

Article

Differences and Driving Mechanisms of the Vegetation Dual-Track Recovery Process After Forest Fires Based on the Vegetation Index

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Highlights

What are the main findings?

- Post-fire vegetation recovery showed clear structural–functional asynchrony, with Solar-Induced Chlorophyll Fluorescence indicating slower functional recovery than Enhanced Vegetation Index-based structural greenness.
- Counterfactual Transformer modeling revealed that most burned forests recovered structurally within three years, whereas photosynthetic function remained substantially incomplete.

What are the implications of the main findings?

- Integrating EVI and SIF provides a dual-perspective remote sensing framework for detecting hidden post-fire recovery lags that greenness indices alone may overlook.
- The identified effects of climate, topography, and burn severity offer practical guidance for prioritizing post-fire monitoring, restoration, and forest resilience management.

Abstract

Vegetation recovery after forest fires is a vital indicator of ecosystem resilience. However, the specific differences between structural and functional recovery after fire have remained unclear. In this study, we quantified and compared post-fire recovery using two distinct vegetation indicators: the Enhanced Vegetation Index (EVI) for structural recovery and Solar-Induced Chlorophyll Fluorescence (SIF) for functional recovery. We analyzed the spatiotemporal dynamics and drivers of post-fire recovery. A Transformer model was used to simulate pre- and post-fire variations in EVI and SIF, while a Random Forest model was employed to identify the key drivers of recovery. We analyze the spatiotemporal dynamics and drivers of post-fire recovery. A Transformer model simulates pre- and post-fire variations in EVI and SIF, while a Random Forest model identifies key drivers of recovery. Our results show a steep decline in both indicators after fires, with SIF recovering more slowly than EVI. Three years after the fire, about 78% of burned areas regain at least 80% of their pre-fire EVI levels, but SIF recovery reaches only 70%. Bivariate dependency analysis indicates that precipitation and temperature promote recovery, whereas topography and the Differenced Normalized Burn Ratio (dNBR) have the opposite effect. This study advances a phased, analytical approach to post-fire forest vegetation recovery, offering a dual-perspective framework for understanding forest resilience and providing actionable insights for sustainable restoration and management.

Keywords: forest fires; vegetation recovery; Random Forest model; transformer model



Academic Editor: Luis A. Ruiz

Received: 28 April 2026

Revised: 25 June 2026

Accepted: 28 June 2026

Published: 3 July 2026

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1. Introduction

Forests are a crucial component of the biosphere, storing carbon and providing essential ecosystem services [1,2]. Fire is a recurring disturbance that, when combined with climate change, land-use shifts, and biological invasions, profoundly alters forest ecosystems [3–5]. Recent mega-fires, such as the Black Summer in Australia (2019–2020) and those in Canada in 2023, vividly demonstrate fire’s capacity to disrupt forest structure, function, and resilience [6,7]. The increasing frequency and severity of these events, driven by human activities and climate change, threaten forest recovery and the continuity of ecosystem services [8–11]. Given these challenges, it is crucial to focus on understanding post-fire forest recovery, which is essential for maintaining ecosystem resilience and informing effective management strategies [12].

Although researchers have conducted numerous studies on vegetation recovery processes, the recovery mechanisms of different vegetation communities in various geographic environments remain unclear. Remote sensing vegetation indices, such as leaf area index (LAI), normalized vegetation index (NDVI), enhanced vegetation index (EVI), and solar-induced chlorophyll fluorescence (SIF), which are sensitive to forest vegetation recovery, have been widely used in ecological monitoring and vegetation change analysis [13–15]. These studies have generally explored post-fire vegetation recovery by comparing individual vegetation indices to pre-fire vegetation levels. However, relying on a single vegetation index may not fully capture the differences between structural recovery and functional recovery. The recovery of vegetation after fires is influenced by various factors, among which temperature and precipitation are key determinants of forest vegetation communities. Several studies have revealed significant differences in limiting factors and vegetation recovery after forest fires across regions [16–19].

Through literature comparison studies, controversy has arisen over the duration of vegetation recovery in previous research. This controversy is mainly due to three reasons. Firstly, different vegetation types exhibit varying resilience to forest fires [20]. Secondly, the natural environment influences post-fire vegetation recovery [21,22]. Thirdly, it is unclear which indicators best characterize the restoration of vegetation [23]. Post-fire vegetation recovery includes both structural recovery, such as canopy greenness, and functional recovery, such as photosynthetic activity. Understanding these stages is crucial for forest carbon cycling and management. However, the recovery of forest vegetation structure and function after fire remains unclear. In particular, whether structural and functional recovery occur synchronously across different vegetation and soil types, and how their recovery is jointly regulated by climatic, topographic, soil moisture, and fire severity factors, remains insufficiently understood.

To investigate the impact of forest fires on vegetation and its subsequent recovery, this study employed a two-dimensional analytical framework. It combines the EVI (representing vegetation structure) and the SIF (representing photosynthetic function). By integrating these two indices, the study captures both the structural and functional aspects of post-fire vegetation dynamics. A Transformer-based time-series model was applied to analyze temporal fluctuations in EVI and SIF and to reconstruct the no-fire baseline to quantify post-fire deviations. Previous research has focused on the primary factors driving the recovery of entire forest ecosystems, often overlooking how different vegetation and soil types affect recovery after fires. This study addresses these gaps by examining differences in post-fire recovery among broad forest vegetation formations and the influence of various driving factors on this process. Here, vegetation formations refer to major forest vegetation types, including evergreen needleleaf forest, deciduous needleleaf forest, evergreen broadleaf forest, deciduous broadleaf forest, and mixed forest. We selected 18 typical forest fires from the Americas, Europe, Australia, and Asia, each with large, clearly defined burned areas

and limited to a single occurrence within a 9-year window (the fire year, 4 years prior, and 4 years after). This design rules out the effects of multiple fires. We used a Random Forest model to identify the dominant driving factors and quantify their contributions across soil and vegetation types.

This study proposes a phased, analytical approach to post-fire forest vegetation recovery. The findings could provide scientific support for targeted and differentiated restoration strategies. By linking structural and functional recovery with vegetation type, soil conditions, climate, topography, and fire severity, this study provides a basis for more targeted post-fire restoration strategies under different ecological contexts.

2. Materials and Methods

2.1. Selection of Forest Fires

We selected 18 representative forest fires globally (Figure 1), located across different climate zones. Fire events were selected according to the following criteria: (1) the burned area was large and spatially continuous; (2) the fire perimeter was clearly identifiable; (3) the burned area was dominated by forest vegetation; (4) no repeated fire occurred within the nine-year study window; and (5) complete EVI, SIF, meteorological, topographic, soil, and burn-severity data were available. The absence of repeated fires was verified using burned-area products and fire perimeter records within the study period. For transparency and reproducibility, key information for each fire event, including fire year, location, burned area, dominant vegetation type, dNBR-derived burn-severity range, and the FireCCI51 annual burned-area records used to verify the absence of repeated fires within the nine-year study window, is summarized in Table 1. This approach eliminates the impact of recurrent fires on vegetation recovery. Cases are widely distributed in Asia, Europe, the Americas, and Australia, covering major global forest regions. We chose a study period of four years before and after each fire, for a total of nine years. This period allows us to analyze changes in vegetation indices and assess ecosystem resilience after forest fires. The selected fires cover 4,841,321 grids, each with a spatial resolution of $0.0022^\circ \times 0.0022^\circ$ in the WGS84 coordinate system, corresponding to more than 500 m. Using these cases, this study aims to reveal how vegetation recovers after forest fires.

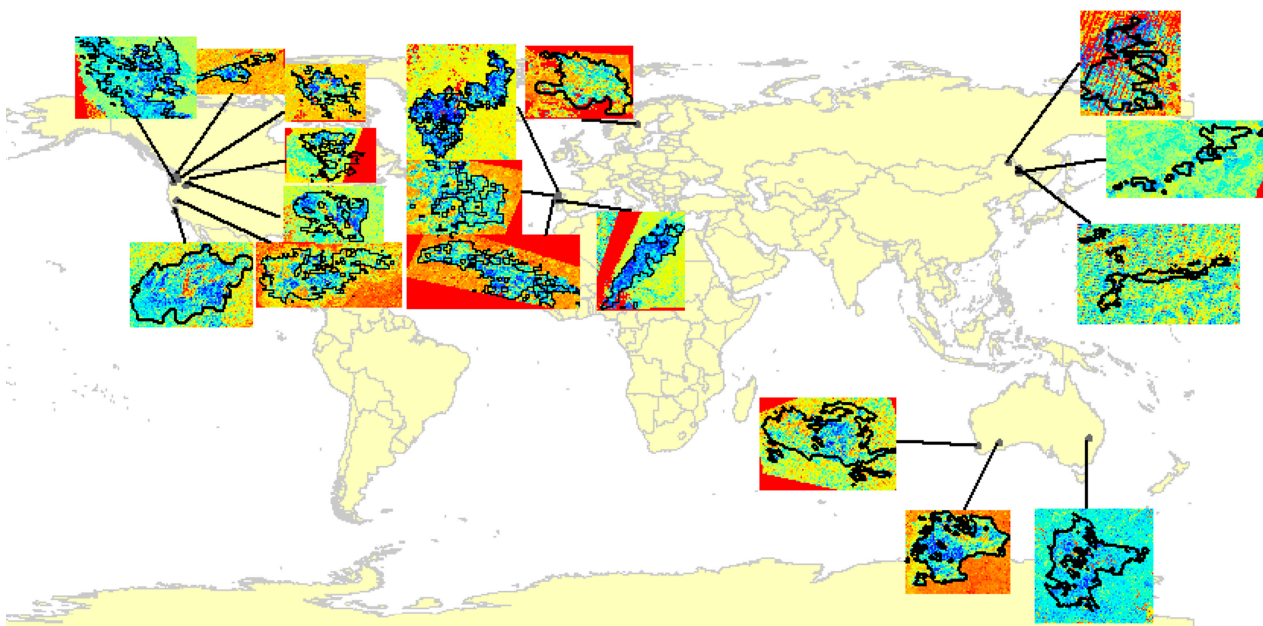


Figure 1. Forest fires and their location information.

Table 1. Sampling information on the fire-burned area.

