

Spatially differentiated ecological vulnerability across China's southwest borderlands

Hedong Wang

Guangxi University

Ruyi Yang

Guangxi University

Liangen Zeng

zengliangen@pku.edu.cn

Guangxi University

Zhuxia Wei

Guangxi University

Article

Keywords: Borderlands, land-use transitions, ecological vulnerability, coupled human–environment systems, infrastructure corridors, spatial governance

Posted Date: October 14th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10914967/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: No competing interests reported.

Spatially differentiated ecological vulnerability across China's southwest borderlands

Abstract: Borderlands concentrate tensions between ecological recovery and development pressure, yet composite indices can conceal where these processes diverge. Using 1-km multi-source remote-sensing data, land-transition records and a Sensitivity - Resilience - Pressure (SRP) framework, this study assessed 15 prefectures in China's southwest borderlands from 2001 to 2023. Grassland expanded by 13,722 km² and forest area changed little, whereas impervious surface increased by 172.4% (+664 km²), with gains concentrated in selected border trade prefectures. Mean ecological vulnerability rose from 0.306 to 0.350 as Pressure increased from 0.048 to 0.231, despite the inverted Resilience component falling from 0.380 to 0.358, indicating improved vegetation-based recovery capacity. This resilience-pressure paradox separated persistent high vulnerability in the topographically sensitive Tibetan sector from the fastest deterioration in Yunnan-Guangxi trade-corridor prefectures. Vulnerability remained strongly clustered; NPP and NDVI showed the strongest spatial correspondence with the index, while night-time light became more informative over time and in combination with vegetation indicators. Pressure declined with distance from the international boundary, but mean vulnerability varied little because stronger near-border vegetation resilience partly offset higher pressure. The findings support differentiated governance for high-altitude sensitivity protection, corridor-scale land-conversion control and transition-zone monitoring.

Keywords: Borderlands; land-use transitions; ecological vulnerability; coupled human-environment systems; infrastructure corridors; spatial governance

1 Introduction

Land-use transitions are simultaneously ecological processes and territorial outcomes of decisions about infrastructure, trade, settlement, agriculture and conservation. Their consequences are especially visible in borderlands, where national development strategies encounter environmentally heterogeneous places and where ports and transport corridors concentrate flows within relatively narrow spaces (Ascensão et al. 2018; Jin et al. 2021; Paasi 1998; State Council Information Office of the People's Republic of China 2023). Global land change has already altered ecosystem stability and exposure to degradation at unprecedented scales (IPBES 2019; Lambin et al. 2003; Song et al. 2018; Steffen et al. 2015). Vulnerability scholarship accordingly treats environmental change as a product of coupled human-environment relations rather than of biophysical conditions alone (Adger 2006; Füssel 2007; Liu et al. 2007; Smit and Wandel 2006; Turner et al. 2003). From a human and integrative geographical perspective, the central question is therefore not only where vulnerability is high, but how uneven development and environmental policy redistribute sensitivity, recovery capacity and pressure across a border region.

China's southwest borderlands bring these tensions into sharp relief. The region crosses the Tibetan Plateau margin, the Hengduan Mountains and tropical and subtropical lowlands, contains globally important biodiversity, and is commonly framed as an ecological barrier zone (Ferdinand 2016; Mittermeier et al. 2011; Myers et al. 2000). Since 2000, ecological restoration programmes, including Grain-for-Green and natural-forest protection, have been associated with extensive vegetation recovery in southwest China (Chen et al. 2019; Ouyang et al. 2016; Piao et al. 2020; Qiao et al. 2021; Tong et al. 2018; Zhang et al. 2021). During the same period, China-ASEAN trade integration and infrastructure expansion have coincided with urban and construction growth around selected valleys, ports and border nodes (Ferdinand 2016; State Council Information

Office of the People's Republic of China 2023). These processes do not necessarily operate at the same scale: restoration gains may be spatially diffuse, whereas development pressure can be sharply concentrated. We use the term resilience–pressure paradox to describe the condition in which vegetation-based recovery capacity improves at the regional scale while localised anthropogenic pressure grows sufficiently to raise overall ecological vulnerability. The paradox is a governance problem because a favourable trend in one component can coexist with deterioration in the composite outcome.

Ecological vulnerability studies offer several frameworks for analysing such interactions, including the Vulnerability Scoping Diagram, Sensitivity–Resilience–Pressure (SRP), Pressure–State–Response and coupled human–natural systems approaches (Adger 2006; Fussler 2007; Gu et al. 2023; Hinkel 2011; Hu and Xu 2019; Li et al. 2021; Li et al. 2022; Liu et al. 2007; Luo et al. 2024; Polsky et al. 2007; Smit and Wandel 2006; Turner et al. 2003; Xu 2013; Xu et al. 2019; Zheng et al. 2022). Indicator-based assessments and spatial statistics have improved the comparability and mapping of vulnerable landscapes (Anselin 1995; Gu et al. 2023; Jin et al. 2021; Wang et al. 2016). The SRP framework is particularly useful here because it separates relatively persistent environmental sensitivity, vegetation-based resilience and externally generated pressure. Yet much of this literature remains organised around ecological-condition inventories: pressure is often represented as a spatially general input, administrative units are treated as self-contained containers, and policy recommendations are derived from the composite index alone. Those conventions are limiting in border regions, where ecological capacity follows strong altitudinal and climatic gradients while human activity may be nodal and corridor-shaped (Jin et al. 2021; Li et al. 2020; Seto et al. 2012). Night-time light and impervious-surface data can reveal that concentration, although they remain proxies for human activity rather than direct measures of trade, infrastructure policy or institutional change (Elvidge et al. 2017; Li et al. 2020; Yang and Huang 2021).

Three related gaps motivate this study. First, the southwest border zone has more often been examined through sector-specific karst, restoration or economic-corridor cases than as an internally differentiated borderland policy region (Jin et al. 2021; Qiao et al. 2021; Tong et al. 2018; Zhang et al. 2021). Second, ecological restoration and urbanisation are commonly evaluated in parallel, leaving unclear whether resilience gains and pressure growth coexist, offset one another or dominate in different locations. Third, proximity to an international boundary is rarely examined together with the environmental gradient that runs from high-altitude Tibet to the Yunnan–Guangxi lowlands. A border-distance pattern should therefore not be interpreted as a causal "border effect" without considering this underlying geography. We ask: (1) how did land-use transitions and the three SRP components change between 2001 and 2023; (2) does their spatial and temporal relationship support a resilience–pressure paradox; and (3) how do baseline sensitivity, change trajectories, spatial clustering and distance from the border distinguish structurally vulnerable areas from places experiencing rapidly intensifying development pressure?

To answer these questions, we analyse 15 prefectures across Tibet, Yunnan and Guangxi at 1-km resolution. Annual land-cover data are combined with vegetation, topographic, meteorological and night-time-light indicators in an equal-weight SRP index; land-transition and landscape metrics identify the form of change; Moran's I and

local indicators of spatial association describe clustering (Anselin 1995; Moran 1950); GeoDetector characterises the spatial explanatory structure of the index (Song et al. 2020; Wang et al. 2016); and distance bands identify how SRP components vary with proximity to the international boundary (Natural Earth n.d.). Because the GeoDetector covariates also contribute to the index, its statistics are interpreted as a decomposition of spatial stratification rather than as independent causal estimates. The study contributes, first, a component-based account of why restoration gains and development pressure can coexist; second, an integrative geography of high baseline vulnerability and rapid corridor-associated deterioration; and third, a policy framework that matches intervention to sensitivity, resilience and pressure instead of relying on a single regional ranking.

2 Materials and methods

2.1 Study area

The study area comprises 15 prefectural-level administrative units along China's southwest international border (Fig. 1), located at the intersection of the Tibetan Plateau, Hengduan Mountains, and South China karst region. It spans approximately latitude 21°N–35°N and longitude 79°E–109°E, encompassing the western sector (Tibet: Ali, Rikaze, Shannan, Linzhi), central sector (Yunnan: Nujiang, Baoshan, Dehong, Lincang, Puer, Xishuangbanna, Honghe, Wenshan), and eastern sector (Guangxi: Baise, Chongzuo, Fangchenggang). Administratively, it crosses three provincial-level units and 15 prefectural-level units, with a total area of approximately 96.4×10^4 km². The terrain slopes from northwest to southeast, with the lowest elevation below 100 m in the Beibu Gulf coastal plain (Fangchenggang) and the highest elevation exceeding 5,000 m on the southeastern Tibetan Plateau margin (Ali, Rikaze). There is a significant difference in altitude across the region, with an elevation range exceeding 5,000 m, creating pronounced vertical zonation of ecosystems. The climate is characterised by strong spatial heterogeneity, transitioning from highland continental in the northwest to tropical monsoon in the southeast, with mean annual precipitation ranging from approximately 500 mm (western Tibet) to over 2,500 mm (Yunnan–Guangxi sector) and mean annual temperature from –2 °C to 22 °C. The ecosystem types include alpine desert, alpine meadow, subalpine coniferous forest, subtropical evergreen broadleaf forest, tropical rainforest, and karst vegetation, representing exceptional ecological diversity and sensitivity. Forest and grassland are the dominant land cover types, collectively accounting for approximately 79.4% of the total area in 2001.

