

Article

Construction of a Coupling Framework for Production-Living-Ecology Function Interactions: A Case Study of the Guizhou-Guangxi Karst Region, Southwest China

Jingxin Li ^{1,2}, Ze Han ^{2,*}, Zhaotong Zhang ³ and Suju Li ¹

¹ National Disaster Reduction Center, Ministry of Emergency Management, Beijing 100124, China; lijx.18b@igsnrr.ac.cn (J.L.); lisujuff@vip.sina.cn (S.L.)

² Key Laboratory of Land Surface Pattern and Simulation, Institute of Geographic Sciences and Natural Resources Research, Chinese Academy of Sciences, Beijing 100101, China

³ School of Geographical Sciences, Hebei Normal University, Shijiazhuang 050024, China; zhangzt.19b@igsnrr.ac.cn

* Correspondence: hanze@igsnrr.ac.cn

Abstract

Karst regions face acute conflicts among production, living, and ecology (PLE) functions under the constraints of rugged terrain and rocky desertification. Existing studies have separately examined driving factors, interaction directions and intensities, and nonlinear thresholds, while how these dimensions co-evolve across space and time remains unclear. To address this gap, we used seven concentric buffers radiating from the built-up area as a spatial proxy for human activity intensity and constructed a framework within each buffer using Geodetector to identify core driving factors, Pearson correlation to quantify the direction and intensity of three pairwise interactions, and Pareto frontier analysis to capture nonlinear thresholds and tipping points. In the Guizhou-Guangxi karst region (2010–2019), the core drivers of production and ecology functions shifted from construction land through elevation to precipitation, while population consistently drove the living function. Along this gradient, the coupling relationships fluctuated in the core but improved in the periphery. Although trade-off intensities eased beyond 10 km, three Pareto frontier curves shifted from inverted-U patterns to monotonic trade-offs, indicating that this improvement was only quantitative while the interaction structure degraded. Tipping points disappeared in these curves, eroding the carrying-capacity buffers where win-win synergies remained attainable. Averaged correlation coefficients obscured this contrast between apparent improvement and structural degradation, and linear correlation analysis alone would not have detected it. These findings highlight the need for zone-specific management in karst regions, where monitoring based on Pareto-derived structural indicators can provide early warning of coupling degradation that averaged correlations mask.

Keywords: production-living-ecology (PLE) functions; interaction; driving factors; Pareto frontier curve; gradient analysis; karst region

Academic Editor: Dingde Xu

Received: 24 June 2026

Revised: 20 July 2026

Accepted: 23 July 2026

Published: 24 July 2026

Copyright: © 2026 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and

conditions of the [Creative Commons Attribution \(CC BY\)](https://creativecommons.org/licenses/by/4.0/) license.

1. Introduction

Land use patterns are both the outcome of complex human activities and a potential constraint on them [1]. With rapid population growth, industrialization, and urbaniza-

tion, regional land use is undergoing drastic change. Industrial and urban land continue to expand, usually occupying high-quality cropland and disturbing the surrounding natural environment, so that production-living-ecology (PLE) lands generally encroach on one another [2–4]. Because land resources are multifunctional and suitable for multiple uses, interactions among PLE functions are widespread [5–9]. Meanwhile, imbalances between supply and demand of PLE land and inappropriate human activities can induce or exacerbate trade-offs among these functions [10–14], resulting in overall PLE-function degradation and consequent ecological security risks and economic constraints [15–17]. Therefore, quantitatively characterizing PLE-function interactions and clarifying the driving mechanisms is essential for coordinating PLE land use and ensuring regional sustainable development.

The spatiotemporal patterns of PLE functions are jointly governed by natural and anthropogenic factors. Natural conditions such as climate, terrain, and soil determine the inherent potential distribution of functions, whereas anthropogenic influences such as population and construction land continuously reshape their actual intensity and structure [18,19]. Identifying the dominant driving factors therefore is a prerequisite for understanding the formation and evolution of individual function patterns, as well as the interactions among functions. To quantify the contribution of each factor, prior studies have extensively employed correlation analysis, geographically weighted regression, random forests, and the Geodetector, and more recently interpretable machine-learning models such as gradient-boosted trees [20], to assess the explanatory power of individual factors and their interactions with respect to the spatial differentiation of functions [21–23]. Among these methods, the Geodetector requires no assumption of linearity and can simultaneously characterize the explanatory power of single factors and the enhancement effect arising from factor interactions, and it has therefore been adopted particularly widely [24].