ID	Time	Longitude	Latitude	dNBR min	dNBR max	Burned Area (km ²)	Dominant Tree Species
AU1	2015.11	122.64	−32.23	−0.0061	0.4944	781.11	<i>Eucalyptus salubris</i>
AU2	2016.01	116.05	−32.43	0.3163	1.1500	651.14	<i>Eucalyptus marginata</i>
AU3	2018.01	149.35	−30.35	0.0346	1.0789	1755.62	<i>Callitris glaucophylla</i>
CN1	2016.05	124.75	51.39	−0.0455	0.5962	852.33	<i>Larix gmelinii</i>
CN2	2010.10	128.50	48.64	0.0279	0.3144	105.55	<i>Pinus koraiensis</i>
CN3	2015.10	128.37	48.98	0.2459	0.7698	112.34	<i>Pinus koraiensis</i>
EU1	2017.06	−8.16	39.97	0.3912	1.1390	961.69	<i>Eucalyptus globulus</i>
EU2	2017.10	−8.92	39.91	0.3953	1.1945	380.13	<i>Pinus pinaster</i>
EU3	2016.08	−8.16	40.95	0.2535	1.1669	315.99	<i>Eucalyptus globulus</i>
EU4	2016.08	−8.36	40.57	0.2325	1.0777	161.07	<i>Eucalyptus globulus</i>
EU5	2018.07	15.35	61.95	0.1126	1.4142	271.06	<i>Pinus sylvestris</i>
US1	2018.11	−121.52	39.77	−0.0570	1.1363	1752.62	<i>Pinus ponderosa</i>
US2	2015.08	−117.75	44.57	0.1947	1.0103	517.64	<i>Pinus ponderosa</i>
US3	2015.09	−121.35	46.22	−0.0132	1.1685	267.77	<i>Pseudotsuga menziesii</i>
US4	2015.09	−118.57	44.26	0.0428	1.1889	773.08	<i>Pinus ponderosa</i>
US5	2017.09	−121.37	46.49	0.0568	1.7173	634.51	<i>Pseudotsuga menziesii</i>
US6	2017.09	−121.91	45.61	0.1244	1.7748	1072.47	<i>Pseudotsuga menziesii</i>
US7	2016.08	−121.78	36.36	0.1926	1.1360	995.99	<i>Sequoia sempervirens</i>

2.2. Data Sources

2.2.1. Vegetation Index Data

Enhanced Vegetation Index (EVI) and Solar-induced Chlorophyll Fluorescence (SIF) were selected to represent two complementary aspects of forest vegetation recovery after fire. Specifically, EVI serves as a structural indicator, derived from canopy reflectance [24], that captures changes in vegetation greenness, canopy density, and biomass, while SIF functions as a functional indicator by directly reflecting photosynthetic activity through quantification of chlorophyll fluorescence during photosynthesis [25]. Thus, EVI highlights structural recovery, and SIF indicates functional status, underscoring their complementary roles. The study integrates these indicators by analyzing EVI and SIF in parallel for each site and time point. This enables a two-dimensional framework that jointly tracks the structural regrowth and functional recovery of vegetation. EVI data were sourced from monthly MOD13A3.061 vegetation index products on Google Earth Engine (GEE) at 1 km resolution. Monthly means were calculated from all overlapping MOD13A2 products, weighted by data quality and temporal proximity. SIF was obtained from the National Tibetan Plateau Data Center [26] and serves as an approximation of the total primary productivity of terrestrial ecosystems. These data are modeled using a neural network with MODIS reflectance and SIF observations, generating SIF values at high spatial ($0.05^\circ \times 0.05^\circ$) and temporal (4-day) resolution. The original SIF data were provided at 4-day temporal resolution. To match the monthly EVI product, all 4-day SIF images were first assigned to calendar months according to the year and day-of-year information in their filenames. For each month, all available SIF images were averaged pixel-by-pixel to generate monthly mean SIF composites. Thus, both EVI and SIF were analyzed at a consistent monthly temporal scale, which is appropriate for characterizing post-fire recovery trajectories rather than short-term physiological fluctuations.

EVI is derived from MODIS broadband reflectance, utilizing an algorithm that reduces atmospheric and soil background effects by utilizing blue and infrared bands. Additionally, EVI maintains high sensitivity in areas with medium to high-density vegetation. Therefore, it is recognized as one of the best proxy variables to characterize the plant community status of the vegetation canopy—namely, horizontal coverage, leaf area index, and green biomass changes. In contrast to EVI, SIF directly detects the far-red fluorescence emit-

ted by chlorophyll molecules during photosynthesis. Unlike EVI, SIF reflects the actual, intrinsic physiological activities of plants in real time at the leaf or even cellular scale. SIF is highly coupled with instantaneous changes in gross primary productivity (GPP) and is relatively unaffected by the saturation effect of community structure. Put simply, while EVI reflects whether vegetation regrows after a forest fire and the extent of coverage restored, SIF further reveals whether the regrown vegetation is healthy and whether photosynthetic activity has recovered. Together, this dual-track monitoring strategy, combining “coverage–photosynthetic activity,” can more comprehensively and promptly identify the asynchronous recovery trajectories of ecosystem structure and function. This approach, compared with relying solely on NDVI, LAI, or GPP, provides more robust, mechanistic remote-sensing evidence for post-fire ecological assessment. In addition, EVI and SIF differ in their seasonal responses. EVI mainly reflects seasonal changes in canopy greenness and vegetation structure, whereas SIF is mainly related to photosynthetic activity and affected by phenological processes such as leaf development and senescence. Therefore, these seasonal differences may cause EVI and SIF to show different recovery trajectories when characterizing post-fire structural and functional recovery.

2.2.2. Meteorological Data

Meteorological data used in this study include 2 m temperature (2 m above ground), precipitation, LST, and soil moisture content from the ERA5-Monthly Terrestrial Aggregates-ECMWF Climate Reanalysis product on GEE, with a monthly temporal resolution and a spatial resolution of 11.1 km. ERA5-Land has been produced by replaying the land component of the ECMWF ERA5 climate reanalysis.

2.2.3. Topographic Data

Digital Elevation Model (DEM) data for this study were obtained from the Shuttle Radar Topography Mission (SRTM) dataset, which was provided by the US Geological Survey (USGS). The dataset has a spatial resolution of 30 m and covers the globe. Slope and aspect data are computed using relevant Geographic Information Systems (GIS) algorithms based on the DEM.

2.2.4. Vegetation Type and Soil Type Data

The vegetation type data were sourced from the GEE MCD12Q1.061 MODIS Land Cover Type product. Based on the reclassified vegetation-type data, the burned areas in this study primarily encompassed five broad vegetation types: Shrublands, Evergreen Broadleaf Forests, Deciduous Broadleaf Forests, Evergreen Needleleaf Forests, and Deciduous Needleleaf Forests. To provide additional ecological context for interpreting post-fire vegetation recovery, we further summarized the dominant tree species for each fire event by geographic location and regional forest composition. These species represent contrasting forest community types and functional strategies, including broadleaf evergreen forests, deciduous and evergreen coniferous forests, and species with different regeneration and resprouting capacities. This information was used to support the ecological interpretation of the observed differences in structural and functional recovery among fire events. The soil type data were compiled from the World Soil Database, developed by the FAO, IIAS, NSLRI, and the Joint Research Center of the European Commission.

2.2.5. Fire Intensity Data

The assessment of fire intensity relies on calculating the Normalized Burn Ratio (NBR) and its variation (dNBR) using OLI/TIRS sensor data from the Landsat 8 satellite (LANDSAT/LC08/C02/T1_L2).

To ensure spatial consistency across multi-source datasets, all raster variables were projected to the same coordinate system and resampled to a common 500 m grid prior to analysis. The dNBR raster was used as the reference layer because it directly represents fire-induced disturbance and defines the spatial units of burned-area analysis. Continuous variables, including EVI, SIF, LST, temperature, precipitation, soil moisture, elevation, slope, and aspect, were resampled to the dNBR grid using bilinear interpolation or pixel-level averaging. In contrast, categorical variables, such as soil type and vegetation cover type, were resampled using the nearest-neighbor method to preserve class labels. All explanatory variables and recovery indicators were then extracted based on the 500 m dNBR grid.

2.3. Methodology

2.3.1. The Vegetation Index Prediction After Fire Based on Transformer Modeling

The Transformer is a deep learning model that uses its self-attention mechanism to capture long-range dependencies, process historical data, and generate predictions using an encoder–decoder architecture [27]. The Transformer model was used to reconstruct counterfactual vegetation-index trajectories under a no-fire scenario. In contrast to direct post-fire observations, this counterfactual prediction represents the expected vegetation condition driven by historical vegetation dynamics and meteorological forcing in the absence of wildfire. Separate models were trained for each fire event, vegetation type, and target vegetation index, including EVI and SIF. For each target variable, the input features included monthly precipitation, air temperature, the previous 24 monthly observations of the target vegetation index, 12-month-lagged precipitation, 12-month-lagged temperature, and two seasonal harmonic terms. Compared with a simple seasonal baseline model that estimates vegetation conditions only from the mean seasonal cycle of the pre-fire period, the Transformer model incorporated actual monthly precipitation and air temperature, lagged meteorological variables, and seasonal harmonic terms. Therefore, it could adjust the counterfactual vegetation index prediction in response to interannual climatic variability rather than relying solely on fixed monthly averages. The seasonal terms were calculated as sine and cosine transformations of calendar months to represent the annual cycle in monthly vegetation dynamics. This process produced 30 input features for each monthly record, which were then scaled to the range $[-1, 1]$ using MinMax normalization. The training period included only pre-fire observations, whereas the prediction period started from the first post-fire month. The 4-year post-fire prediction window was selected to characterize early- to medium-term vegetation recovery. This window provided 48 monthly observations for evaluating post-fire trajectories and enabled consistent comparison across all 18 fire events, while reducing potential confounding effects from repeated fires, land-cover conversion, or longer-term climatic shifts. Therefore, the 4 years were considered sufficient to assess early- to medium-term recovery patterns, although longer-term recovery beyond this period may occur in some forests. A sliding-window strategy was used to construct supervised samples, in which the previous 24 months were used to predict the vegetation index of the following month. The model was implemented as an encoder-only Transformer for time series. The input feature vector was first projected to a hidden dimension of 64 using a fully connected layer. Sinusoidal positional encoding was then added to retain temporal order information. The Transformer encoder consisted of three encoder layers, each with four self-attention heads, a feed-forward dimension of 256, a dropout rate of 0.2, residual connections, and layer normalization. The final hidden state of the sequence was passed to a prediction head consisting of a linear layer, ReLU activation, dropout, and a final linear layer to generate the vegetation index prediction. Model training was performed using the AdamW optimizer with a learning rate of 3×10^{-4} . Other AdamW parameters followed the PyTorch (V1.13.1) default settings. The

model was trained for 400 epochs. Each model was trained in a full-batch manner, and the effective batch size equaled the number of training samples generated from the pre-fire sliding-window sequences for each event-specific model. The training objective was the Huber loss function as Equation (1):

$$L_{\delta}(y - \hat{y}) = \begin{cases} \frac{1}{2}(y - \hat{y})^2, & |y - \hat{y}| \leq \delta \\ \delta |y - \hat{y}| - \frac{1}{2}\delta^2, & |y - \hat{y}| > \delta \end{cases} \quad (1)$$

where y is the observed vegetation index, $\hat{y}$ is the predicted vegetation index, and δ controls the transition from squared error to absolute error. Given that the target variable was normalized to $[-1, 1]$, this threshold corresponds to 50% of the normalized target range. After training, recursive prediction was conducted for the post-fire period. During the post-fire counterfactual prediction, the actual monthly precipitation and air temperature observed after fire were used as dynamic meteorological inputs, rather than assuming constant pre-fire climatic conditions. In addition, seasonal harmonic terms were included to account for intra-annual phenological cycles. Therefore, the predicted no-fire baseline represents the expected vegetation trajectory under the actual post-fire meteorological conditions but without fire disturbance. The last pre-fire 24-month sequence was used as the initial input. For each subsequent month, the predicted vegetation-index value was inserted back into the input sequence, while the corresponding meteorological variables were retained, allowing the model to generate a continuous no-fire counterfactual trajectory. Prediction uncertainty was estimated using Monte Carlo dropout. Specifically, dropout was kept active during inference, and 100 stochastic forward passes were performed for each prediction step. The mean prediction was used as the counterfactual vegetation-index estimate, while the 2.5th and 97.5th percentiles were used as the lower and upper bounds of the 95% uncertainty interval (Figure 2).

Compared with traditional recurrent models, the Transformer can more efficiently capture long-range temporal dependencies through self-attention. The use of Monte Carlo dropout further enabled uncertainty estimation for the counterfactual predictions, thereby supporting a more reliable assessment of post-fire recovery trajectories.

2.3.2. Contribution Analysis of Driving Factors for Post-Fire Vegetation Recovery Based on the Random Forest Model

Random Forest (RF) is an ensemble learning model that constructs multiple decision trees and aggregates their predictions, making it suitable for quantifying nonlinear relationships between post-fire recovery and multiple environmental drivers [28,29]. In this study, we aimed to analyze how different soil and vegetation cover types affect post-fire vegetation recovery by applying a Random Forest model. To do so, we first reclassified preprocessed data from 18 fires based on soil types (defined by the World Reference Base for Soil Resources, WRB) and vegetation cover types. Next, we constructed Random Forest models separately for each soil and vegetation cover type, enabling us to identify the key factors influencing vegetation recovery.