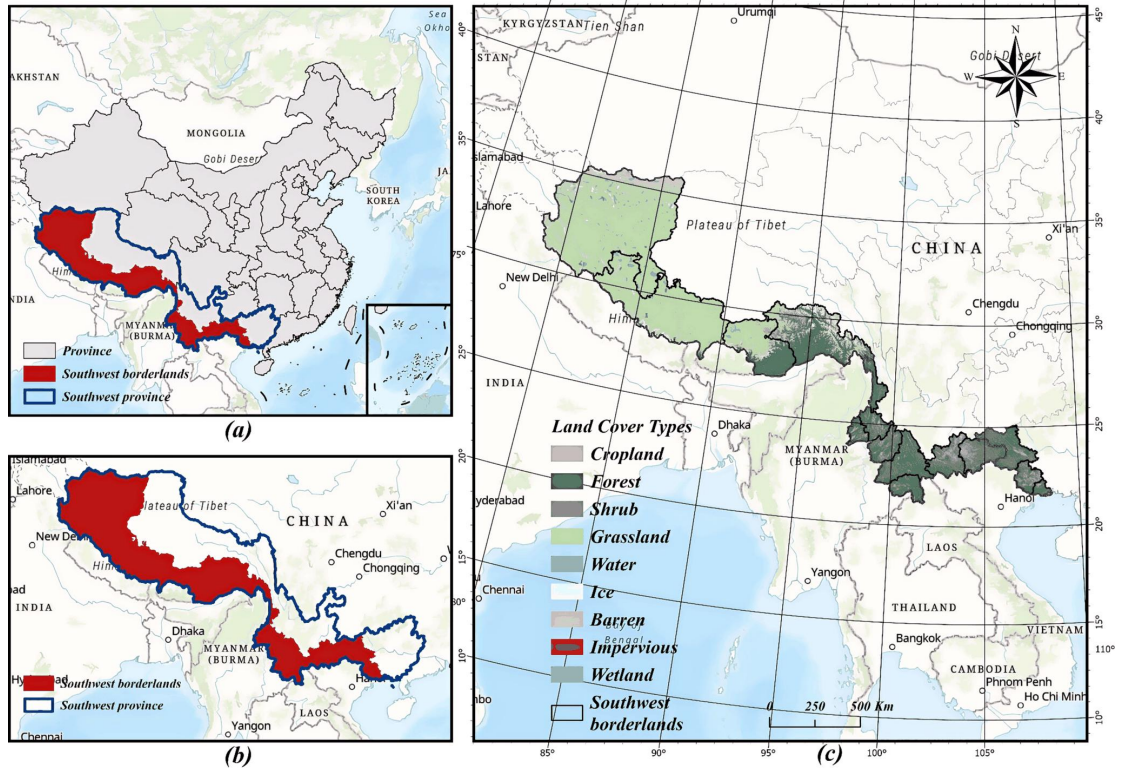


Figure 1. Study area and land-cover context of China's southwest borderlands. (a) Location of the southwest borderlands within China; (b) detailed spatial extent of the study area across Tibet, Yunnan, and Guangxi, including the 15 border prefectural-level administrative units; (c) land-use/cover pattern of the study area in 2001, classified into cropland, forest, shrub, grassland, water, snow/ice, barren land, impervious surface, and wetland. The study area is located at the intersection of the Tibetan Plateau, Hengduan Mountains, and South China karst region, and represents a typical ecological transition zone along China's southwest international border. Country-boundary linework is based on Natural Earth, and topographic context is based on SRTM.

2.2 Data sources and preprocessing

The data used in this research include land-use/cover, vegetation, topographic, meteorological, and socioeconomic night-time-light data (Table 1). All remote sensing data were processed using Google Earth Engine (GEE) and resampled to a unified 1-km grid under the Albers Equal Area Conic projection (central meridian 105°E, standard parallels 25°N and 47°N), consistent with the native projection of the CLCD land-use dataset. The 30-m CLCD data were aggregated to the 1-km grid using majority-class assignment, preserving the categorical integrity of land-use types without cross-projection resampling artefacts (Yang and Huang 2021; Yang and Huang 2023). Vegetation indicators were derived from MODIS NDVI and NPP products (Didan 2021; Huang et al. 2021; Huete et al. 2002; Running and Zhao 2021), meteorological variables from TerraClimate (Abatzoglou et al. 2018), topographic variables from SRTM (Farr et al. 2007), and international border geometry from Natural Earth (Natural Earth n.d.). Harmonised DMSP-OLS/VIIRS night-time light data were used to represent long-term anthropogenic activity intensity (Elvidge et al. 2017; Li et al. 2020; Sanderson et al. 2002; Venter et al. 2016).

Table 1. Data sources used in this study

Type	Data	Source	Resolution	Temporal coverage
Land use	CLCD	Wuhan University (Yang and Huang 2021; Yang and Huang 2023)	30 m	2001–2023
Vegetation	NDVI	MODIS MOD13Q1.061	1 km	2000–present
Vegetation	NPP	MODIS MOD17A3HGF.061	500 m	2000–present
Socioeconomic	NTL	Harmonised DMSP- OLS/VIIRS (Li et al. 2020)	~500 m	1992–2023
Meteorological	Precipitation, Temperature	TerraClimate	~4 km	1958–present
Topographic	DEM, Slope	SRTM	30 m	Static (2000)

2.3 Methodology

The technical workflow for ecological vulnerability assessment in the southwest borderlands consisted of four sequential steps: multi-source data preprocessing, construction of the SRP-based EVI, land-use transition and landscape-pattern analysis, and spatial-pattern analysis using spatial autocorrelation, GeoDetector and border-distance gradients. Figure 2 summarises the conceptual and analytical framework linking land-use transitions, SRP components, spatial clustering and governance implications in the southwest borderlands.

2.3.1 SRP model and evaluation index system

The SRP model takes into account the sensitivity of ecosystems to external disturbance, the state of resilience capacity for self-recovery, and the pressure exerted on the environment by socioeconomic development (Gu et al. 2023; Li et al. 2021; Li et al. 2022). Sensitivity indicates the inherent fragility or exposure of ecosystems to extrinsic perturbation, determined by topographic and climatic background conditions, including elevation, slope, precipitation, and temperature. Resilience represents the capacity of ecosystems to respond to disturbance and recover functionality, measured through vegetation productivity and coverage. Pressure reflects the effects of human intervention and economic activities on ecosystems, captured through night-time light (NTL) intensity as a proxy for urbanisation and economic activity (Elvidge et al. 2017; Li et al. 2020; Sanderson et al. 2002; Venter et al. 2016), and built-up land intensity derived from CLCD land-use classification as an indicator of construction-driven land-surface sealing (Yang and Huang 2021; Yang and Huang 2023). Based on the ecological characteristics of the southwest borderlands and related vulnerability studies (Gu et al. 2023; Hu and Xu 2019; Jin et al. 2021; Li et al. 2021; Li et al. 2022; Luo et al. 2024), this study selected nine indicators across three dimensions to construct the evaluation system (Table 2).

Table 2. Ecological vulnerability evaluation indicator system

Criteria layer	Indicator	Ecological significance	Direction
----------------	-----------	-------------------------	-----------

Criteria layer	Indicator	Ecological significance	Direction
Sensitivity	Elevation (DEM)	Reflecting exposure to erosion and frost weathering at higher elevations	Positive
Sensitivity	Slope	Reflecting geomorphological instability of steeper terrain	Positive
Sensitivity	Annual precipitation	Reflecting hydrological stress potential in mountainous terrain	Positive
Sensitivity	Annual temperature	Reflecting thermal background stress on ecosystem stability	Positive
Resilience	NDVI	Characterising vegetation cover state, reflecting ecosystem recovery capacity	Negative
Resilience	NPP	Reflecting ecosystem self-regulation and self-restoration ability	Negative
Resilience	Forest coverage fraction	Reflecting ecosystem service capacity and habitat integrity	Negative
Pressure	NTL intensity	Reflecting anthropogenic pressure from urbanisation and economic activity	Positive
Pressure	Built-up land intensity	Reflecting land-surface sealing pressure from construction expansion	Positive

2.3.2 Standardisation

As the evaluation indicators have different dimensions and orders of magnitude, this study adopts the min–max normalisation method for standardisation to eliminate the influence of magnitude. All indicator values are uniformly mapped into the interval [0, 1], making the different indicators comparable to each other. The formula reads as follows:

$$\text{Positive indicator: } X_i = \frac{x_i - \min(x)}{\max(x) - \min(x)}$$

$$\text{Negative indicator: } X_i = \frac{\max(x) - x_i}{\max(x) - \min(x)}$$

Specifically, Night-time Light data were obtained from the harmonised global dataset to ensure long-term consistency, and Land Use/Cover data were derived from high-resolution annual datasets. Considering the potential extreme values in night-time light and impervious-surface data, we applied a 5% - 95% quantile robust normalisation method. For each year and each indicator, the 5th percentile ($X_{\min}$) and 95th percentile ($X_{\max}$) were calculated to normalise the raw value:

2.3.3 Ecological vulnerability index

This study calculates the Ecological Vulnerability Index (EVI) for each year by combining the standardised indicators and dimensional weights to determine composite vulnerability. We assigned equal weights to the three dimensions to keep the index transparent and comparable across heterogeneous ecological zones; this is a modelling assumption rather than an empirically estimated weighting scheme:

$$\text{Sensitivity: } S = \frac{S_{\text{elev}} + S_{\text{slope}} + S_{\text{precip}} + S_{\text{temp}}}{4}$$

$$\text{Resilience (inverted): } R_{\text{inv}} = \frac{(1-R_{\text{NDVI}}) + (1-R_{\text{NPP}}) + (1-R_{\text{forest}})}{3}$$

$$\text{Pressure: } P = \frac{P_{\text{NTL}} + P_{\text{built}}}{2}$$

$$\text{Ecological Vulnerability Index: } EVI = \frac{S + R_{\text{inv}} + P}{3}$$

EVI values range from 0 (least vulnerable) to 1 (most vulnerable). To interpret the grading of ecological vulnerability, EVI was divided into five levels commonly used in regional vulnerability studies: Potential (< 0.2), Light (0.2–0.4), Moderate (0.4–0.6), Heavy (0.6–0.8), and Extreme (> 0.8) (Gu et al. 2023; Hu and Xu 2019; Jin et al. 2021; Li et al. 2021; Li et al. 2022; Luo et al. 2024).

