojiang Fault Zone using available data, methodologies, and experimental procedures. Experimental data are given in standardised tables. Every result was checked three times, replicated, and precision-checked to guarantee the reliability of the data and analytical rigour, as described in the following.

3.1. Crustal deformation and hazard: hidden dangers

The monitoring error of the InSAR deformation rate field was minimised to less than 0.3 mm/year using GNSS data. There is good model performance, as the validation set accuracy of the logistic regression model was 89.6%. The spatial variations in crustal deformation differ across the study zone, as revealed by InSAR monitoring, which can be characterised by overall compressional deformation. There are two notable deformation anomalies in the northeast; one has a deformation rate of 9.2 mm/year, and the other has a rate of 8.7 mm/year, both significantly higher than the region's average annual deformation rate. Using a slope greater than 35 degrees as the high-risk terrain factor, obtained from LiDAR DEM, and a logistic regression model to determine the likelihood of landslide occurrence, three high-risk landslide hazard areas with a total area of 1.2 km² were marked. Hazard zones are all found in the active part of the Xiaojiang Fault Zone, with high spatial overlap with deformation anomalies. These hazard zone boundaries are well correlated with fault structural properties. In Table 1, the detailed experimental data are give.

Table 1. Core experimental data on crustal deformation and high-risk hazard zones

Indicator Type	Specific Content	Value/Result
Deformation Verification Accuracy	GNSS Verification Error	±0.3 mm/year

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Table 1. (continued)

Model Performance	Logistic Regression Model Accuracy	89.6%
Regional Deformation Rate Range	Whole Area Deformation Interval	-12.3 mm/year ~ 4.5 mm/year
Deformation Anomaly Area 1	Coordinate/Deformation Rate	103°22′E, 26°08′N / 9.2 mm/year
Deformation Anomaly Area 2	Coordinate/Deformation Rate	103°25′E, 26°05′N / 8.7 mm/year
No.1 High-Risk Hazard Area	Area	0.42 km²
No.2 High-Risk Hazard Area	Area	0.38 km²
No.3 High-Risk Hazard Area	Area	0.40 km²
Total Area of High-Risk Hazard Areas	Total	1.20 km²

3.2. Disaster quantification results

The precision of object-based classification from drone imagery was 91.2%, and the error in the calculated area was 5% or less. In contrast, the error in the calculated landslide volume was 8% or less, which is sufficient to quantify disasters. The simulated post-disaster surface damage in the study area was 0.8 km², including 0.496 km² of landslide volume (62% of the total damaged area), 0.24 km² of bare ground, and 0.064 km² of vegetation damage. Using DEM-based differential modelling, the mean thickness of landslide bodies in the study area was found to be 4.65 m, with a mean volume of 2.3×10^4 m³. Landslide volume maxed at 3.8×10^4 m³ and min at 0.9×10^4 m³. The average TRI in the study area before the disaster was 18.2, and increased to 25.8 after the disaster, representing a 42 per cent increase. Surface morphological changes were highest in the landslide-affected area, where the TRI rose by 68.3%. In Table 2, particular experimental data is indicated.

Table 2. Core experimental data of disaster quantification

Indicator Type	Specific Content	Value/Result
Classification Model Performance	Support Vector Machine Classification Accuracy	91.2%
Accuracy Verification	Area Error/Volume Error	≤5% / ≤8%
Total Surface Damage Area	Total	0.80 km²
Landslide Area/Proportion	Area/Proportion	0.496 km² / 62%
Bare Land Area	Total	0.24 km²
Vegetation Damage Area	Total	0.064 km²
Average Landslide Thickness	Average Value	4.65 m
Average Landslide Volume	Average Value	2.3×10^4 m³
Maximum/Minimum Landslide Volume	Extreme Values	3.8×10^4 m³ / 0.9×10^4 m³
Pre-disaster Average TRI	Baseline Value	18.2
Post-disaster Average TRI	Measured Value	25.8
Overall TRI Increase Rate	Proportion	42%
TRI Increase Rate in Landslide Areas	Proportion	68.3%
TRI Increase Rate in Bare Land	Proportion	15.7%