Methods for quantifying interactions have evolved in tandem with changes in data availability. Early studies relied predominantly on administrative-unit statistics and adopted models such as the coupling coordination degree to characterize inter-functional relationships. Although such approaches provide strong temporal continuity, they privilege quantitative associations over spatial explicitness, rendering them difficult to reconcile with spatially explicit driving factors [16,25]. With the advancement of remote sensing and geospatial big data, the integration of multi-source data, including nighttime lights, points of interest (POI), and population density, has enabled the spatialization of PLE functions at the grid scale, permitting interactions and driving factors to be examined at a consistent spatial resolution [15,26]. On this basis, correlation analysis has become the predominant approach for characterizing trade-offs and synergies [22,26,27]. Nevertheless, correlation analysis yields only linear, averaged measures of association. It fails to capture the nonlinear structure of interactions as function levels vary, and cannot identify the tipping points at which functional relationships reverse under the influence of drivers [28]. The Pareto frontier curve, originally conceptualized in economics and adapted for ecological constraint analysis [29,30], partially overcomes this limitation by fitting the boundary points of the response variable across successive levels of the constraint variable, characterizing the limiting relationship and the associated tipping points and thereby establishing a robust link between interaction characteristics and driving mechanisms.

Although both the identification of driving factors and the characterization of interactions have advanced considerably, the direction and intensity of interactions, their nonlinear structure, and the associated thresholds are typically examined in isolation. For instance, even recent gradient-based and grid-scale assessments that document how trade-offs and synergies shift across the urban–rural transition still treat the interaction outcome and its dominant drivers as separate analyses, so the correspondence between a shifting driver structure and a changing interaction pattern is seldom made explicit [23,31]. Such

a fragmented approach hinders the simultaneous identification of overall trends and critical features of inter-function relationships. Moreover, driver identification and relationship characterization are frequently undertaken as separate exercises, which obstructs the establishment of explicit correspondences between driving factors and interaction patterns. Interactions are inherently dynamic. As PLE function intensities vary interannually, their directions, magnitudes, and corresponding tipping points may shift over time. As a result, the gradient regularity governing the co-evolution of drivers and interactions across space and time is frequently obscured, constraining understanding of PLE-function interaction mechanisms in complex environments. There is therefore a need for an integrated spatiotemporal analytical framework that unifies driving factors and interaction dynamics within a single structure [21,22].

The Guizhou-Guangxi karst region in southwest China is both an important ecological barrier and one of the areas most severely affected by rocky desertification. Under the dual constraints of rugged terrain and rocky desertification, production and living land are extremely scarce and highly sensitive to human disturbance, resulting in acute supply-demand conflicts among PLE functions [19,32–34]. These conditions make the region a suitable case for investigating the drivers of PLE functions and their interactions. Accordingly, using the human activity intensity gradient as a quasi-control variable, we construct a PLE-function interaction framework that integrates interaction direction, intensity, non-linear thresholds, and driving factors along this gradient. Based on this framework, we conduct an integrated spatiotemporal analysis for the period 2010–2019 to reveal how PLE function drivers and interactions correspond to and co-evolve with each other along the gradient, and to identify structural degradation of the coupling state and early-warning signals. This study aims to advance the understanding of PLE-function interaction mechanisms in complex environments and to offer a reference for coordinating PLE land use and implementing ecological restoration projects in karst and other ecologically vulnerable regions. Guided by this objective, we test three expectations. First, along the human-activity-intensity gradient, the dominant drivers of the natural-background functions (production and ecology) hand over in an orderly sequence from anthropogenic to terrain and then climatic factors, whereas the living function remains population-driven throughout (H1). Second, the direction and intensity of the three pairwise interactions reorganize in step with this driver succession rather than independently of it (H2). Third, the inter-annual evolution of coupling need not be internally consistent: an apparent easing of trade-off intensity may coexist with a degradation of interaction structure, so that quantitative and structural signals diverge (H3). Whether these expectations hold is examined in Sections 4 and 5. The remainder of this paper is organized as follows: Section 2 introduces the study area; Section 3 describes the methods and data; Section 4 presents the results; Section 5 discusses the mechanistic interpretation, structural degradation, and management implications; and Section 6 concludes.

2. Study Area

Delineated from the karst landform map of South China and the distribution map of karst landforms in Asia, the study area comprises nine prefecture-level cities in central and southern Guizhou and seven in central and western Guangxi (22°08'54"–28°12'27" N, 104°18'27"–110°20'40" E; 2.114×10^5 km²). Lying in the transition from the Yunnan–Guizhou Plateau to the Guangxi hills, it descends from north to south and from west to east (Figure 1), and spans peak-cluster depressions, peak-forest plains, karst plateaus, and karst gorges. Its subtropical monsoon humid climate yields a mean annual temperature of 15–22 °C and precipitation of 990–2040 mm, though rainfall is highly variable in space and time. Forest dominates land cover (57.07% in 2010 and 57.19% in 2019), followed by cropland (25.91% in 2010 and 25.36% in 2019) and grassland (14.24% in 2010 and 13.96%

in 2019), with cropland concentrated in the valley plains and intermontane basins of the southeast. Rapid infiltration and a thin, discontinuous soil mantle leave water conservation and soil retention vulnerable, and rocky desertification, most pronounced in the central and northern mountains, is the principal ecological constraint on regional development [35,36]. Pressure on the limited non-ecological land is correspondingly severe: built-up land expanded from 2.1% of the regional area in 2010 to 5.0% in 2019, while moderate-to-severe rocky desertification (Table 1) covers just under one-quarter (23.82% in 2010 and 23.14% in 2019) of the territory.