2.3.4 Landscape pattern metrics

To characterise the structural response of landscapes to land-use transitions, three widely used landscape metrics were computed from the CLCD data: Shannon's Diversity Index (SHDI), which reflects heterogeneity and evenness of land-use composition; Patch Density (PD), which measures landscape fragmentation by counting the number of discrete patches per unit area; and Largest Patch Index (LPI), which indicates the spatial dominance of the largest contiguous patch (McGarigal and Marks 1995). The CLCD data were downsampled to 150-m effective resolution (5× from 30 m) to enable computational tractability over the large study area. SHDI was derived from pixel-frequency histograms computed within 1-km grid cells; PD and LPI were computed using connected component labelling on the downsampled raster for each study year.

2.3.5 Spatial autocorrelation and GeoDetector-based spatial decomposition

To characterise the spatial dependence of ecological vulnerability, global Moran's I and local indicators of spatial association (LISA) were calculated for EVI in 2001, 2006, 2009, 2012, 2018 and 2023 (Anselin 1995; Moran 1950). The 1-km EVI rasters were aggregated to approximately 5-km grid cells and all years were restricted to a common valid spatial mask. Queen contiguity defined the spatial weights, and pseudo p values were obtained through random permutation. GeoDetector was then used to characterise the spatial stratification of EVI associated with each constituent indicator (Song et al. 2020; Wang et al. 2016). Its q-statistic ranges within [0, 1], with larger values indicating stronger spatial correspondence between a constituent indicator and EVI. The statistic is:

$$q = 1 - \frac{\sum_{h=1}^L N_h \sigma_h^2}{N \sigma^2}$$

where N denotes the total count of samples; L stands for the count of factor strata; N_h represents the sample size of stratum h; σ_h^2 reflects the variance of ecological vulnerability within stratum h; σ^2 denotes the variance of EVI across the entire region.

Pairwise detection evaluates whether the spatial co-stratification associated with two indicators is stronger than that associated with either indicator alone. We retain GeoDetector's formal categories: when the paired q-value exceeds the larger individual q-value but remains below their sum, it is classified as 'bi-factor enhancement'; when it exceeds their sum, it is classified as 'nonlinear enhancement'. These categories are descriptive statistical relationships and are not interpreted as causal interactions.

GeoDetector was used as a descriptive decomposition of the index's spatial stratification. EVI was retained as the dependent variable, and the nine constituent

indicators—elevation, slope, annual precipitation, annual mean temperature, NDVI, NPP, forest coverage fraction, NTL intensity and CLCD-derived impervious-surface fraction—were evaluated individually. Because these variables are mathematically embedded in EVI, their q-statistics describe the spatial correspondence between each input and the composite index and cannot be interpreted as independent causal effects. Systematic sampling at five-pixel intervals was retained for consistency with the spatial-autocorrelation grid. Zero-inflated variables such as NTL were stratified by treating zero values as a separate class before applying quantile classification to positive values; the remaining continuous variables were classified into five equal-frequency strata.

2.3.6 Border-distance gradient analysis

To explore the spatial relationship between ecological indicators and proximity to international boundaries, the Euclidean distance from each sampling point to the nearest international border segment was computed. Border segments were extracted from the Natural Earth admin-0 boundary lines dataset (Natural Earth n.d.), selecting only segments shared between China and its six neighbouring countries (Myanmar, Laos, Vietnam, India, Nepal, Bhutan). Sampling points were grouped into six distance bands (0–20 km, 20–50 km, 50–100 km, 100–200 km, 200–500 km, >500 km), and the mean values of EVI, NDVI, NPP, NTL, Sensitivity, inverted Resilience, and Pressure were calculated for each band, enabling identification of distance-dependent ecological gradients associated with border proximity.

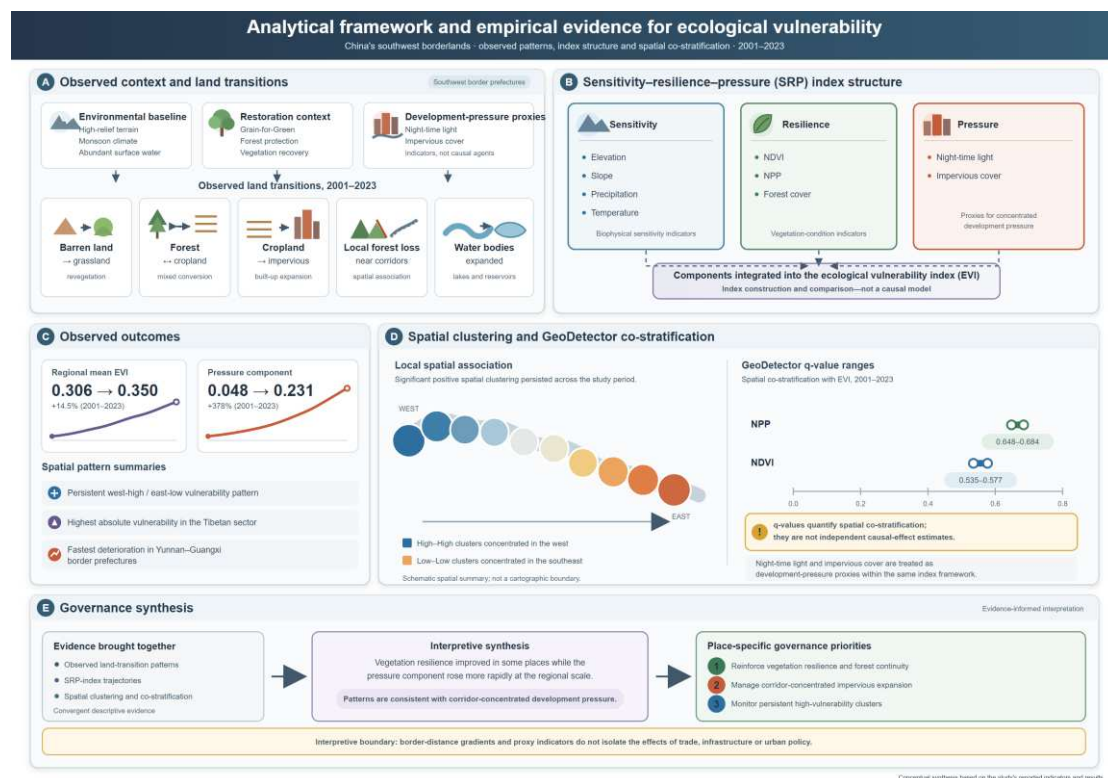


Figure 2. Conceptual and analytical framework linking land-use transitions and ecological vulnerability in China's southwest borderlands. The framework shows how topographic-climatic conditions, vegetation-based resilience and observed development proxies are represented within the Sensitivity–Resilience–Pressure assessment, and how their spatial patterns inform differentiated governance. It describes index structure and spatial association rather than causal effects of trade or infrastructure policy.

3 Results

3.1 Land-use change and landscape dynamics

Across the 23-year study period (2001–2023), land-use configuration in the southwest borderlands underwent substantial transformation (Fig. 3a,b). Grassland and forest collectively dominated the landscape, accounting for approximately 79.3% of the total study area. The 2001 baseline was characterised by grassland prevalence (483,975 km², 50.2%), substantial forest cover (279,968 km², 29.0%), and extensive barren land (105,548 km², 11.0%), with cropland at 49,023 km² (5.1%) and impervious surfaces at a negligible 385 km² (0.04%).