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3.3. Ecological response characteristics

The variance contribution rate of the four RSEI component indicators was ≥15%, and the cumulative variance contribution rate was 82.7%, indicating that the principal component analysis was effective. The ecological quality in the research location was severely reduced after the disaster, and the mean RSEI value decreased significantly from 0.72 before the disaster to 0.45 after the disaster. The ecological quality level was downgraded to Poor. Mean NDVI also dropped at the same time and showed a strong negative correlation with landslide distance ($R^2 = 0.68$), implying that vegetation damage was greater near landslide bodies. The event caused the re-organisation of the surface topography and resulted in distinct changes in hydrological conditions in the region. The alteration rates for surface runoff paths were set to 35 per cent. Debris from landslides blocked river channels and altered the direction of runoff, increasing catchment capacity in the area but causing much more severe soil erosion. In Table 3, Spatial heterogeneity in ecological impacts was observed with a core zone centred on the landslide mass and the effects decreasing radially.

Table 3. Core experimental data of ecological response

Indicator Type	Specific Content	Pre-disaster Value	Post-disaster Value	Change Range/Result
Indicator Effectiveness	Cumulative Variance Contribution Rate of Four Indicators	82.7%	-	-
Mean RSEI	Core Index of Ecological Quality	0.72	0.45	Decreased by 37.5%
Proportion of Excellent RSEI Areas	RSEI≥0.8	32.5%	8.9%	Decreased by 23.6 percentage points
Proportion of Good RSEI Areas	0.6≤RSEI<0.8	51.3%	34.7%	Decreased by 16.6 percentage points
Proportion of Poor RSEI Areas	RSEI<0.6	16.2%	56.4%	Increased by 40.2 percentage points
Mean NDVI	Indicator of Vegetation Growth Status	0.68	0.39	Decreased by 42.6%
Correlation Analysis	Correlation Coefficient between NDVI Decline Rate and Distance to Landslides	-	-	r=-0.83
Hydrological Response	Surface Runoff Path Change Rate	-	35%	-
Hydrological Response	Runoff Velocity Change Rate	-	-	Increased by 18.9%

4. Discussion

The paper uses a combination of multi-source remote sensing technologies to develop a reproducible, comprehensive evaluation structure that would overcome the shortcomings of conventional monitoring approaches. The study confirms the feasibility and utility of multi-source remote sensing in disaster-ecology interaction studies, specifically examining the synergistic benefits of the technologies, the scientific implications of the findings, research constraints, and areas for optimisation. Experimental outcomes cannot be repeated.

InSAR and LiDAR integration can effectively address the limitations of single-source remote sensing: InSAR enables accurate monitoring of millimetre-level deformations over large areas and

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detects disaster precursors, and LiDAR provides precise terrain information used as the basis for deformation interpretation and landslide hazard detection. The overall findings correlate with the regional geological structural characteristics and confirm the reliability of the approach. Remote sensing by UAVs contributes to the accuracy of disaster quantification. Nevertheless, limited by endurance and flight range, subsequent efforts ought to incorporate high-resolution satellite-based remote sensing to increase the scale of monitoring and achieve a combination of high-precision and comprehensive monitoring.

The spatial heterogeneity of ecological responses presented in this paper is consistent with findings from studies on ecosystem changes after the Wenchuan earthquake, which confirm the general trends in the effects of geological hazards on ecosystems. Nonetheless, the present research considered only short-term ecological responses and did not account for long-term climate change or human activity; it was difficult to identify long-term trends in ecosystem development. Future research must include longer time-series data to accurately assess the contributions of both disasters and external factors to the ecological impact.

The technical framework developed in this research provides a reproducible paradigm for equivalent research, addressing the problem of ambiguous steps and the irreproducibility of previous research. Nevertheless, the framework does not go beyond landslide disasters. Other hazards, such as debris flows and earthquakes, require optimisation of model input factors and parameters before generalisability can be achieved. Moreover, the study region has been restricted to the section of the Xiaojiang Fault Zone, namely the Dongchuan part. Future studies must extend their boundaries, allow comparison across different regions, confirm the utility of the framework in various geological and ecological settings, and optimise the technical system.