During model training, we selected input features covering climatic, topographic, and fire-related variables. Specifically, we included dNBR, LST, air temperature, precipitation, soil moisture content, post-fire recovery time (RT), elevation, slope, and aspect. The dNBR reflects the immediate impacts of a fire, while precipitation, temperature, and soil moisture indicate the conditions for hydrothermal recovery. Additionally, elevation, slope, and aspect significantly impact the microclimate and soil. Together, these variables represent the complexity of post-fire vegetation regeneration.

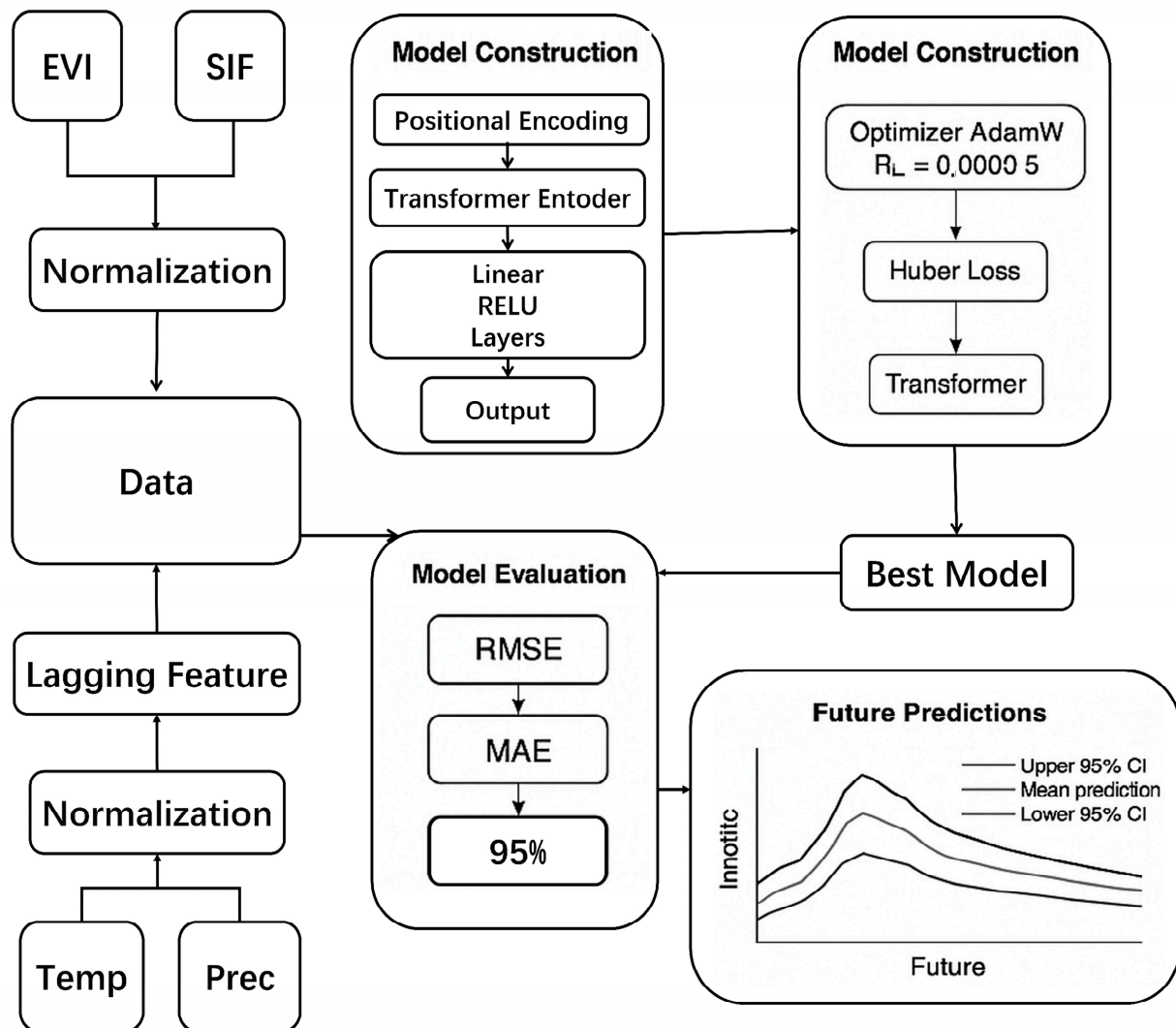


Figure 2. The transformer model framework for time series vegetation index prediction.

The first step is data preprocessing, which begins by using the distribution data for selected typical burned areas as the base map. All raster layers were projected, resampled to 500 m, and aligned with the dNBR-based burned-area grid to ensure spatial consistency. Once this foundation is established, all acquired data are projected uniformly, and the corresponding data are extracted to ensure spatial consistency. In subsequent steps, each raster pixel was treated as an independent sample, and the corresponding vegetation index and driving factor values were extracted within each burned area. To eliminate the effect of differing climatic conditions on model training, key indicators such as temperature, LST, EVI, and SIF are normalized. Furthermore, given significant regional variations in precipitation, temperature, and vegetation, the relevant indicators are standardized for each fire. The specific normalization formula is as follows (Equation (2)):

$$\alpha = \frac{x - \mu}{\sigma} \quad (2)$$

where α is the normalized value, x is the input value, μ is the mean, and σ is the standard deviation. The preprocessed dataset was divided into a 75% training set and a 25% test set. Random division ensured the data's randomness and representativeness. The RF model was implemented using the TreeBagger function with 100 trees. The out-of-bag

(OOB) [30] permutation importance was used to evaluate the relative contribution of each driving factor.

Model performance was measured using root mean square error (RMSE) and the coefficient of determination (R^2). Feature importance analysis validated the impact of each driver on the target variable. Using OOB importance, we quantified each feature's contribution to model predictions. The specific experimental flow is as follows (Figure 3):

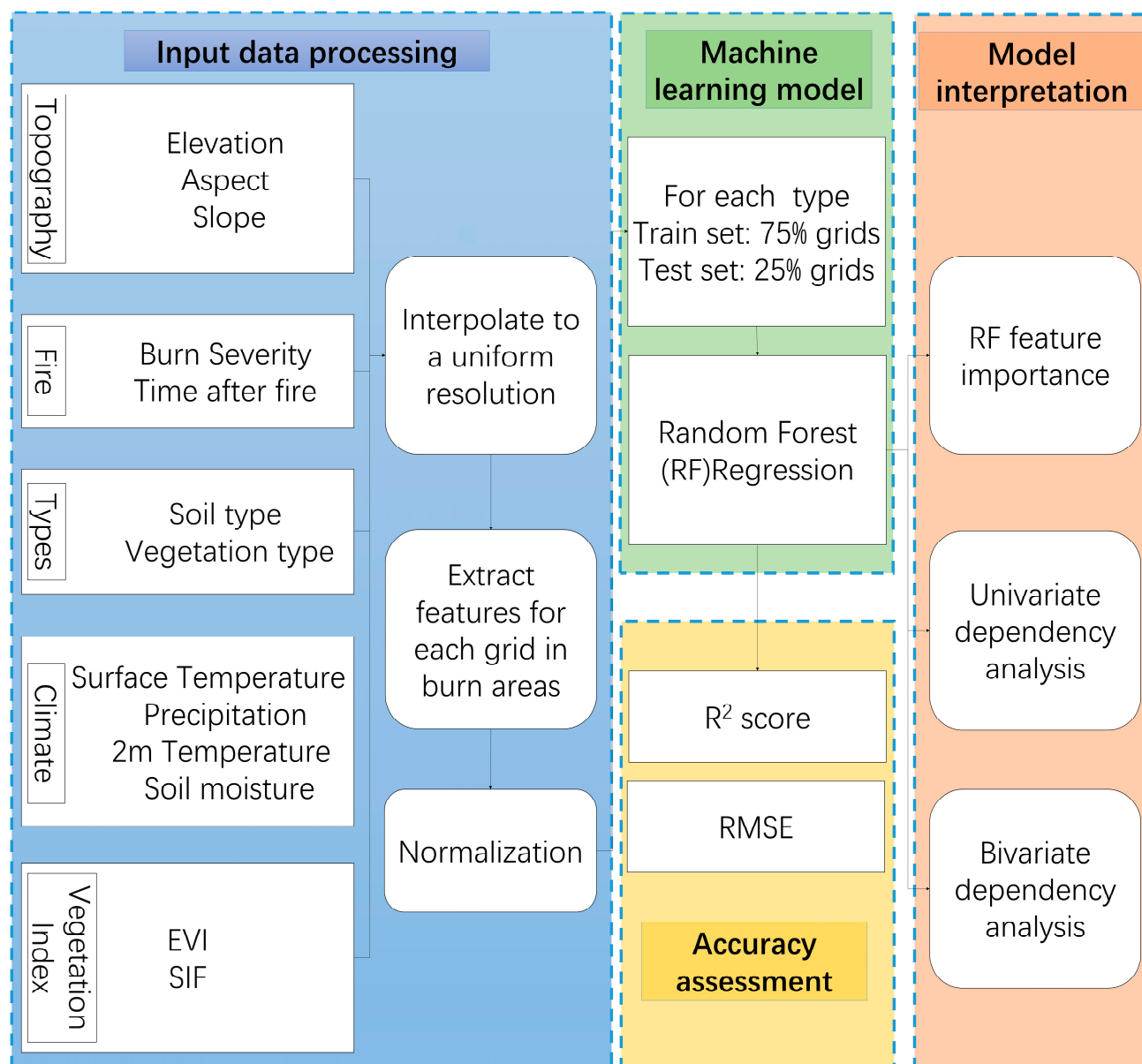


Figure 3. Random Forest model workflow.

3. Results

3.1. The Loss and Recovery of EVI and SIF in Post-Fire Forest Vegetation

This study conducted a time-series analysis of two indicators (EVI and SIF) across 18 large-scale forest fires. The Transformer-derived counterfactual predictions were used as no-fire baselines and were compared with post-fire observations to quantify vegetation loss and recovery. To minimize the influence of seasonal phenology, each post-fire observed EVI or SIF value was compared with the corresponding counterfactual prediction for the same fire event and the same calendar month. Seasonal harmonic terms were also included

in the Transformer model to account for regular seasonal variations in vegetation indices. Therefore, the differences between observed and predicted values mainly reflected fire-induced deviations from the expected seasonal trajectory. Figure 4 shows the regression scatter plot of predicted versus actual values using the transformer model for time series forecasting. The average R^2 for EVI prediction was 0.948. The SIF prediction was 0.965. These values indicate that the model reliably reconstructed vegetation index dynamics prior to the fire. The high prediction accuracy suggests that the Transformer model not only captured the seasonal vegetation cycle but also provided additional predictive ability by incorporating observed meteorological variability, which is not represented in a simple seasonal baseline model based only on monthly climatological means.