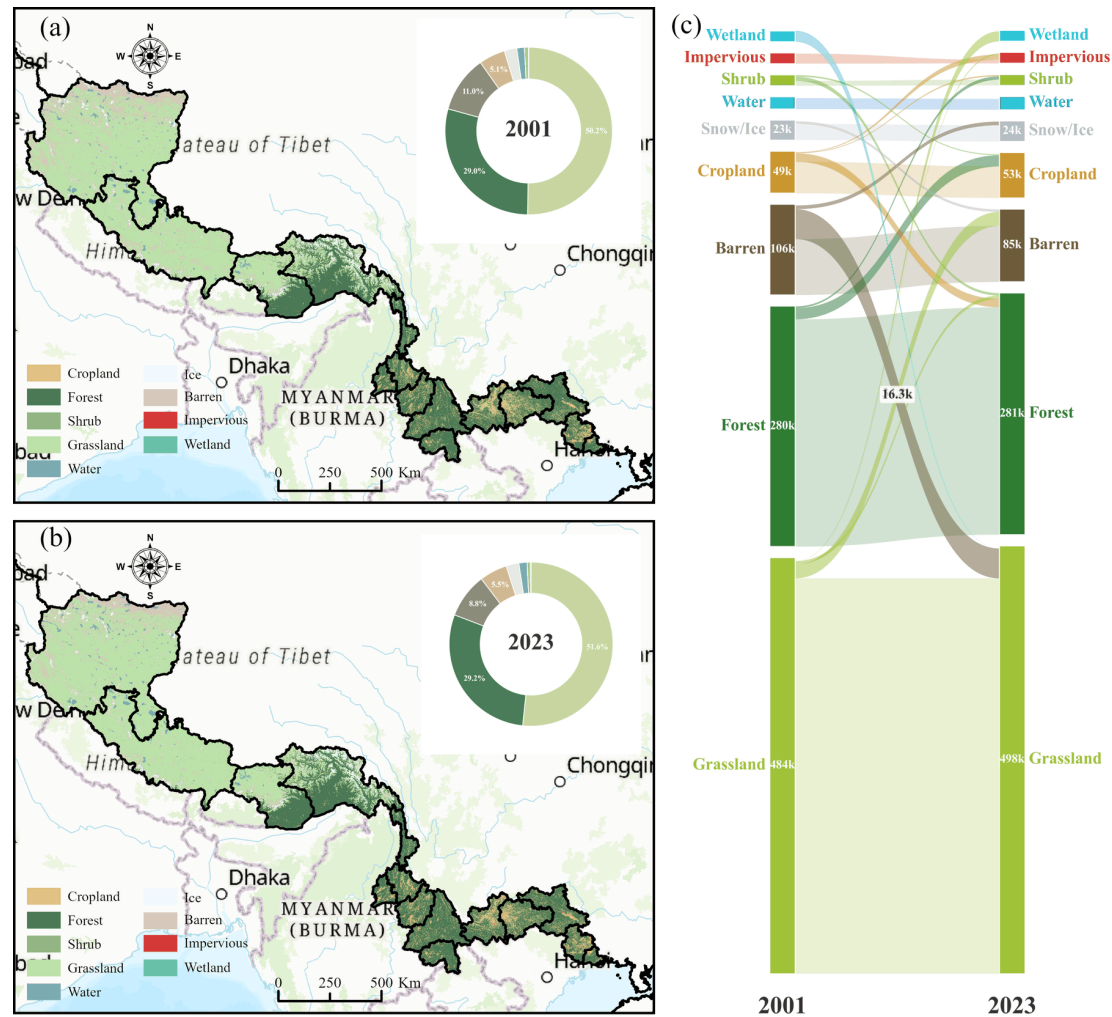


Figure 3. Land-use spatial distribution and transition flows in the southwest borderlands from 2001 to 2023. (a) Land-use/cover pattern in 2001 with proportional area composition; (b) land-use/cover pattern in 2023 with proportional area composition; (c) Sankey diagram showing major land-use/cover transitions between 2001 and 2023. Values in the Sankey diagram are rounded to thousand square kilometres, and land-use classes include cropland, forest, shrub, grassland, water, snow/ice, barren land, impervious surface, and wetland. Country-boundary linework is based on Natural Earth, and topographic context is based on SRTM.

Grassland expanded by 13,722 km² (+2.8%), principally on the Tibetan Plateau margin, where areas classified as barren in 2001 were classified as sparse grassland by 2023. Barren land decreased by 20,564 km² (–19.5%), the largest absolute change among all

land-cover types, concentrated in the western Tibetan sector (Ali, Rikaze and Shannan). Cropland expanded by 3,732 km² (+7.6%), with gains concentrated in Guangxi (Baise: +1,702 km²; Fangchenggang: +375 km²) and Yunnan (Honghe: +706 km²; Lincang: +351 km²; Dehong: +292 km²). Impervious surfaces increased by 664 km² (+172.4%), a nearly threefold rise from the 2001 baseline, with gains concentrated in Baise (+119.2 km²), Honghe (+102.8 km²), Dehong (+70.0 km²) and Fangchenggang (+67.5 km²). Forest area changed little in net terms (+1,209 km², +0.43%), but this stability masked gains in Linzhi (+1,727 km²), Wenshan (+1,139 km²) and Baoshan (+443 km²), and losses in Baise (−1,238 km²), Fangchenggang (−393 km²) and Xishuangbanna (−383 km²). Water bodies expanded by 1,333 km² (+9.4%), and shrub declined by 1,090 km² (−14.4%). Overall, grassland and barren land showed a reciprocal trend, while cropland, impervious surfaces and water increased. The land-use transition matrix (Fig. 3c) shows that Barren→Grassland (16.3 × 10³ km²) was the largest flow and Cropland→Impervious (497 km²) the principal transition into impervious land. These classifications describe observed transitions and do not, by themselves, identify the climatic or policy processes that caused them.

The broad spatial arrangement of land-use categories maintained sectoral coherence across study years while concealing pronounced within-region contrasts. Tibetan prefectures (Ali, Rikaze and Shannan) were characterised primarily by barren-to-grassland transitions with negligible impervious growth, dominated by alpine meadow and desert-steppe ecosystems. In the Yunnan sector, forest loss in selected lowland valleys, cropland expansion on hillslopes and rapid impervious-surface growth occurred together in several border-corridor prefectures. The Guangxi sector (Baise, Chongzuo and Fangchenggang) experienced the most intense urban expansion, including conversion of subtropical forest and cropland to impervious surfaces along the China–Vietnam border economic corridor. These patterns coincided spatially with trade and infrastructure development, but the present design does not attribute land conversion to a particular policy or investment programme.

The temporal trajectory of impervious expansion showed two phases: moderate growth during 2001–2012 (+283 km², +73%) and larger absolute gains during 2012–2023 (+381 km², +57%). Post-2012 gains were larger in absolute terms. This timing coincides with intensified regional connectivity and infrastructure development, but the present design does not identify policy causality.

Landscape pattern metrics further corroborated these structural shifts. SHDI followed an inverted-U trajectory (0.743 → peak 0.762 in 2018 → 0.739 in 2023), PD declined from 156.8 to 141.4 patches/100 km² (−9.8%), and LPI rose from 44.7% to 46.9%, collectively indicating regional landscape consolidation dominated by grassland expansion, alongside localised fragmentation in urbanising border corridors.

3.2 Spatiotemporal evolution of ecological vulnerability

Over the 23-year assessment period (2001–2023), ecological vulnerability across the southwest borderlands followed a persistent upward trajectory (Fig. 4d), while the spatial maps show a clear regional grade transition between 2001 and 2023 (Fig. 4a,b). At the pixel scale, light vulnerability (EVI: 0.2–0.4) constituted the dominant grade in 2001 (820,008 km², 85.0%), shifting to moderate vulnerability (EVI: 0.4–0.6) by 2023 (574,933

km², 59.6%), indicating a region-wide upward grade transition. Potential vulnerability (EVI < 0.2) declined sharply from 113,957 km² (11.8%) to near zero, while heavy and extreme grades remained negligible throughout. At the prefecture scale, 12 of 15 prefectures maintained mean EVI within the light range (0.2–0.4), with the regional simple mean rising from 0.306 to 0.350 (+14.5%).

EVI remained comparatively stable during 2001–2009 before increasing more rapidly after 2012, coinciding with post-2012 growth in NTL; the analysis does not isolate the policy or economic sources of that growth.

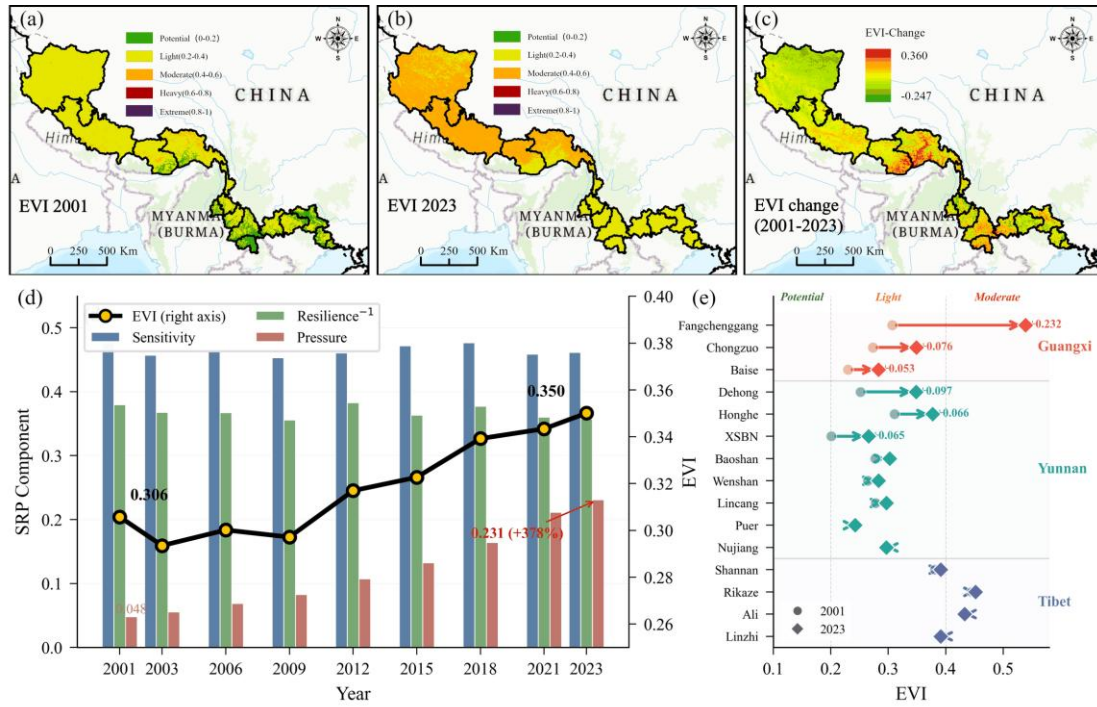


Figure 4. Spatiotemporal evolution of ecological vulnerability and SRP components in the southwest borderlands from 2001 to 2023. (a) Spatial distribution of EVI classes in 2001; (b) spatial distribution of EVI classes in 2023; (c) EVI change from 2001 to 2023; (d) temporal trajectories of regional mean EVI and SRP components; (e) prefecture-level EVI changes from 2001 to 2023, grouped by Tibet, Yunnan, and Guangxi. EVI classes include Potential, Light, Moderate, Heavy, and Extreme vulnerability. Country-boundary linework is based on Natural Earth, and topographic context is based on SRTM. In panel (e), XSBN denotes Xishuangbanna.