Built-up land is largely confined to valley basins, forming discrete urban cores set within a matrix of terrain and rocky-desertification constraints. The resulting gradient of human activity intensity radiating outward from these cores provides a natural basis for the gradient-based quasi-control-variable design adopted here. Over the past two decades, urbanization and industrialization have pushed cultivation onto steeper positive-terrain slopes [26], exacerbating erosion of fragile karst soils, while the Grain for Green program, integrated rocky desertification control, and poverty-alleviation relocation have proceeded in parallel, leaving PLE land in rapid coupled transformation. Strong natural constraints, intensifying anthropogenic pressure, and pronounced spatial heterogeneity make the Guizhou–Guangxi karst region well suited to examining PLE interaction mechanisms and detecting early-warning signals of degradation along a human-activity-intensity gradient.

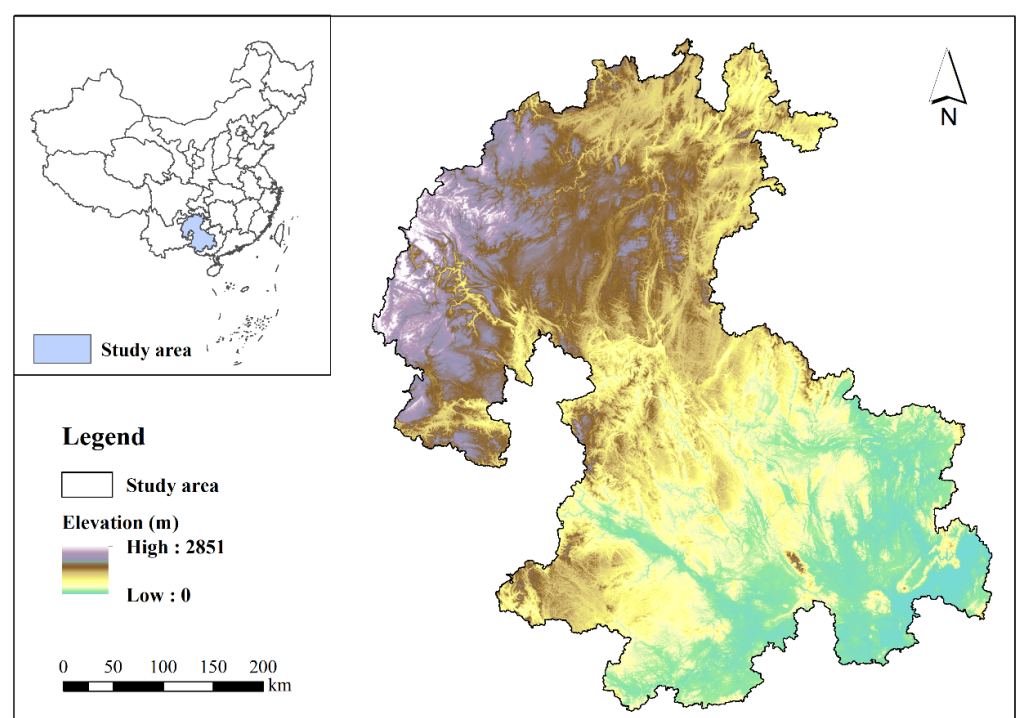


Figure 1. Location of the study area.

Table 1. Classification system of PLE land use types.

Primary Land Use Types	Secondary Land Use Types	Tertiary Land Use Types	Land Use Type Codes
1 Production land	11 Agricultural production land	Cropland/orchard and other land for agricultural production	11, 12, 24
	12 Industrial production land	Other construction land (except transportation/special land use)	53 (partial)
2 Living land	21 Urban living land	Urban land	51
	22 Rural living land	Rural settlements	52

3 ecology land	23 Other construction land	Other construction land (Transportation/special land use)	53 (partial)
	31 Priority ecology land	Forest land/grassland/wetland/water under priority protection, etc.	21, 22, 31, 41, 42, 43, 46
	32 Ecological restoration land	Moderate and severe rocky desertification areas	62, 65, 66
	33 General ecology land	Other ecology land	23, 32, 33, 63, 64, 67