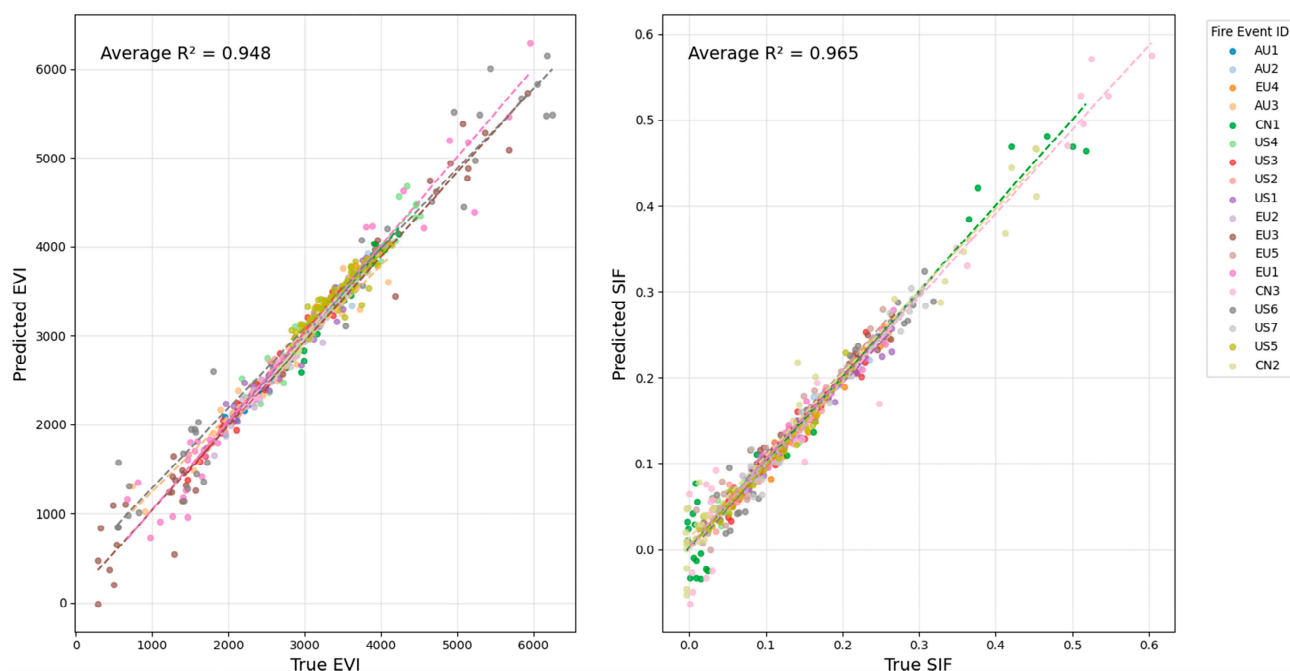


Figure 4. Model performance of the Transformer-based vegetation-index prediction. Scatter plots compare observed and predicted EVI and SIF values across the training samples. The coefficient of determination (R^2) was used to evaluate prediction accuracy.

After fires, both EVI and SIF of forest vegetation decrease sharply in the year following the fire. EVI drops to 45–60% of its predicted value and SIF to 40–55%. Four years after a fire, 61% of burned areas have restored EVI to pre-fire levels, and an additional 17% have nearly recovered. These results are consistent with a previous study [31]. SIF recovery lags behind EVI. Three years after a fire, 85% of burned areas reach 80% of their original vegetation levels, but SIF usually recovers to only 70% of its original level. Ecologically, this difference suggests that the apparent recovery of canopy greenness may overestimate the recovery of ecosystem function. Although vegetation structure may largely recover within a few years, photosynthetic activity and carbon uptake capacity remain impaired, implying a delayed recovery of post-fire ecosystem functioning. Figure 5 illustrates that the first three years following the fire are characterized by rapid vegetation recovery. However, recovery trends clearly differ between fire cases.

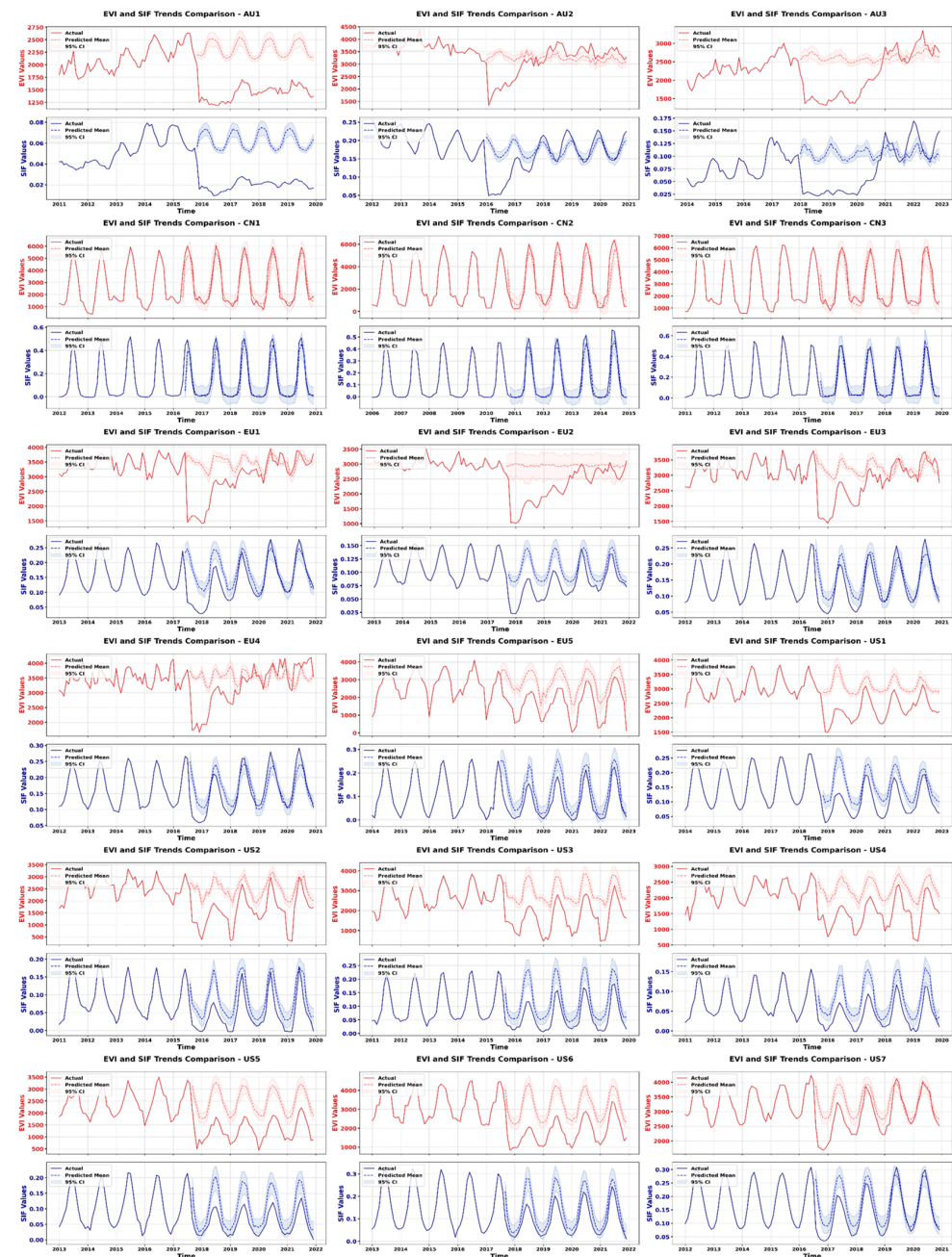


Figure 5. Monthly series of observed and predicted vegetation indices after a fire. Observed EVI and SIF values in burned areas were compared with Transformer-predicted no-fire baselines. The difference between the observed and predicted trajectories represents the vegetation loss and recovery process after fire.

The fitted Logistic curves indicated that recovery indices across the 18 fire events followed clear nonlinear trajectories, suggesting that post-fire vegetation recovery was characterized by rapid early recovery followed by gradual stabilization rather than a linear increase (Figure 6). Recovery rates differed substantially among events, with k ranging from 0.0256 to 5.0000. US5 showed the slowest recovery, whereas CN1 exhibited the fastest recovery, indicating strong spatial heterogeneity in post-fire recovery dynamics. Overall, 44.7% of the burned forest areas recovered within 1–3 years, while 22.2% required more than six years. Three fire events in China reached $RI = 0.90$ within one year, which may be related to vegetation regeneration capacity, favorable climatic conditions, and strict fire management. Among the vegetation indicators, SIF generally recovered more slowly than

EVI, particularly in fires with prolonged recovery trajectories, defined here as events in which vegetation recovery did not reach the selected recovery threshold within the early post-fire period. In these cases, the time required for SIF to reach a comparable recovery level was more than 1.5 times that required for EVI.

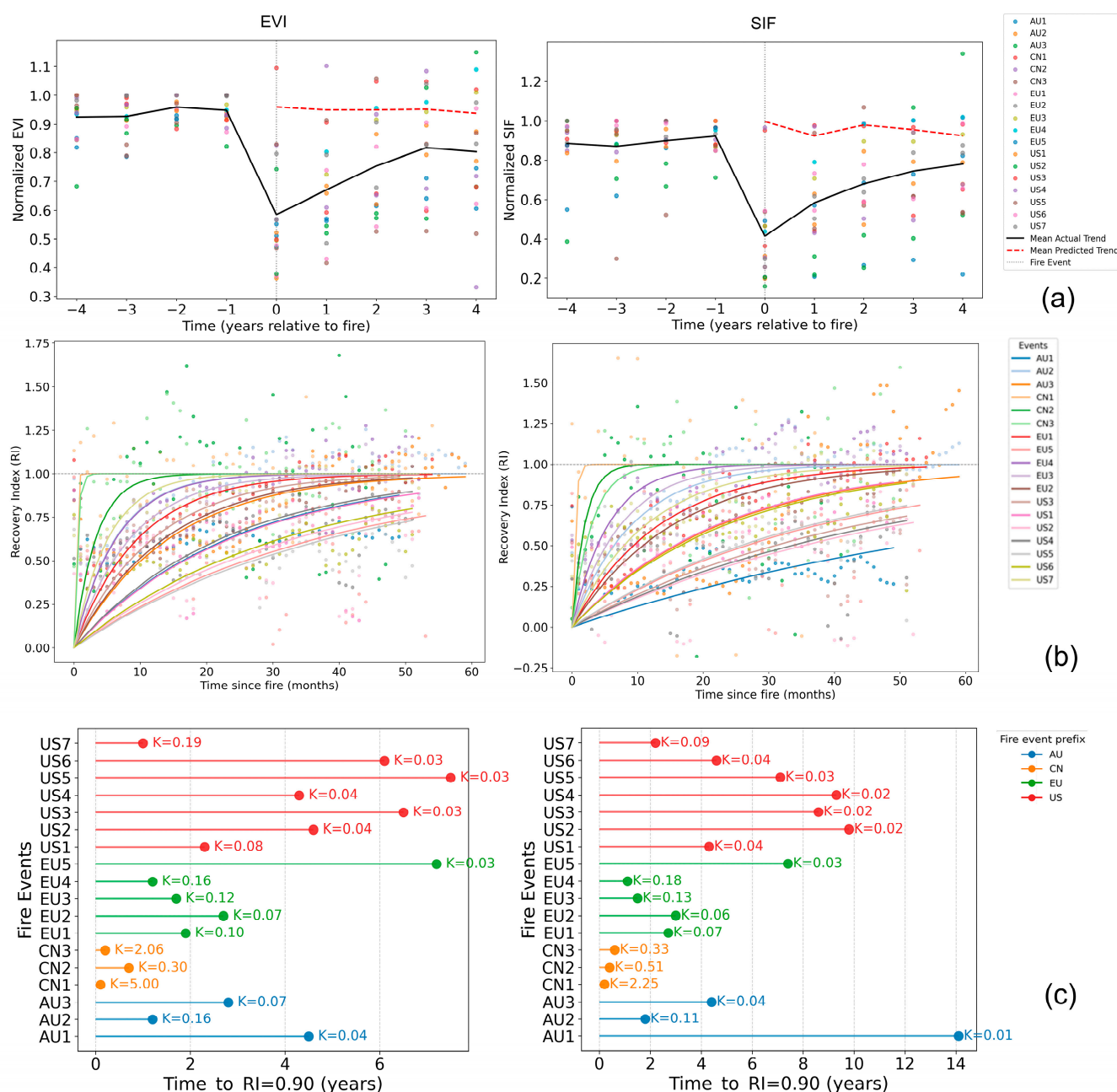


Figure 6. Logistic fitting of post-fire vegetation recovery trajectories. (a) Normalized monthly EVI and SIF recovery trajectories after fire; scatter points represent observations from individual fire events, and the black solid line indicates the mean recovery trajectory. (b) Logistic recovery curves fitted for each fire event. (c) The estimated time required for the recovery index (RI) to reach 0.90. The parameter k represents the fitted recovery rate, with higher k values indicating faster recovery.