At the prefecture level, EVI in 2023 ranged from 0.242 (Puer) to 0.539 (Fangchenggang), with most prefectures remaining below 0.45 (Fig. 4e). The five most deteriorated prefectures—Fangchenggang (+0.232, from 0.307 to 0.539), Dehong (+0.097, from 0.252 to 0.348), Chongzuo (+0.076), Honghe (+0.066), and Xishuangbanna (+0.065)—are all Yunnan–Guangxi border trade hubs with NTL increases exceeding 0.16 DN. Fangchenggang, which contains a major ASEAN-facing port, showed pronounced impervious expansion (+67.5 km²) alongside the highest EVI deterioration. Conversely, Tibetan prefectures (Linzhi: −0.002, Ali: −0.001) and the high-altitude Yunnan prefecture of Nujiang (−0.004) remained stable or improved where measured NTL and impervious-surface pressure was negligible. Rikaze maintained the highest absolute EVI among Tibetan prefectures throughout (0.445 → 0.452) in the context of extreme topographic sensitivity, followed by Ali (~0.433, mean elevation ~4,700 m); both remained stable

rather than worsening. Intermediate prefectures (Baise: +0.053, Baoshan: +0.026, Wenshan: +0.019, Lincang: +0.018, Puer: +0.002) experienced modest EVI increases reflecting moderate urbanisation pressure partially offset by vegetation improvement. The upward shift from a light-dominant distribution (85.0%) to a moderate-dominant distribution (59.6%) occurred across the region; within the index decomposition, the increase was dominated by the rising Pressure component rather than by localised extreme deterioration.

The China-Vietnam corridor around Fangchenggang-Chongzuo and the China-Myanmar zone around Dehong-Xishuangbanna formed two visible belts of vulnerability intensification. Their spatial coincidence with impervious expansion and NTL growth is consistent with corridor-concentrated development pressure, but it does not establish that cross-border trade caused the observed change.

3.3 Spatial autocorrelation patterns

Spatial autocorrelation analysis showed that ecological vulnerability had a strong and statistically significant positive spatial dependence throughout 2001–2023 (Fig. 5). Based on the common six-year valid grid, Moran's I remained consistently high: 0.953 in 2001, 0.927 in 2006, 0.927 in 2009, 0.931 in 2012, 0.915 in 2018, and 0.958 in 2023, with pseudo $p = 0.010$ for all years. This indicates that ecological vulnerability is not randomly distributed but forms stable spatial clusters. The slight decline from 2001 to 2018 followed by a rebound in 2023 suggests that vulnerability clustering weakened modestly during the intermediate period but intensified again by the end of the study period, consistent with the emergence of concentrated vulnerability intensification belts along border trade corridors and persistent high-background vulnerability in the western high-altitude sector.

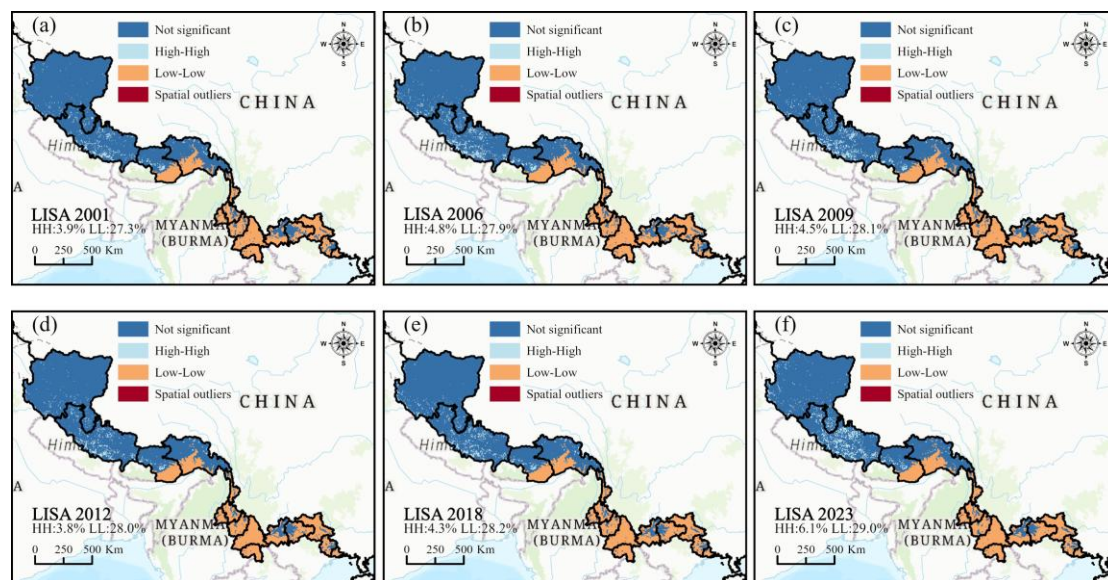


Figure 5. LISA cluster maps of ecological vulnerability in the southwest borderlands. Local indicators of spatial association were calculated for EVI in 2001, 2006, 2009, 2012, 2018, and 2023. The maps show non-significant cells, High-High clusters, Low-Low clusters, and spatial outliers. HH and LL percentages indicate the share of valid grid cells belonging to High-High and Low-Low clusters, respectively. Country-boundary linework is based on Natural Earth, and topographic context is based on SRTM.

LISA cluster maps further revealed a persistent west–east clustering structure. High-high clusters were mainly concentrated in the western high-altitude sector and Hengduan Mountain margin, where high terrain sensitivity and low ecological recovery capacity coincided with high vulnerability. Low-low clusters were mainly distributed in the southeastern subtropical sector, especially in vegetation-rich Yunnan–Guangxi areas with comparatively low absolute EVI. According to the proportions marked in Fig. 5, the share of high-high clusters varied from 3.8% to 6.1% of valid grid cells, reaching its highest value in 2023, whereas low-low clusters increased slightly from 27.3% in 2001 to 29.0% in 2023. High-low and low-high outliers accounted for almost no area, indicating that the vulnerability pattern is dominated by broad regional clustering rather than isolated local anomalies. Compared with simple correlation analysis between EVI and its component variables, this spatial autocorrelation approach more directly characterises the geographic aggregation of vulnerability and avoids circular interpretation caused by correlating EVI with indicators already embedded in the SRP index.

3.4 Spatial explanatory structure and border-distance gradients

The GeoDetector-based decomposition of the nine constituent indicators showed that vegetation-productivity variables registered the largest q-statistics across all six periods (Fig. 6). NPP had the largest single-indicator q-statistic in every focal year: 0.657 (2001), 0.649 (2006), 0.684 (2009), 0.655 (2012), 0.675 (2018) and 0.648 (2023). NDVI ranked second, with q-values from 0.535 to 0.577. Temperature ranked third ($q = 0.463\text{--}0.522$), followed by elevation ($q = 0.404\text{--}0.500$) and precipitation ($q = 0.303\text{--}0.361$). Slope, NTL and impervious-surface fraction had low individual q-values ($q < 0.03$ for most years), although the NTL q-value increased from 0.009 in 2006 to 0.066 in 2023. Forest-cover fraction had negligible individual explanatory power ($q \approx 0.000$). These values identify the constituent indicators that align most closely with the spatial pattern of the composite index; they do not establish that those indicators independently cause EVI.