5. Conclusion

This paper will concentrate on the Dongchuan segment of the Xiaojiang Fault Zone, where InSAR, LiDAR, and UAV multi-source remote sensing technologies are integrated to develop a repeatable, integrated technical system that encompasses deformation monitoring, disaster identification, and ecological response. Core results achieved through experimental validation were

The deformation rate field from InSAR is verified by GNSS, with an error of ±0.3 mm/year in the monitoring. The logistic regression model had a validation set accuracy of 89.6 per cent and was quite effective. Two major crustal deformation anomalies were detected in the northeastern part of the study area at the coordinates 103°22 E, 26°08 N and 103°25 E, 26°05 N; their deformation rates were 9.2 mm/year and 8.7 mm/year, respectively, which are significantly higher than the average annual deformation rate of the region. Three high-risk landslide areas were found to cover 0.42 km^2, 0.38 km^2, and 0.40 km^2, totalling 1.2 km^2. All three zones are found in the active section of the Xiaojiang Fault Zone. Analysis of disasters after simulation showed that the total area of surface damage constituted 0.8 km^2, including: - Landslide mass area: 0.496 km^2 (62% of the total damage) - Bare ground area: 0.24 km^2 - Vegetation damage area: 0.064 km^2 Average landslide thickness: 4.65 m Average volume: 2.3×10^4 m^3 Maximum volume: 3.8×10^4 m^3 Minimum volume: 0.9×10^4 m^3 (minimum volume of 0.9×10^4 m^3). Pre-disaster TRI mean was 18.2, which increased to 25.8 post-disaster, an overall increase of 42 per cent, with the landslide body distribution area TRI shooting up by 68.3 per cent. The total variance contribution rate for the four RSEI indicators was 82.7%. After the disaster, the RSEI mean was reduced to 0.45, and the NDVI mean decreased to 0.39. There was a correlation coefficient of 0.68 between the decline in NDVI and landslide distance. The rate of change in surface runoff paths was 35 per cent, the rate of increase in runoff velocity was 18.9 per cent, and the ecological effects were spatially heterogeneous. The developed integrated technical

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framework consisted of standardised processes and predictable outcomes, which enabled comprehensive disaster monitoring and ecological response evaluation throughout the disaster chain.

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Appendix

The model's training and validation sets comprised 70 per cent and 30 per cent of the data, respectively. Model validity was assessed using the ROC curve, which ultimately identified high-risk areas within landslide hazard zones [4]. The corresponding Python code is given below to provide model reproducibility:

```
import pandas as pd
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import roc_auc_score, roc_curve
import matplotlib.pyplot as plt
# Import data (including deformation rate, slope, aspect, landslide label)
data = pd.read_csv("landslide_factors.csv")
X = data[['deformation_rate', 'slope', 'aspect']]
y = data['landslide_label']
# Split training set and verification set (7:3)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,
random_state=42)
# Construct logistic regression model
lr_model = LogisticRegression(random_state=42, max_iter=1000)
lr_model.fit(X_train, y_train)
# Output model parameters
```

```
print("Model constant term β0:", lr_model.intercept_[0])
print("Regression coefficients β1-β3:", lr_model.coef_[0])
# Model verification (ROC curve)
y_pred_prob = lr_model.predict_proba(X_test)[:, 1]
auc = roc_auc_score(y_test, y_pred_prob)
fpr, tpr, _ = roc_curve(y_test, y_pred_prob)
# Plot ROC curve
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, label=f'AUC = {auc:.3f}')
plt.plot([0, 1], [0, 1], 'k--')
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve of Logistic Regression Model')
plt.legend()
plt.savefig("roc_curve.png", dpi=300)
# Identify high-risk areas (P≥0.7)
data['risk_probability'] = lr_model.predict_proba(X)[:, 1]
high_risk_areas = data[data['risk_probability'] >= 0.7]
high_risk_areas.to_csv("high_risk_landslide_areas.csv", index=False)
```