3.2. Importance Analysis of Driving Factors for Vegetation Recovery After Forest Fires

Using the RF model, we first evaluated the drivers of changes in vegetation EVI and SIF across different soil types. Figure 7 reveals the importance of various factors for post-fire EVI and SIF recovery across different soil types. The most influential feature is 'DEM,' which accounts for approximately 20% of the feature importance among the

nine driving factors. The following are fire-related factors: dNBR accounts for 19%, and post-fire recovery time for 14%, both showing high importance across all soil types. These results indicate that topography, fire severity, and recovery time jointly controlled post-fire vegetation recovery across soil types.

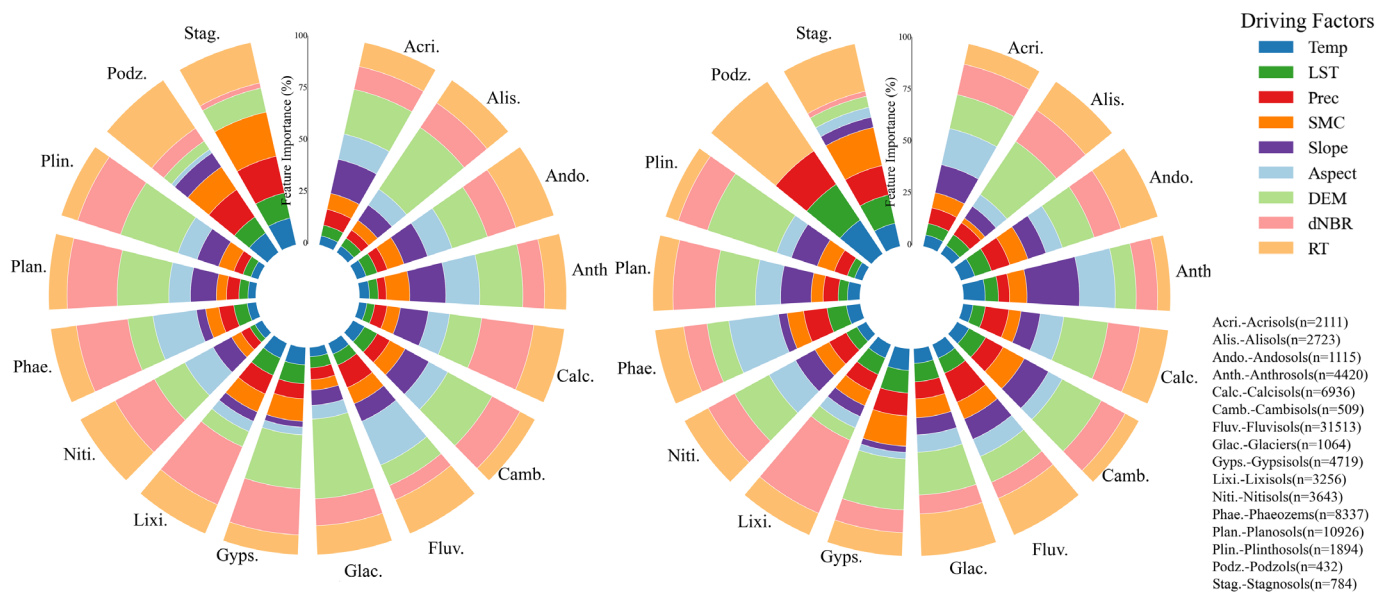


Figure 7. Random Forest-based feature importance of driving factors for EVI and SIF recovery across different soil types. Feature importance values represent the relative contribution of each climatic, topographic, fire-related, and recovery-time variable to model prediction. The sample-size information indicates the number of valid pixels used for each soil type.

Considering the differences in vegetation recovery responses to each driving factor (Figure 8), we found that: (1) Elevation contributes substantially to the recovery of all vegetation types, with an average proportion up to 12%. (2) The dNBR's effect on recovery varies significantly; evergreen coniferous forests are most sensitive to dNBR, with this factor contributing up to 28%, more than double that of other types. (3) The precipitation and soil moisture are 5% more important for evergreen coniferous forests, linked to their greater water sensitivity.

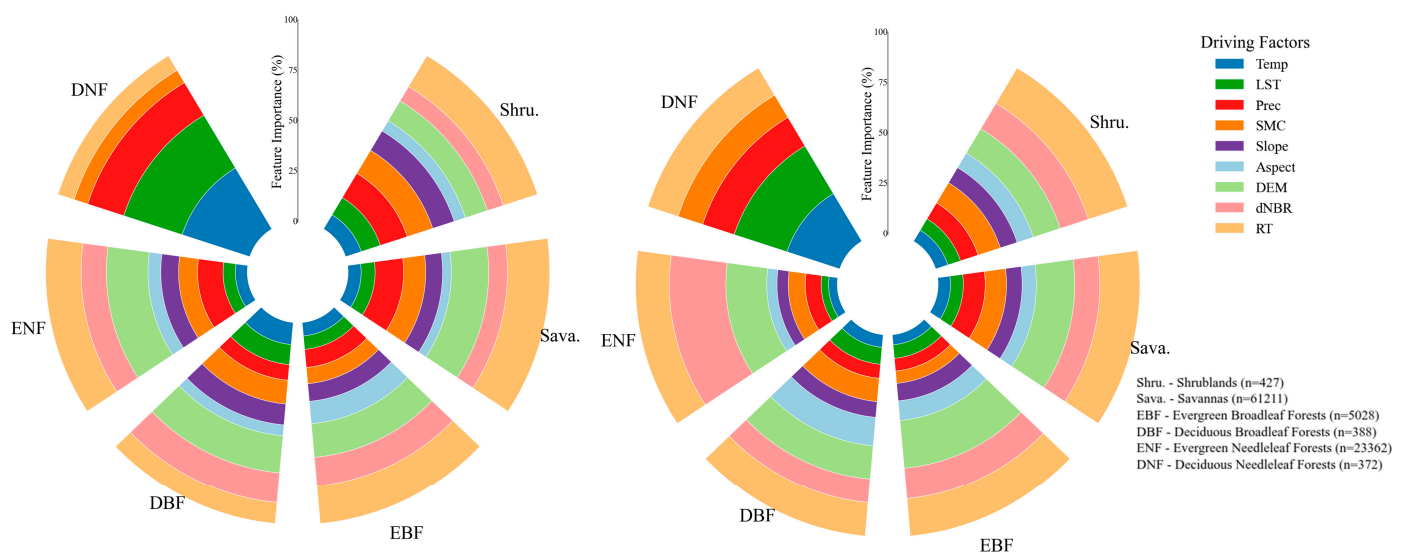


Figure 8. Feature importance maps of EVI and SIF recovery based on different vegetation types and the number of samples for each vegetation type.

4. Discussion

4.1. Model Reliability Evaluation

We modeled soil types and vegetation datasets using SIF and EVI as targets. The model performance was evaluated using root mean square error (RMSE) and the coefficient of determination (R^2). The models fit well, with R^2 above 0.8 on the training set and 0.7 on the test set, indicating high accuracy. We then compared EVI and SIF models. SIF models fit better, with higher R^2 values. Specifically, 78% of SIF models had R^2 values above 0.9, compared with 61% for EVI models. This underscores SIF's stronger predictive power.

By analyzing temporal trends in two vegetation indices, EVI and SIF, before and after fires across 18 typical cases, we found that in 78% of fires, vegetation levels recovered to their original state. This finding is supported by previous studies [32–34]. Notably, vegetation recovered fastest in the first two years following the fires. This rapid recovery may be due to two main factors. First, a shift to younger forests after the fire may support faster growth rates [35]. Second, nutrient release after fire may promote the regeneration of understory vegetation, including herbaceous plants and shrubs, potentially offsetting part of the vegetation loss detected by EVI. However, because our analysis was based on remotely sensed vegetation indicators, we could not explicitly distinguish the contributions of the tree, shrub, and herbaceous layers [36]. However, some burned areas did not recover to pre-fire conditions within four years after fire. Although high fire severity may have contributed to this delayed recovery by causing severe canopy damage, soil degradation, and reduced regeneration potential [37,38], it is unlikely to be the only controlling factor. The vegetation type and habitat conditions, such as soil properties, water availability, topography, and post-fire climate, may also strongly influence recovery trajectories. Therefore, these slow-recovery cases should be interpreted as the result of interacting fire-related, vegetation-related, and environmental constraints [39,40].

Additionally, climate extremes, particularly arid weather exacerbated by global warming, can further hinder vegetation recovery [41,42]. For example, between 2017 and 2019, Australia suffered three years of intense drought [43]. These droughts contributed to the Black Summer wildfires, which burned extensive forest areas and damaged ecosystems. The persistent drought that followed the fires caused post-fire vegetation recovery to stagnate.

4.2. Comparative Analysis of Driving Factor Importance for Post-Fire Vegetation Recovery

The feature importance maps are shown in Figure 9. The average importance contributions of various driving factors to the recovery of two vegetation indices are illustrated under different soil and vegetation types. To further clarify the variability, the coefficient of variation quantifies the extent to which each driving factor contributes across different soil or vegetation types. These feature importance maps reveal clear differences in the rankings of driving factors across vegetation and soil types. This profoundly demonstrates the unique environmental response characteristics of each type.

4.3. Univariate Partial Dependency Analysis

(1) Univariate partial dependency analysis based on vegetation types

Comparing the univariate precipitation PDPs of EVI and SIF shows that precipitation has multiple effects on vegetation recovery (Figure 10). Most vegetation types similarly respond to precipitation, except for Deciduous Broadleaf Forests. In these forests, EVI increases steadily when precipitation is above average. However, SIF decreases after precipitation exceeds half the average. This contrast suggests that, under relatively high precipitation conditions, defined here as standardized precipitation values greater than approximately 3.0, SIF recovery tended to plateau or slightly decline, whereas EVI showed

only a weak response. This indicates that excessive wet conditions may constrain functional recovery, possibly by reducing light availability and photosynthetic light-use efficiency, while having a limited effect on canopy greenness. In Evergreen Needleleaf Forests, precipitation was positively associated with post-fire recovery, likely because sufficient water availability can alleviate post-fire drought stress, enhance soil moisture, and support seedling establishment and photosynthetic recovery. This effect may be especially important for evergreen needleleaf forests, whose structural regrowth is generally slower than that of herbaceous or shrub-dominated vegetation. After a fire, vegetation recovery depends on how well precipitation and soil moisture are utilized, with these processes influenced by factors such as precipitation, soil texture, and slope. Consequently, these elements combine to create a complex feedback mechanism within the ecosystem.