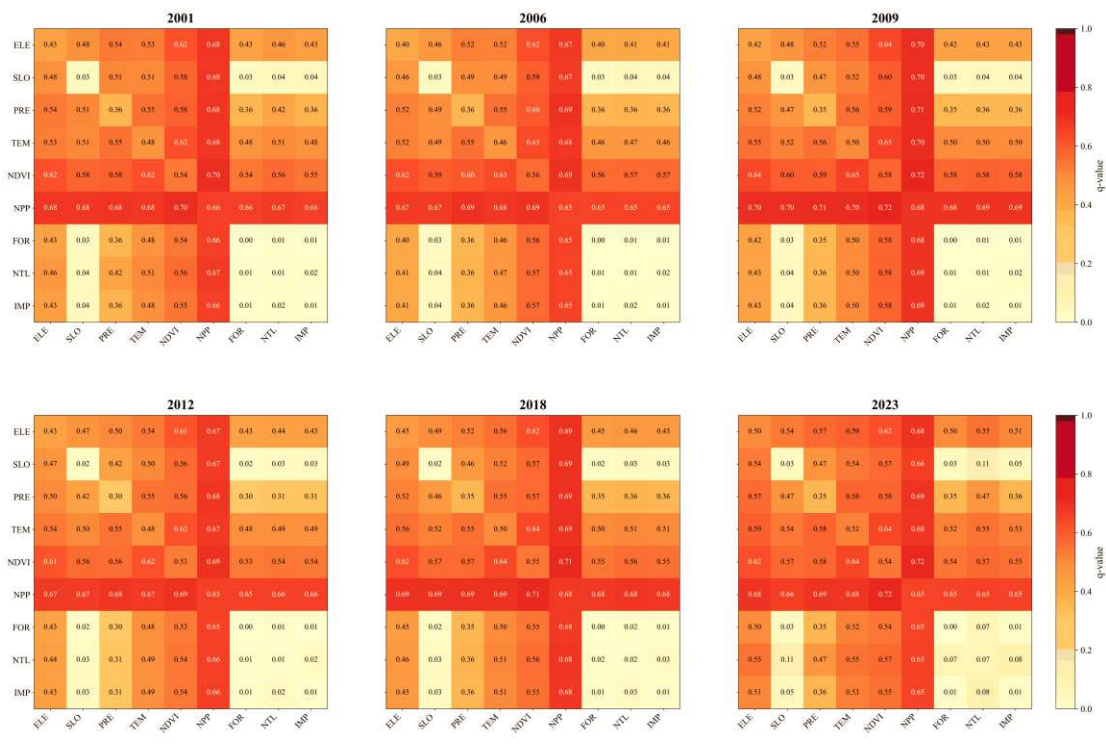


Figure 6. GeoDetector factor and interaction q-statistics for ecological vulnerability in 2001, 2006, 2009, 2012, 2018, and 2023. Diagonal cells represent single-factor q-statistics, and off-diagonal cells represent interaction q-statistics between paired factors. Abbreviations are as follows: ELE, elevation; SLO, slope; PRE, annual precipitation; TEM, annual mean temperature; NDVI, Normalised Difference Vegetation Index; NPP, net primary productivity; FOR, forest coverage fraction; NTL, night-time light intensity; and IMP, impervious surface fraction. Warmer colours indicate stronger explanatory power for EVI spatial differentiation. Because the displayed indicators are also constituents of EVI, these q-statistics describe spatial co-stratification within the index and are not independent causal-effect estimates.

Pairwise GeoDetector results showed stronger co-stratification for most non-forest indicator pairs than for either indicator alone (Fig. 6). The largest paired q-values were observed for NDVI $\times$ NPP ($q = 0.701$ in 2001 and 0.722 in 2009), followed by precipitation $\times$ NPP ($q = 0.682\text{--}0.706$) and temperature $\times$ NPP ($q = 0.677\text{--}0.704$). NTL also co-stratified more strongly with vegetation indicators than it did alone: NPP $\times$ NTL remained approximately $0.654\text{--}0.689$ and NDVI $\times$ NTL approximately $0.54\text{--}0.58$ across the six focal years. These paired statistics are best read as overlapping spatial structure between ecological capacity and measured human pressure. Because both indicators are used to construct EVI, the formal ‘enhancement’ categories do not represent causal interaction effects.

The preceding decomposition identifies which constituent indicators align most strongly with the spatial pattern of EVI; it does not identify independent causes. It also does not show how measured anthropogenic pressure is organised relative to the international boundary. The following distance-gradient analysis addresses this complementary descriptive question.

Complementing the factor detection, the border distance gradient analysis revealed distinct ecological patterns relative to international boundary proximity. EVI showed a relatively flat spatial profile across distance bands ($0.353\text{--}0.376$), with a slight peak at $200\text{--}500$ km, driven by the offsetting combination of high Pressure near the border and high inverted Resilience (low vegetation recovery capacity) in the interior. NDVI and NPP were highest near the border ($0.549\text{--}0.558$; $0.772\text{--}0.788$ within 50 km) and declined systematically with distance (0.365 ; 0.333 beyond 500 km), a pattern consistent with the shift from tropical/subtropical lowlands with abundant precipitation to progressively higher and drier terrain. This gradient underscores why absolute EVI levels alone are misleading without SRP decomposition—low-elevation border areas maintain relatively low EVI despite higher Pressure because stronger vegetation Resilience partly offsets higher measured Pressure in the composite index.

Measured Pressure declined monotonically from 0.457 in the $0\text{--}20$ -km band to 0.299 beyond 500 km. The inverted Resilience component generally increased from 0.452 in the $0\text{--}20$ -km band to 0.589 at $200\text{--}500$ km, with a small dip at $20\text{--}50$ km (0.447) and a near-plateau beyond 500 km (0.587). The opposing component gradients explain why mean EVI remained comparatively flat across the distance bands. The Pressure pattern is consistent with corridor-concentrated development pressure in border-proximate areas, but the distance gradient cannot distinguish cross-border trade effects from urbanisation, infrastructure, regional environmental gradients or other spatially correlated processes.

4 Discussion

4.1 The resilience–pressure paradox as a borderland governance problem

The regional mean EVI rose from 0.306 to 0.350 between 2001 and 2023 even as the inverted Resilience component fell from 0.380 to 0.358, indicating stronger vegetation-based recovery capacity. Pressure, by contrast, increased from 0.048 to 0.231. Within the equal-weight SRP framework, the pressure increase was therefore large enough to outweigh the improvement in resilience. This is the empirical core of the resilience–pressure paradox. It should not be read as evidence that restoration failed: the analysis has no counterfactual with which to estimate what vulnerability would have been without restoration. Rather, it shows that recovery in one ecological dimension can coexist with deterioration in another and that reporting greening alone provides an incomplete account of borderland sustainability (Chen et al. 2019; Ouyang et al. 2016; Piao et al. 2020; Qiao et al. 2021; Tong et al. 2018; Zhang et al. 2021).

The spatial organisation of the two trends gives the paradox its borderland significance. Vegetation recovery was broad, whereas the largest increases in impervious surface and night-time light were concentrated in selected Yunnan–Guangxi trade prefectures and lowland corridors. This pattern is consistent with a borderland in which connectivity and development are spatially selective rather than evenly distributed (Ascensão et al. 2018; Jin et al. 2021; Paasi 1998; State Council Information Office of the People’s Republic of China 2023). It does not establish that trade liberalisation or any particular infrastructure programme caused the observed EVI change, because the study does not directly measure policy exposure, trade flows or project timing. The appropriate inference is narrower but still important: restoration and corridor-concentrated development pressure occupied different geographies and moved in opposite directions, producing a scale mismatch that composite regional averages can obscure.

4.2 Land-use transitions and divergent regional trajectories

Land-use transitions reveal the material form of this mismatch. Impervious area increased by 664 km², or 172.4%, and the gains were concentrated in prefectures such as Fangchenggang, Honghe and Dehong. Although this area was small relative to the forest–grassland matrix, its location matters. Land sealing and conversion around ports, urban nodes and narrow valleys can interrupt ecological continuity in places where development is already concentrated (Elvidge et al. 2017; Güneralp and Seto 2013; Sanderson et al. 2002; Seto et al. 2012; Venter et al. 2016). Fangchenggang combined the largest increase in EVI (+0.232) with substantial impervious expansion and night-time-light growth, while Dehong also combined rapid deterioration (+0.097) with strong increases in built-up land and light intensity. These concordant patterns identify priority locations for closer planning scrutiny; they should not be treated as causal effect estimates.

The comparison between sectors also separates the level of vulnerability from its direction of change. Tibetan prefectures retained high absolute EVI because of topographic sensitivity, but most were stable; several Yunnan–Guangxi prefectures began from lower levels and deteriorated more rapidly. A policy based only on the latest EVI would emphasise the plateau and understate emerging corridor pressure, whereas a policy based only on change would overlook landscapes whose structural sensitivity

remains high. The findings therefore support a two-axis reading of the maps: current vulnerability indicates the stock of ecological constraint, while change in Pressure and EVI indicates the trajectory of new stress. This distinction converts a descriptive west-high/east-low pattern into a governance-relevant typology of persistent sensitivity, buffered pressure and rapidly intensifying pressure.

4.3 Scale-dependent interpretation of spatial explanatory patterns

GeoDetector results further illustrate why scale matters. NPP ($q = 0.648\text{--}0.684$) and NDVI ($q = 0.535\text{--}0.577$) registered the largest q -statistics, while temperature and elevation represented the macro-geographical transition from the Tibetan Plateau to the subtropical lowlands. NTL and impervious fraction had much lower individual q -values, but the q -value for NTL increased by 2023 and its combinations with vegetation variables were markedly stronger than NTL alone. This does not mean that vegetation is a causal "driver" or that urbanisation is unimportant. EVI is constructed from these same indicators, so GeoDetector describes the internal spatial architecture of the index rather than identifying exogenous causes (Song et al. 2020; Wang et al. 2016). Moreover, a spatially sparse corridor signal can be locally consequential while explaining little of a vast mountainous region on its own. The interaction results are best read as co-stratification: ecological capacity and human pressure overlap in ways that a single-factor regional statistic does not reveal.

The border-distance results reinforce this interpretation. Pressure declined from 0.457 within 20 km of the international boundary to 0.299 beyond 500 km, whereas vegetation-based resilience was generally weaker towards the interior. Mean EVI consequently varied within a relatively narrow range of 0.353–0.376. Boundary proximity is therefore not a simple scalar exposure: near-border areas combined higher pressure with stronger vegetation capacity, while the high-altitude interior combined lower measured pressure with greater structural ecological constraint. The observed profile is the superposition of a corridor/proximity geography and a latitudinal–altitudinal environmental geography. Treating the relatively flat EVI gradient as evidence of "no border effect" would miss the sharp change in its components.