Pre- and post-disaster TRI values were derived, and the difference was used to determine the degree of surface-morphology change due to the disaster [5]. The appropriate Python code looks like this:

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```
import gdal
import numpy as np
# Import pre-disaster and post-disaster DEM data
dem_pre = gdal.Open("dem_pre.tif").ReadAsArray()
dem_post = gdal.Open("dem_post.tif").ReadAsArray()
geotrans = gdal.Open("dem_pre.tif").GetGeoTransform()
pixel_area = geotrans[1] * abs(geotrans[5])  # Area of a single grid
# Calculate elevation difference (hi)
height_diff = dem_pre - dem_post
height_diff[height_diff < 0] = 0  # Set the difference of non-landslide areas to
0
# Calculate total landslide volume
total_volume = np.sum(height_diff) * pixel_area
print(f"Total landslide volume: {total_volume:.2e} m³")
# Calculate Terrain Roughness Index (TRI)
def calculate_tri(dem):
 tri = np.zeros_like(dem)
    for i in range(1, dem.shape[0]-1):
        for j in range(1, dem.shape[1]-1):
            neighborhood = dem[i-1:i+2, j-1:j+2]
            center = dem[i, j]
            diff_sq = (neighborhood - center) ** 2
 tri[i, j] = np.sqrt(np.sum(diff_sq) / 8)
    return tri
tri_pre = calculate_tri(dem_pre)
tri_post = calculate_tri(dem_post)
tri_increase = (tri_post - tri_pre) / tri_pre * 100
print(f"Pre-disaster average TRI: {np.mean(tri_pre):.1f}")
print(f"Post-disaster average TRI: {np.mean(tri_post):.1f}")
print(f"Overall TRI increase rate: {np.mean(tri_increase):.1f}%")
```

The Pearson correlation coefficient between the drop in NDVI and the distance between landslides was analysed using SPSS software. Surface runoff path extraction and the calculation of alteration rates along the runoff path were performed using ArcGIS hydrological analysis tools. The methods provided a comprehensive evaluation of the ecological response behaviour of the disaster [8]. The following is the relevant Python code:

```
import pandas as pd
import numpy as np
from sklearn.decomposition import PCA
from sklearn.preprocessing import MinMaxScaler
import matplotlib.pyplot as plt
# Import four ecological indicators data
indices_data = pd.read_csv("ecological_indices.csv")
X = indices_data[['NDVI', 'WET', 'NDBSI', 'LST']]
# Normalize indicators (0~1)
scaler = MinMaxScaler()
X_normalized = scaler.fit_transform(X)
# Principal Component Analysis (PCA) dimensionality reduction
pca = PCA(n_components=1)
rsei = pca.fit_transform(X_normalized)
indices_data['RSEI'] = rsei
# Calculate the correlation between NDVI decline rate and distance to landslides
indices_data['NDVI_decline'] = (indices_data['NDVI_pre'] -
indices_data['NDVI_post']) / indices_data['NDVI_pre']
corr_coef = np.corrcoef(indices_data['NDVI_decline'],
indices_data['landslide_distance'])[0, 1]
r_squared = corr_coef ** 2
# Plot correlation scatter plot
plt.figure(figsize=(8, 6))
plt.scatter(indices_data['landslide_distance'], indices_data['NDVI_decline'],
alpha=0.6)
plt.xlabel('Distance to Landslide (m)')
plt.ylabel('NDVI Decline Rate')
plt.title(f'NDVI Decline vs Landslide Distance (R²={r_squared:.2f})')
plt.grid(True, alpha=0.3)
plt.savefig("ndvi_correlation.png", dpi=300)
print(f"RSEI cumulative variance contribution rate:
{np.sum(pca.explained_variance_ratio_):.3f}")
print(f"R² between NDVI decline rate and distance to landslides:
{r_squared:.2f}")
```