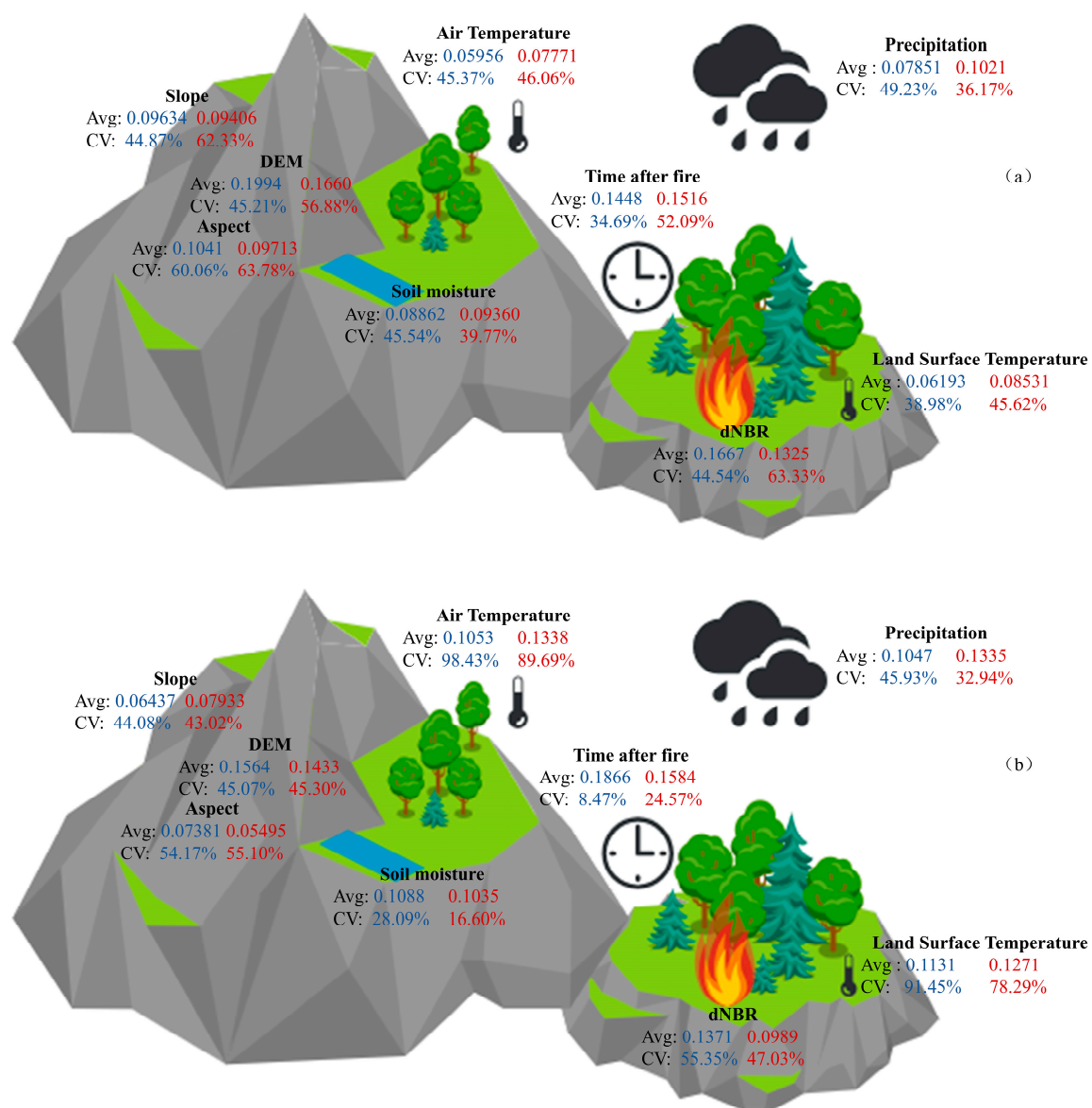


Figure 9. The average feature importance (Avg) and the coefficient of variation values (CV) of key driver factors for EVI and SIF under soil (a) and vegetation types (b). The results, indicated in blue and red font, represent their values using EVI and SIF as the target variables, respectively.

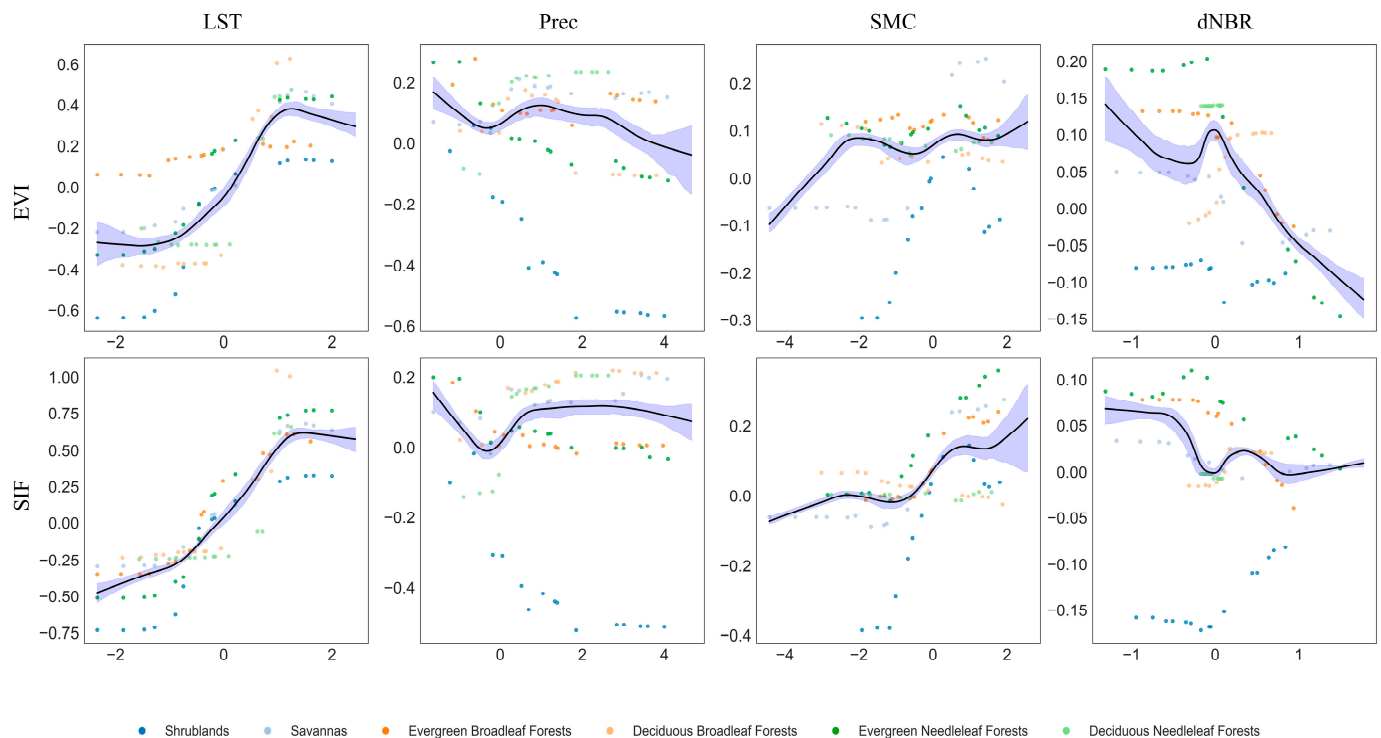


Figure 10. Univariate dependence curve of precipitation (Prec), LST, soil moisture (SMC), and dNBR based on vegetation types.

The marginal effect of LST on both vegetation indices shows a trend of accelerating recovery as LST increased, with recovery rates accelerating around 50% of the local mean LST and stabilizing at 75% of the local maximum. Suitable temperatures are necessary for vegetation growth, with LST representing the surface energy balance that can constrain or promote recovery. While LST's marginal effect is similar across indices, vegetation types respond differently, likely due to their physiological traits and adaptability. Shrublands are notably sensitive, with their contribution to recovery increasing 2–3 times as LST rises from the local average to 1.5 times that value.

We conducted univariate partial dependence analysis for SMC. Deciduous Broadleaf Forests, Deciduous Needleleaf Forests, and Shrublands show similar EVI and SIF response trends to changes in soil moisture. In contrast, Evergreen Broadleaf Forests and Evergreen Needleleaf Forests showed different responses to soil moisture. SIF increased markedly when the standardized soil moisture content exceeded approximately 0.5, whereas EVI showed a weaker, nonlinear response, increasing under low-to-moderate soil moisture but plateauing or fluctuating under wetter conditions. This suggests that soil moisture is more directly associated with functional recovery than with structural recovery, whereas EVI-based greenness recovery may also depend on canopy reconstruction, leaf-area development, and vegetation-specific regeneration traits. Photosynthesis in evergreen forests is therefore highly sensitive to soil moisture, possibly due to distinct physiological traits. While shrublands are more sensitive to soil moisture, this may reflect their presence in dry areas and their need for water. In contrast, Deciduous Broadleaf and Needleleaf Forests respond more steadily, possibly due to deep roots or good water storage.

Across vegetation types, EVI and SIF showed broadly consistent responses along the dNBR gradient. Both indicators generally showed higher recovery under low dNBR conditions and lower recovery as dNBR increased, indicating that increasing fire severity constrained both structural and functional vegetation recovery. EVI responds more strongly to fire severity than SIF does, indicating that fire severity influences vegetation structure and

growth more than photosynthetic activity. Fire severity affects vegetation types differently. Shrublands consistently decline with increasing dNBR, whereas most other types show slight increases in EVI and SIF at low fire severity, suggesting a possible “facilitative effect.” This likely results from the release of nutrients, including nitrogen, phosphorus, and potassium, from burned litter and fuel, thereby enhancing soil fertility and spurring regrowth. However, the low stature, shallow roots, and exposed tissues of shrublands make them vulnerable to fire damage, resulting in slow and suppressed recovery. This indicates low resilience and limited adaptive ability to fire.

(2) Univariate partial dependency analysis based on soil types

In precipitation experiments, PDPs calculated for different soil types revealed clear differences in their responses to precipitation (Figure 11). For example, the responses varied when EVI and SIF were used as target variables. Specifically, in 63% of the soil types, EVI recovery showed a relatively flat trend in response to precipitation, with only small fluctuations. In contrast, 31% of soil types showed a decreasing trend in EVI with increasing precipitation. This indicates that vegetation under the first group of soil types is less sensitive to precipitation changes, possibly due to better water-holding capacity or drought-resistant plant communities. Meanwhile, in the second group, the greater contribution to vegetation recovery occurred when precipitation was below 60% of the local maximum. This difference may be related to soil characteristics [44].

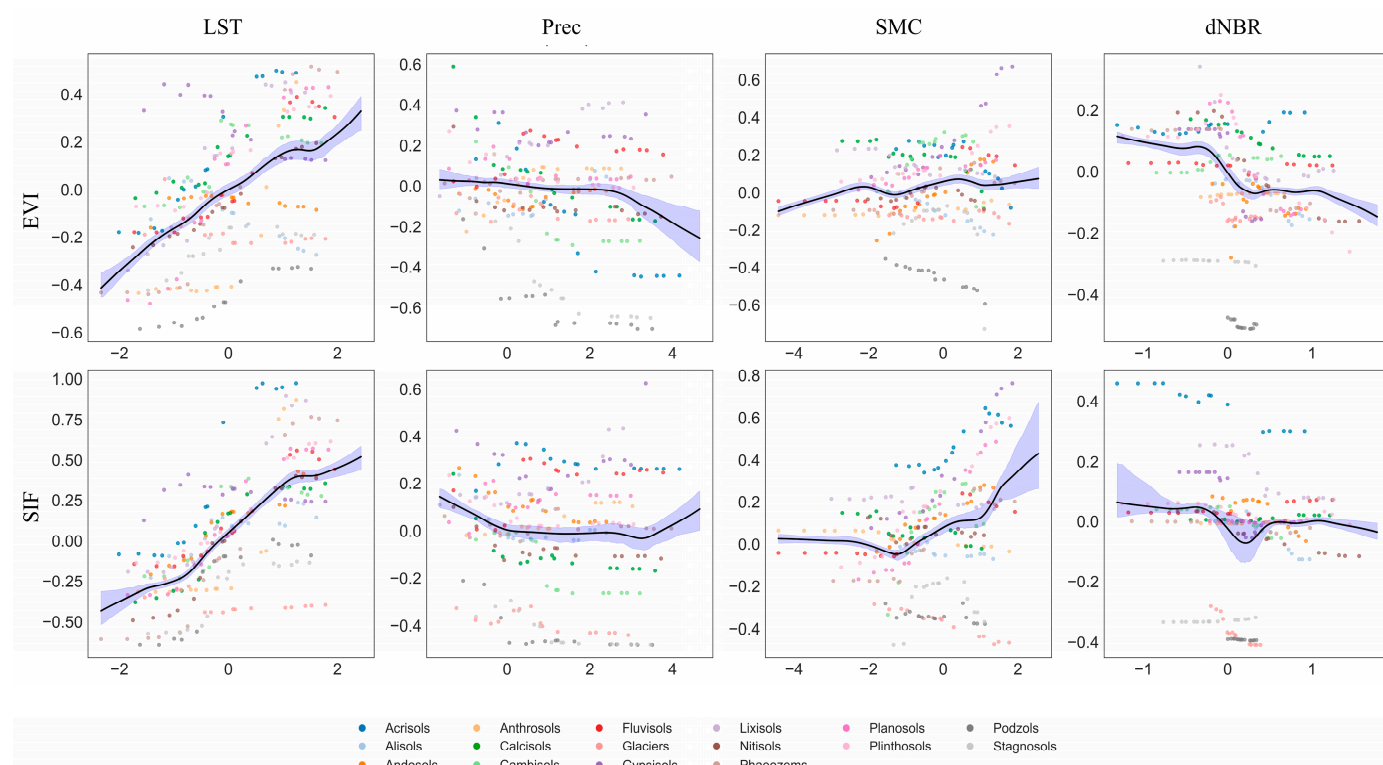


Figure 11. Univariate partial dependence curve of precipitation (Prec), LST, soil moisture (SMC), and dNBR based on soil types.