4.4 From composite assessment to differentiated spatial governance

These distinctions call for component- and scale-specific spatial governance. In the Tibetan sector, where baseline sensitivity dominates, priority should be given to disturbance avoidance and continuity of high-altitude ecosystems; restoration targets should not imply that structural fragility can be eliminated. In mountainous Yunnan, policy should preserve vegetation recovery while preventing new valley development from fragmenting recovering landscapes. In the Yunnan–Guangxi trade corridors, where Pressure and land conversion increased most rapidly, project appraisal and municipal land allocation should assess cumulative sealing around ports and transport nodes, prioritise compact development and ecological connectivity, and monitor impervious expansion and night-time light as early-warning signals. Intermediate areas require transition monitoring based on changes in individual SRP components rather than waiting for total EVI to cross a high-vulnerability threshold (Ascensão et al. 2018; Cash et al. 2006; Cumming et al. 2006).

This framework does not presume that border opening and conservation are mutually exclusive, nor does the present analysis quantify the economic or social benefits of connectivity. It can identify where the ecological side of the trade-off is intensifying and which component requires intervention, but it cannot determine the socially optimal level of development. That decision requires governance across scales: corridor and port projects, prefectural land allocation and regional restoration programmes should use a shared spatial evidence base and evaluate cumulative rather than project-by-project effects (Ascensão et al. 2018; Cash et al. 2006; Cumming et al. 2006). Where development is retained, siting, density and mitigation should be calibrated to local resilience and sensitivity. In this sense, the policy contribution of the SRP decomposition is diagnostic: it indicates whether a place needs protection from disturbance, stewardship of recovery capacity or direct regulation of pressure.

4.5 Limitations and research agenda

Several limitations delimit these conclusions. First, equal weighting improves transparency but assumes that Sensitivity, Resilience and Pressure contribute equally across very different environments; alternative weights and uncertainty and sensitivity analyses are needed. Second, because GeoDetector uses variables that also construct EVI, its q-statistics and interactions cannot independently identify drivers; future work should test external explanatory variables and causal mechanisms. Third, NTL and impervious cover do not capture non-luminous pressures such as grazing, agricultural inputs, informal construction or seasonal mobility. Fourth, the 1-km grid and prefectural comparisons may conceal changes around individual border towns and infrastructure sites. Fifth, distance from the boundary is correlated with the region's east-west altitudinal and climatic structure, so the gradient cannot isolate a border effect. Finally, the study covers only the Chinese side and contains no direct measures of trade volumes, infrastructure opening dates, implementation practices, distributional consequences or community responses. Future research should combine fine-resolution land and project data with panel or quasi-experimental designs, cross-border comparison and interviews with local institutions and affected communities. Scenario modelling can then examine how alternative land-use and corridor policies redistribute both ecological risk and development opportunity (Liang et al. 2021; Liu et al. 2017; Meyfroidt et al. 2022; Verburg et al. 2002; Verburg et al. 2015).

5 Conclusion

Between 2001 and 2023, mean EVI in China's southwest borderlands increased from 0.306 to 0.350. The Pressure component rose from 0.048 to 0.231, while the inverted Resilience component declined from 0.380 to 0.358, indicating improved vegetation-based recovery capacity. Impervious area increased by 172.4% (+664 km²) and was concentrated in several border trade prefectures. At the same time, Tibetan prefectures retained high but comparatively stable vulnerability arising largely from topographic sensitivity, whereas the fastest deterioration occurred in Yunnan–Guangxi corridor prefectures. The region therefore contains two different governance problems: persistent background constraint and rapidly accumulating development pressure.

The resilience–pressure paradox names the spatial mismatch between these trends. It does not establish that trade or border policy caused ecological deterioration. Rather, the

joint pattern of land conversion, night-time light and distance gradients is consistent with corridor-concentrated development pressure superimposed on an altitudinal–climatic geography of ecological capacity. GeoDetector similarly provides a decomposition of the index's spatial structure, not independent causal-driver evidence. These qualifications sharpen the study's contribution: composite vulnerability can remain relatively flat or moderate while its constituent pressures move in policy-relevant directions.

Borderland governance should therefore use both the level and trajectory of each SRP component. High-altitude areas require sensitivity protection; mountainous Yunnan requires stewardship of vegetation recovery and valley landscapes; rapidly changing Yunnan–Guangxi corridors require cumulative land-conversion control and ecological connectivity; and intermediate zones require early-warning monitoring. Future causal and mixed-method research is needed to determine how particular trade, infrastructure and land-management institutions produce these patterns and how ecological costs and development benefits are distributed. The present analysis supplies the spatial diagnosis on which that governance inquiry can build.

Declarations

Data availability

The source datasets used in this study are publicly available. The China Land Cover Dataset (CLCD) is available through Zenodo (<https://doi.org/10.5281/zenodo.8176941>). MODIS/Terra products MOD13Q1.061 and MOD17A3HGF.061 are available from NASA LP DAAC and were accessed through Google Earth Engine. TerraClimate data are available from the University of Idaho and Google Earth Engine; SRTM data are available from NASA/USGS; the harmonised DMSP-OLS/VIIRS night-time-light data are described by Li et al. (2020); and international-boundary data are available from Natural Earth. Processed 1-km indicators, summary data underlying the tables and figures, and derived statistics are available from the corresponding authors upon reasonable request.

Acknowledgements

The authors acknowledge the institutions and research teams that produced and maintained the CLCD, MODIS, TerraClimate, SRTM, harmonised night-time-light and Natural Earth datasets used in this study.

Funding

Funding information has been withheld from the anonymous manuscript and is supplied separately to the editorial office.

Competing interests

The authors declare no competing interests.

References

- Abatzoglou JT, Dobrowski SZ, Parks SA et al (2018) TerraClimate, a high-resolution global dataset of monthly climate and climatic water balance from 1958–2015. *Scientific Data* 5:170191. <https://doi.org/10.1038/sdata.2017.191>
- Adger WN (2006) Vulnerability. *Global Environmental Change* 16:268–281. <https://doi.org/10.1016/j.gloenvcha.2006.02.006>

- Anselin L (1995) Local indicators of spatial association—LISA. *Geographical Analysis* 27:93–115. <https://doi.org/10.1111/j.1538-4632.1995.tb00338.x>
- Ascensão F, Fahrig L, Clevenger AP et al (2018) Environmental challenges for the Belt and Road Initiative. *Nature Sustainability* 1:206–209. <https://doi.org/10.1038/s41893-018-0059-3>
- Cash DW, Adger WN, Berkes F et al (2006) Scale and cross-scale dynamics: governance and information in a multilevel world. *Ecology and Society* 11:8. <https://doi.org/10.5751/ES-01759-110208>
- Chen C, Park T, Wang X et al (2019) China and India lead in greening of the world through land-use management. *Nature Sustainability* 2:122–129. <https://doi.org/10.1038/s41893-019-0220-7>
- Cumming GS, Cumming DHM, Redman CL (2006) Scale mismatches in social-ecological systems: causes, consequences, and solutions. *Ecology and Society* 11:14. <https://doi.org/10.5751/ES-01569-110114>
- Didan K (2021) MODIS/Terra Vegetation Indices 16-Day L3 Global 250m SIN Grid V061. NASA EOSDIS Land Processes DAAC. <https://doi.org/10.5067/MODIS/MOD13Q1.061>
- Elvidge CD, Baugh K, Zhizhin M et al (2017) VIIRS night-time lights. *International Journal of Remote Sensing* 38:5860–5879. <https://doi.org/10.1080/01431161.2017.1342050>
- Farr TG, Rosen PA, Caro E et al (2007) The Shuttle Radar Topography Mission. *Reviews of Geophysics* 45:RG2004. <https://doi.org/10.1029/2005RG000183>
- Ferdinand P (2016) Westward ho—the China dream and ‘one belt, one road’: Chinese foreign policy under Xi Jinping. *International Affairs* 92:941–957. <https://doi.org/10.1111/1468-2346.12660>
- Füssel HM (2007) Vulnerability: a generally applicable conceptual framework for climate change research. *Global Environmental Change* 17:155–167. <https://doi.org/10.1016/j.gloenvcha.2006.05.002>
- Gu H, Huan C, Yang F (2023) Spatiotemporal dynamics of ecological vulnerability and its influencing factors in Shenyang City of China: based on SRP model. *International Journal of Environmental Research and Public Health* 20:1525. <https://doi.org/10.3390/ijerph20021525>
- Güneralp B, Seto KC (2013) Futures of global urban expansion: uncertainties and implications for biodiversity conservation. *Environmental Research Letters* 8:014025. <https://doi.org/10.1088/1748-9326/8/1/014025>
- Hinkel J (2011) Indicators of vulnerability and adaptive capacity: towards a clarification of the science–policy interface. *Global Environmental Change* 21:198–208. <https://doi.org/10.1016/j.gloenvcha.2010.08.002>
- Hu X, Xu H (2019) A new remote sensing index based on the pressure–state–response framework to assess regional ecological change. *Environmental Science and Pollution Research* 26:5381–5393. <https://doi.org/10.1007/s11356-018-3948-0>
- Huang S, Tang L, Hupy JP et al (2021) A commentary review on the use of normalized difference vegetation index in the era of popular remote sensing. *Journal of Forestry Research* 32:1–6. <https://doi.org/10.1007/s11676-020-01155-1>
- Huete A, Didan K, Miura T et al (2002) Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* 83:195–213. [https://doi.org/10.1016/S0034-4257\(02\)00096-2](https://doi.org/10.1016/S0034-4257(02)00096-2)
- IPBES (2019) Global assessment report on biodiversity and ecosystem services. In: Brondizio ES, Settele J, Díaz S, Ngo HT (eds). IPBES Secretariat, Bonn. <https://doi.org/10.5281/zenodo.3831673>
- Jin Y, Li A, Bian J et al (2021) Spatiotemporal analysis of ecological vulnerability along Bangladesh–China–India–Myanmar economic corridor through a grid level prototype model. *Ecological Indicators* 120:106933. <https://doi.org/10.1016/j.ecolind.2020.106933>
- Lambin EF, Geist HJ, Lepers E (2003) Dynamics of land-use and land-cover change in tropical regions. *Annual Review of Environment and Resources* 28:205–241. <https://doi.org/10.1146/annurev.energy.28.050302.105459>
- Li D, Huan C, Yang J et al (2022) Temporal and spatial distribution changes, driving force analysis and simulation prediction of ecological vulnerability in Liaoning Province, China. *Land* 11:1025. <https://doi.org/10.3390/land11071025>