Compared with EVI, the univariate PDP results for SIF showed a smoother, more stable trend, though the overall patterns were similar. Univariate partial dependence analyses based on LST for both target variables showed highly consistent trends. In the univariate partial dependence analysis of soil moisture content for different soil types, 75% of the soil types exhibited high consistency in univariate dependence trends for both vegetation indices as target variables. A total of 81% of soil types, such as Acrisols, Alisols, and Lixisols, were more sensitive to LST, displaying fluctuating trends, possibly due to variations in

texture, porosity, and water retention capacity. In contrast, Fluvisols and Planosols exhibited relatively stable responses, likely due to better drainage or a steady water supply, which ensured vegetation growth under stable soil moisture, thereby reducing their sensitivity. This contrast highlights that the link between soil moisture content and vegetation recovery varies across soil types, in both magnitude and stability.

The univariate analysis of fire severity (dNBR) on post-fire vegetation recovery across different soil types reveals significant differences in response. On soils such as Calcisols, Fluvisols, Anthrosols, and Planosols, plants recover more easily after a fire. These soils retain water and nutrients well, occur on gentle slopes, and have deep, soft layers. Their ability to keep water and nutrients helps plant roots recover. The way these soils are built also protects them from being changed too much by fire.

In contrast, plants on soils like Gypsisols, Lixisols, Andosols, Alisols, and Acrisols struggle more after fire. As the fire intensifies, recovery worsens. This is because these soils have a weaker structure or fewer nutrients.

4.4. Bivariate Feature Dependency Analysis

The bivariate PDP shows how pairs of driving factors interact to influence the target variable. To support post-fire recovery management, we examined two pairs of variables: precipitation and temperature, and precipitation and post-fire recovery time. Specifically, we evaluated how each pair's interaction affects the target variable across different soil and vegetation types.

The joint effects of precipitation and temperature on vegetation cover and photosynthesis closely matched trends in both vegetation indices (Figure 12). For 44% of soil types (Acrisols, Calcisols, and Cambisols), recovery rates reached 90% of the maximum when precipitation was below 40% of the local average and temperature was at 60% of the local maximum, likely due to good water retention and nutrient availability. In contrast, Anthrosols, Nitisols, Phaeozems, and Planosols exhibited significant recovery only when precipitation exceeded 80% of the local maximum, indicating a strong sensitivity to moisture. Similarly, Alisols exhibited higher recovery rates at temperatures above 70% of the maximum and below 30% of the mean precipitation, suggesting unique drought adaptations.

The analysis of different vegetation types shows consistent results using both vegetation indices (Figure 13). Deciduous Broadleaf Forests and Deciduous Needleleaf Forests reached peak recovery rates in areas with both high temperature and high precipitation; Shrublands showed higher recovery increases at lower temperatures (below 30% of the local maximum temperature) in both analyses, when EVI was the target variable. Using SIF as the target variable, recovery rates exceed 90% of the maximum only when precipitation exceeds 50% of the local maximum and temperature remains below 30% of the local maximum. This demonstrates that vegetation cover and photosynthetic recovery in Shrublands have different geographic requirements.

The analysis reveals that SIF recovery was most sensitive to the combined effects of precipitation and recovery time, exhibiting notable volatility when SIF was the target variable (Figure 14). This heightened sensitivity likely stems from SIF's connection to photosynthetic efficiency, which is influenced by several factors during vegetation recovery, including precipitation, recovery time after fire, and their interaction. Alisols, Andosols, and Glaciers consistently maintained high recovery increments and showed smooth responses to precipitation changes 20 months after fire, highlighting the high resilience and stability of these soil types, with better vegetation recovery soon after disturbance. Acrisols, Calcisols, Cambisols, Nitisols, Plinthosols, Podzols, and Stagnosols exhibited a fluctuating upward trend in recovery increment with increasing recovery time, likely due to gradual nutrient accumulation, improved soil structure, and the succession of vegetation communities.

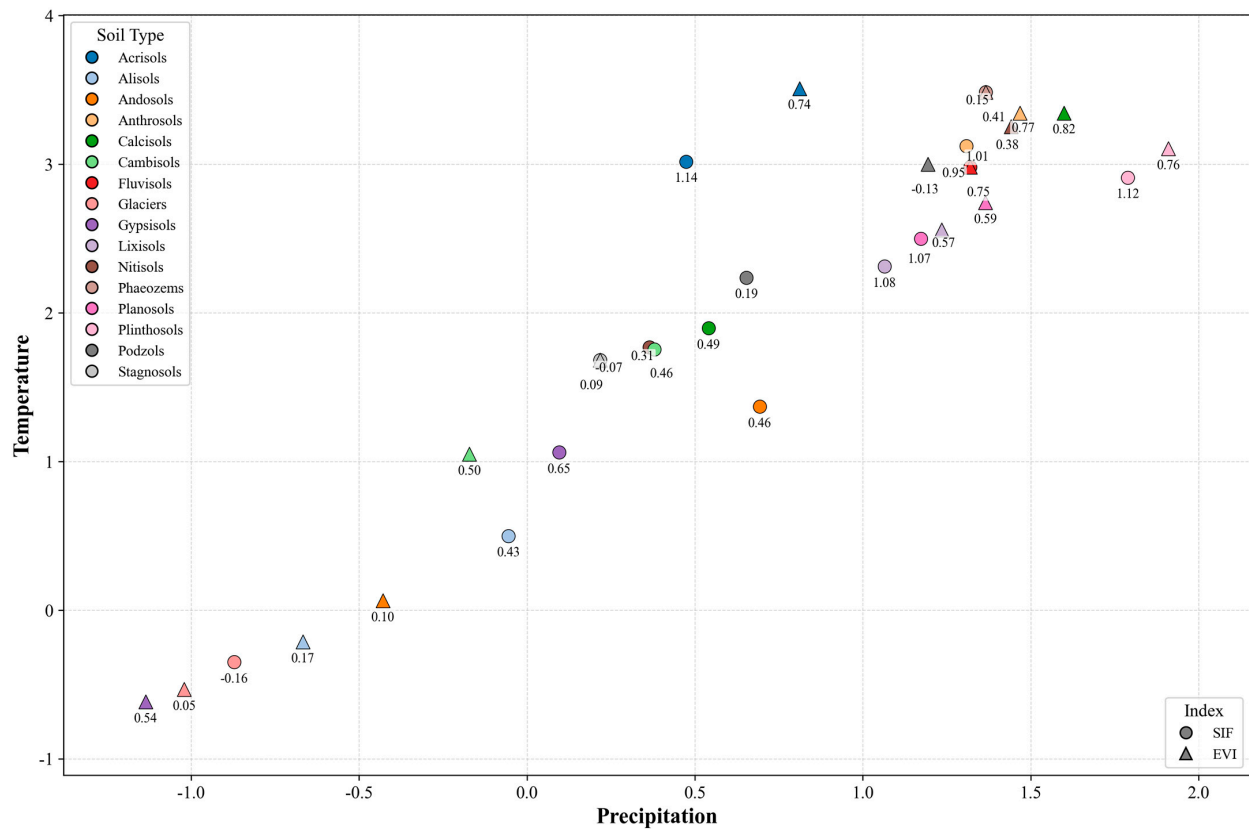


Figure 12. The maximum values of the bivariate partial dependence of precipitation and temperature based on EVI and SIF for different soil types are marked with triangles and circles, respectively.

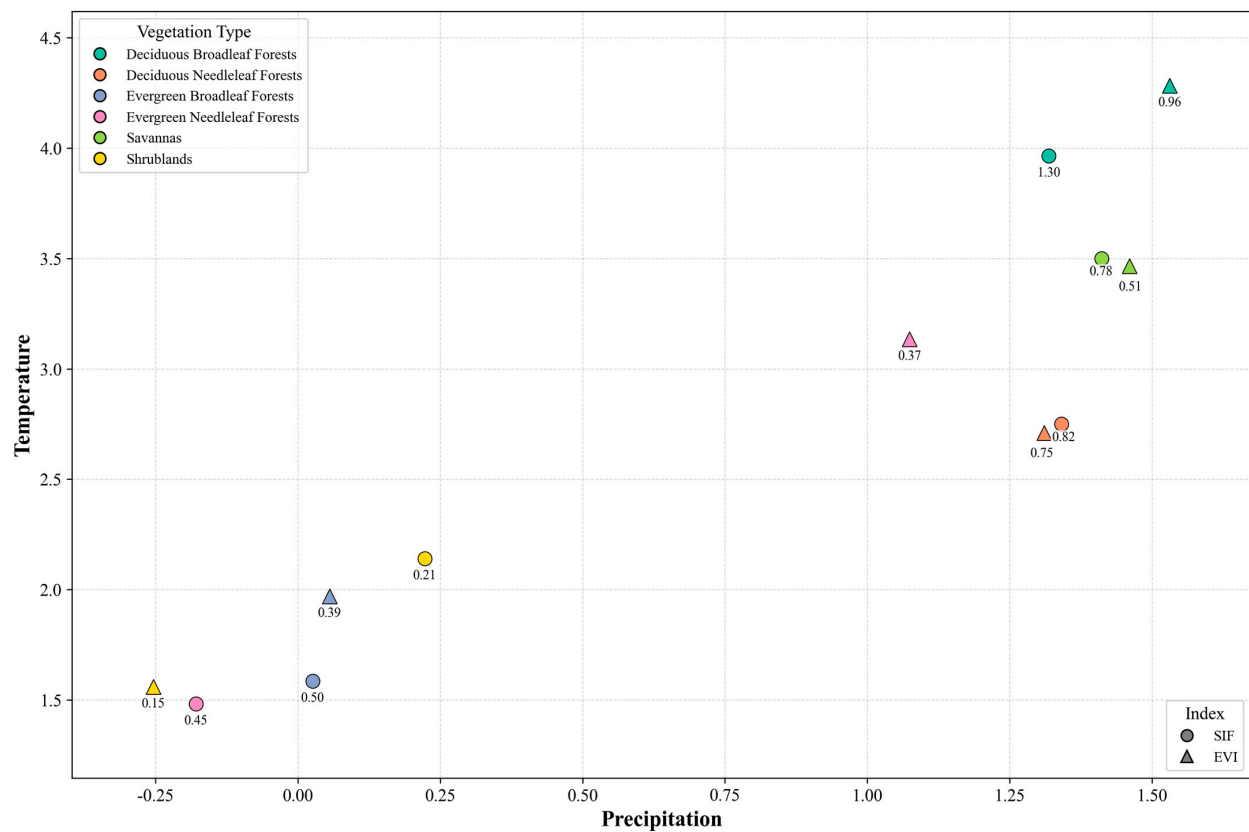


Figure 13. The maximum values of the bivariate partial dependence of precipitation and temperature based on EVI and SIF for different vegetation types are marked with triangles and circles, respectively.

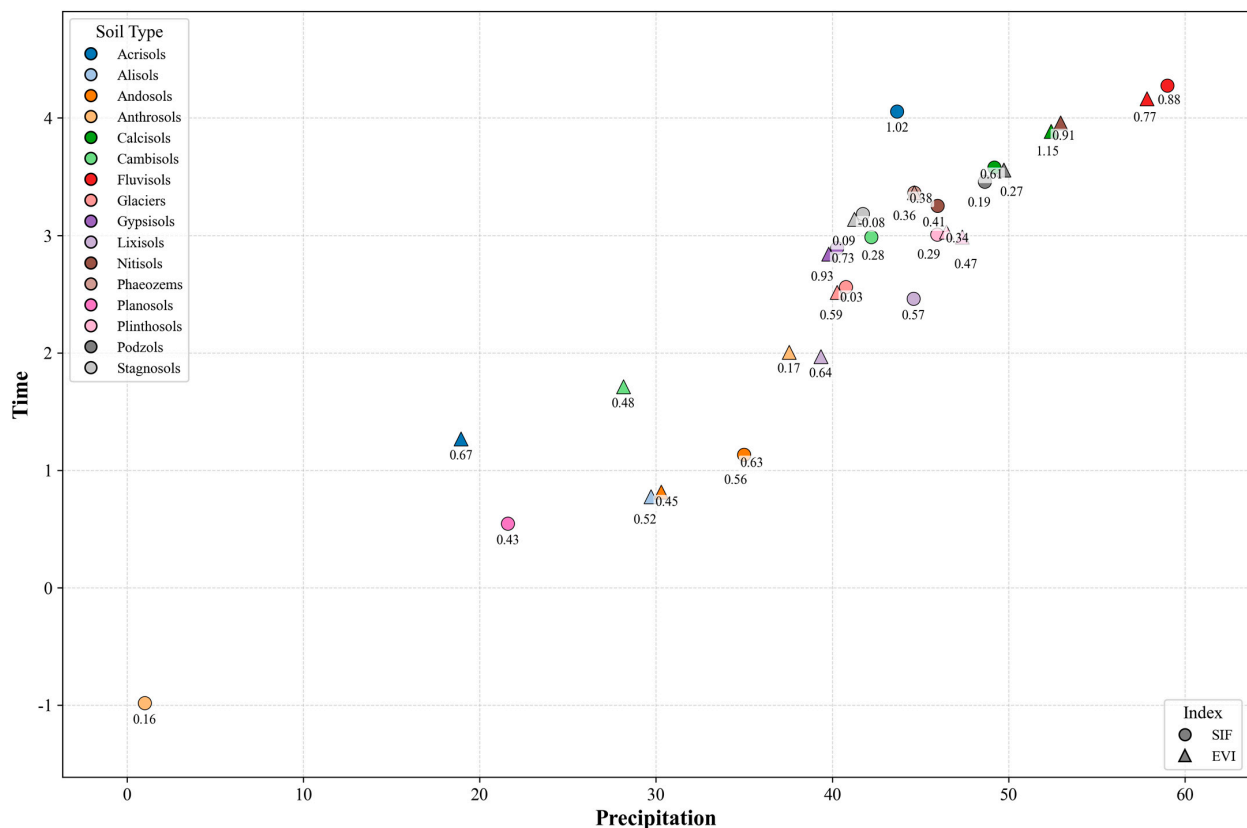


Figure 14. The maximum values of the bivariate partial dependence of precipitation and post-fire recovery time based on EVI and SIF for different soil types are marked with triangles and circles, respectively.

In general, results for SIF and EVI as target variables were consistent across vegetation types, except for Deciduous Broadleaf Forests (Figure 15). In this type, when precipitation exceeded the mean, EVI recovery dropped to approximately 50% of its baseline. However, SIF recovery remained stable at over 90%, indicating stronger resilience. Reduced EVI recovery under high precipitation is likely due to soil waterlogging and hypoxia caused by excess water [45], which directly limits growth and cover. Among types with consistent SIF and EVI responses, Shrublands and Evergreen Needleleaf Forests recovered better when precipitation was above the mean in the first post-fire year. This suggests higher resilience and benefits from post-fire precipitation, which supports physiological activity and tissue repair. Evergreen Broadleaf Forests recovered gradually, with a longer fire time lag, likely due to strong self-repair and succession during recovery.

Overall, the main novelty of this study lies in the dual-track framework that separates post-fire vegetation recovery into structural recovery (represented by EVI) and functional recovery (represented by SIF). This framework moves beyond the traditional reliance on a single greenness-based indicator and reveals that apparent canopy recovery does not necessarily reflect full restoration of photosynthetic function. By combining Transformer-based counterfactual prediction with Random Forest-based driver analysis, this study links recovery trajectories with underlying environmental controls across different vegetation and soil types. The observed lag of SIF behind EVI highlights a structural–functional decoupling in post-fire ecosystems, suggesting that management strategies based only on vegetation greenness may overestimate ecosystem recovery. Therefore, the proposed framework provides a comprehensive and ecologically meaningful basis for assessing forest resilience, identifying vulnerable vegetation types, and designing targeted post-fire restoration strategies.

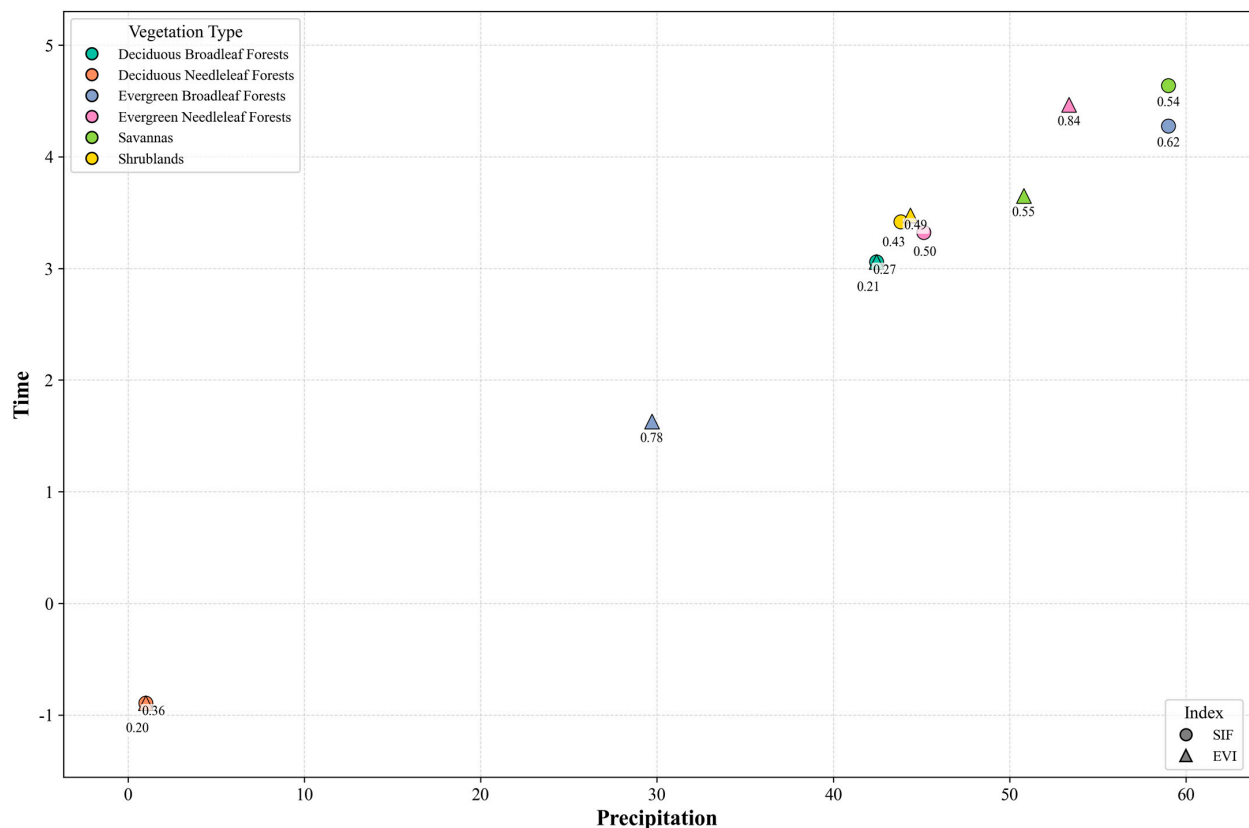


Figure 15. The maximum values of the bivariate partial dependence of precipitation and post-fire recovery time based on EVI and SIF for different vegetation types are marked with triangles and circles, respectively.

5. Conclusions

This study analyzed the effects of forest fires on vegetation recovery using four years of EVI and SIF time series before and after the fires. EVI and SIF values dropped by 45–60% and 40–55%, respectively, the year after the fire. After four years, EVI and SIF in 78% of burned areas recovered to pre-fire levels. The recovery processes of EVI and SIF differed. EVI, which reflects vegetation cover and structure, rebounded more quickly. SIF recovery lagged. Three years after the fire, 85% of burned areas regained 80% of their original EVI. At the same time, SIF typically returned to only 70% of its original value.

Elevation is the most influential factor for both EVI and SIF recovery. dNBR and post-fire recovery time are also important fire-related factors. Their importance is 19% and 14% for EVI and SIF recovery, respectively. The significance of soil moisture content and precipitation varies among soil types. These factors are more influential in the SIF analysis. They show 30% and 14% year-on-year increases in importance. This suggests that chlorophyll fluorescence is more sensitive to changes in moisture.

In the early recovery stage, both indices had similar trends across vegetation types. As environmental drivers increased, SIF showed a larger amplitude than EVI, while EVI's response was more muted. Across soil types, SIF varied more than EVI during recovery, emphasizing SIF's greater sensitivity to environmental changes. Bivariate analysis showed that precipitation, temperature, and time since fire influenced SIF more strongly, producing nonlinear SIF patterns, while EVI's response remained relatively stable.

By integrating EVI and SIF, the two-dimensional analysis framework provides a standardized, replicable method for quantitatively tracking recovery from both perspectives. This approach enables consistent comparisons across regions and vegetation types, provid-

ing actionable insights into vegetation resilience and recovery mechanisms. Collectively, the findings provide a solid foundation for precise and adaptive fire recovery strategies that account for varied soil and vegetation conditions. However, several limitations remain in this study. First, although the Transformer model showed good predictive performance, uncertainties may still arise from model structure, input variables, and the limited length of pre-fire training data. Second, the spatial resolution of remote-sensing datasets may not fully capture fine-scale variations in burn severity, topography, microclimate, and vegetation regeneration. Third, detailed information on dominant species, stand age, forest structure, and post-fire management was not consistently available for all fire events, limiting our ability to explain species-specific recovery mechanisms. Finally, this study only included single-fire events and did not consider the cumulative effects of repeated fires. Future research should integrate higher-resolution observations, species-level information, and repeated-fire histories to improve understanding of post-fire vegetation recovery further.

Author Contributions: Conceptualization, S.W. and X.L.; methodology, S.W.; software, X.L.; validation, S.W., X.L. and R.G.; formal analysis, S.W.; investigation, R.G.; resources, Z.T., J.Z.; data curation, B.M.; writing—original draft preparation, S.W.; writing—review and editing, S.W., X.L.; visualization, S.W., N.W.; supervision, X.L., Z.T., J.Z.; project administration, X.L.; funding acquisition, X.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the Key R&D Project of the Jilin Province Science and Technology Development Plan (20250203076SF) and the National Natural Science Foundation of China (32573604).

Data Availability Statement: Data Availability Statement: Data will be made available upon reasonable request. All code used for data processing and analysis is available on GitHub (<https://github.com/nianxi9979/postfire-recovery-scripts>, accessed on 26 June 2026). Data processing and analysis were performed using PyCharm 2023.1.

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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