- Li X, Song L, Xie Z et al (2021) Assessment of ecological vulnerability on northern sand prevention belt of China based on the ecological pressure–sensitivity–resilience model. *Sustainability* 13:6078. <https://doi.org/10.3390/su13116078>
- Li X, Zhou Y, Zhao M et al (2020) A harmonized global nighttime light dataset 1992–2018. *Scientific Data* 7:168. <https://doi.org/10.1038/s41597-020-0510-y>
- Liang X, Guan Q, Clarke KC et al (2021) Understanding the drivers of sustainable land expansion using a patch-generating land use simulation (PLUS) model: a case study in Wuhan, China. *Computers, Environment and Urban Systems* 85:101569. <https://doi.org/10.1016/j.compenvurbsys.2020.101569>
- Liu J, Dietz T, Carpenter SR et al (2007) Complexity of coupled human and natural systems. *Science* 317:1513–1516. <https://doi.org/10.1126/science.1144004>
- Liu X, Liang X, Li X et al (2017) A future land use simulation model (FLUS) for simulating multiple land use scenarios by coupling human and natural effects. *Landscape and Urban Planning* 168:94–116. <https://doi.org/10.1016/j.landurbplan.2017.09.019>
- Luo M, Jia X, Zhao Y (2024) Ecological vulnerability assessment and its driving force based on ecological zoning in the Loess Plateau, China. *Ecological Indicators* 159:111658. <https://doi.org/10.1016/j.ecolind.2024.111658>
- McGarigal K, Marks BJ (1995) FRAGSTATS: spatial pattern analysis program for quantifying landscape structure. General Technical Report PNW-GTR-351. USDA Forest Service, Pacific Northwest Research Station, Portland, OR
- Meyfroidt P, de Bremond A, Ryan CM et al (2022) Ten facts about land systems for sustainability. *Proceedings of the National Academy of Sciences of the United States of America* 119:e2109217118. <https://doi.org/10.1073/pnas.2109217118>
- Mittermeier RA, Turner WR, Larsen FW et al (2011) Global biodiversity conservation: the critical role of hotspots. In: Zachos FE, Habel JC (eds) *Biodiversity hotspots*. Springer, Berlin/Heidelberg, pp 3–22. https://doi.org/10.1007/978-3-642-20992-5_1
- Moran PAP (1950) Notes on continuous stochastic phenomena. *Biometrika* 37:17–23. <https://doi.org/10.1093/biomet/37.1-2.17>
- Myers N, Mittermeier RA, Mittermeier CG et al (2000) Biodiversity hotspots for conservation priorities. *Nature* 403:853–858. <https://doi.org/10.1038/35002501>
- Natural Earth (n.d.) Free vector and raster map data. <https://www.naturalearthdata.com>. Accessed 12 June 2026
- Ouyang Z, Zheng H, Xiao Y et al (2016) Improvements in ecosystem services from investments in natural capital. *Science* 352:1455–1459. <https://doi.org/10.1126/science.aaf2295>
- Paasi A (1998) Boundaries as social processes: territoriality in the world of flows. *Geopolitics* 3:69–88. <https://doi.org/10.1080/14650049808407608>
- Piao S, Wang X, Park T et al (2020) Characteristics, drivers and feedbacks of global greening. *Nature Reviews Earth & Environment* 1:14–27. <https://doi.org/10.1038/s43017-019-0001-x>
- Polsky C, Neff R, Yarnal B (2007) Building comparable global change vulnerability assessments: the Vulnerability Scoping Diagram. *Global Environmental Change* 17:472–485. <https://doi.org/10.1016/j.gloenvcha.2007.01.005>
- Qiao Y, Jiang Y, Zhang C (2021) Contribution of karst ecological restoration engineering to vegetation greening in southwest China during recent decade. *Ecological Indicators* 121:107081. <https://doi.org/10.1016/j.ecolind.2020.107081>
- Running S, Zhao M (2021) MODIS/Terra Net Primary Production Gap-Filled Yearly L4 Global 500m SIN Grid V061. NASA EOSDIS Land Processes DAAC. <https://doi.org/10.5067/MODIS/MOD17A3HGF.061>
- Sanderson EW, Jaiteh M, Levy MA et al (2002) The human footprint and the last of the wild. *BioScience* 52:891–904. [https://doi.org/10.1641/0006-3568\(2002\)052\[0891:THFATL\]2.0.CO;2](https://doi.org/10.1641/0006-3568(2002)052[0891:THFATL]2.0.CO;2)
- Seto KC, Güneralp B, Hutyrá LR (2012) Global forecasts of urban expansion to 2030 and direct impacts on biodiversity and carbon pools. *Proceedings of the National Academy of Sciences of the United States of America* 109:16083–16088. <https://doi.org/10.1073/pnas.1211658109>

- Smit B, Wandel J (2006) Adaptation, adaptive capacity and vulnerability. *Global Environmental Change* 16:282–292. <https://doi.org/10.1016/j.gloenvcha.2006.03.008>
- Song XP, Hansen MC, Stehman SV et al (2018) Global land change from 1982 to 2016. *Nature* 560:639–643. <https://doi.org/10.1038/s41586-018-0411-9>
- Song Y, Wang JF, Ge Y et al (2020) An optimal parameters-based geographical detector model enhances geographic characteristics of explanatory variables for spatial heterogeneity analysis: cases with different types of spatial data. *GIScience & Remote Sensing* 57:593–610. <https://doi.org/10.1080/15481603.2020.1760434>
- State Council Information Office of the People's Republic of China (2023) China–ASEAN trade expands 120% over a decade. https://english.scio.gov.cn/m/pressroom/2023-08/28/content_108948688.htm. Accessed 12 June 2026
- Steffen W, Broadgate W, Deutsch L et al (2015) The trajectory of the Anthropocene: the Great Acceleration. *Anthropocene Review* 2:81–98. <https://doi.org/10.1177/2053019614564785>
- Tong X, Brandt M, Yue Y et al (2018) Increased vegetation growth and carbon stock in China karst via ecological engineering. *Nature Sustainability* 1:44–50. <https://doi.org/10.1038/s41893-017-0004-x>
- Turner BL, Kasperson RE, Matson PA et al (2003) A framework for vulnerability analysis in sustainability science. *Proceedings of the National Academy of Sciences of the United States of America* 100:8074–8079. <https://doi.org/10.1073/pnas.1231335100>
- Venter O, Sanderson EW, Magrath A et al (2016) Sixteen years of change in the global terrestrial human footprint and implications for biodiversity conservation. *Nature Communications* 7:12558. <https://doi.org/10.1038/ncomms12558>
- Verburg PH, Crossman N, Ellis EC et al (2015) Land system science and sustainable development of the earth system: a global land project perspective. *Anthropocene* 12:29–41. <https://doi.org/10.1016/j.ancene.2015.09.004>
- Verburg PH, Soepboer W, Veldkamp A et al (2002) Modeling the spatial dynamics of regional land use: the CLUE-S model. *Environmental Management* 30:391–405. <https://doi.org/10.1007/s00267-002-2630-x>
- Wang JF, Zhang TL, Fu BJ (2016) A measure of spatial stratified heterogeneity. *Ecological Indicators* 67:250–256. <https://doi.org/10.1016/j.ecolind.2016.02.052>
- Xu H (2013) A remote sensing index for assessment of regional ecological changes. *China Environmental Science* 33:889–897
- Xu H, Wang Y, Guan H et al (2019) Detecting ecological changes with a remote sensing based ecological index produced time series and change vector analysis. *Remote Sensing* 11:2345. <https://doi.org/10.3390/rs11202345>
- Yang J, Huang X (2021) The 30 m annual land cover dataset and its dynamics in China from 1990 to 2019. *Earth System Science Data* 13:3907–3925. <https://doi.org/10.5194/essd-13-3907-2021>
- Yang J, Huang X (2023) The 30 m annual land cover datasets and its dynamics in China from 1985 to 2022. *Zenodo*. <https://doi.org/10.5281/zenodo.8176941>
- Zhang X, Yue Y, Tong X et al (2021) Eco-engineering controls vegetation trends in southwest China karst. *Science of the Total Environment* 770:145160. <https://doi.org/10.1016/j.scitotenv.2021.145160>
- Zheng Z, Wu Z, Chen Y et al (2022) Instability of remote sensing based ecological index and its improvement for time series analysis. *Science of the Total Environment* 814:152595. <https://doi.org/10.1016/j.scitotenv.2021.152595>

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [SupportingPreparation.zip](#)