3. Methods

This section develops an integrated analytical framework that couples the drivers of PLE functions with their interactions along a human activity intensity gradient. The ten PLE sub-functions are spatialized on a common grid, and concentric buffers radiating from urban built-up areas serve as a quasi-control to isolate factor–function and function–function relationships across different activity levels. Within each buffer, Geodetector identifies core and paired drivers, Pearson correlation quantifies interaction direction and intensity, and Pareto frontier analysis captures nonlinear thresholds and tipping points. These buffer-wise results are then synthesized into a coupling model, enabling an integrated interpretation of the co-evolution of drivers and interactions along the gradient and providing a diagnostic basis for detecting structural degradation and early warning signals (Figure 2).

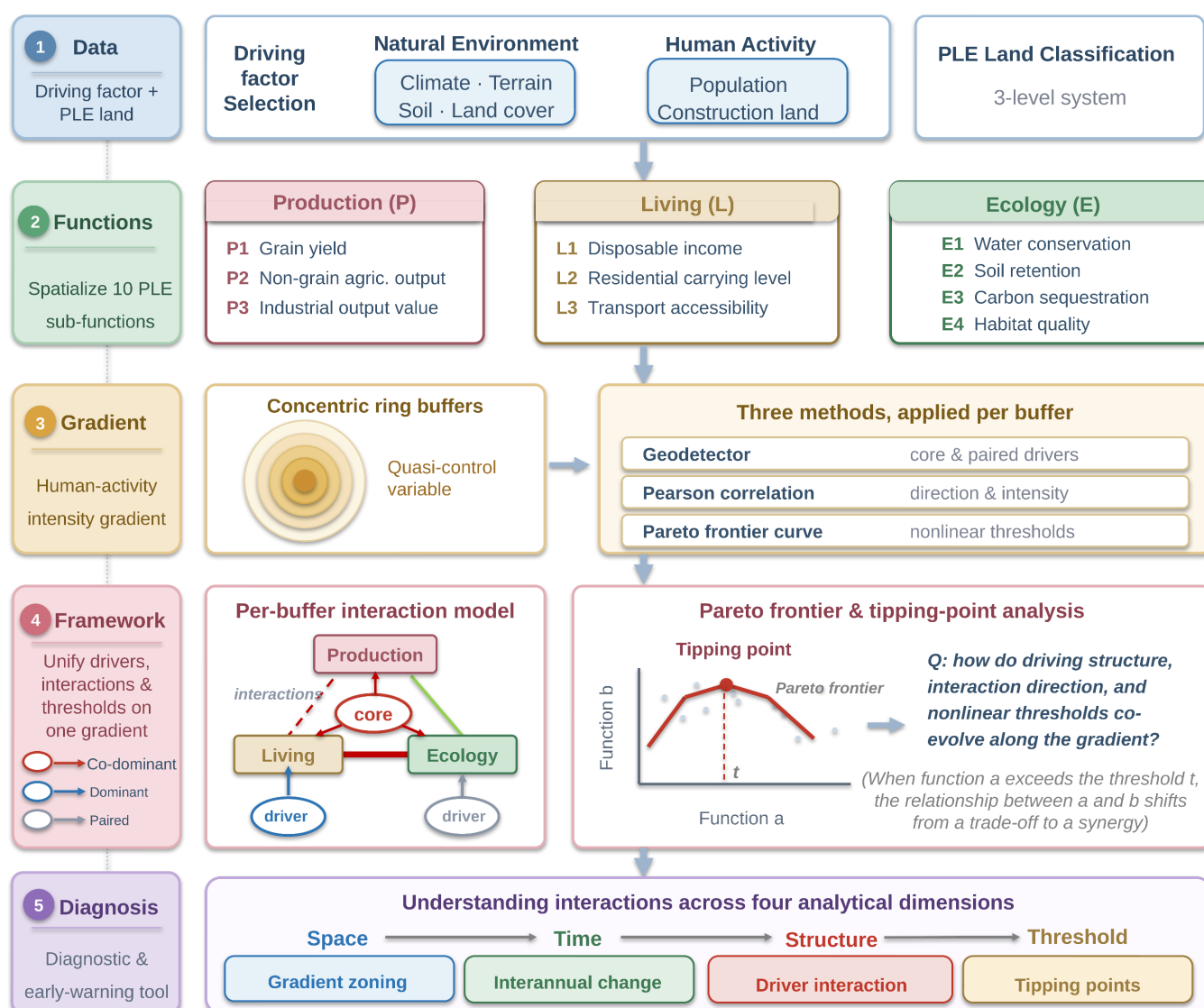


Figure 2. Framework of the research.

3.1. PLE Land Use Types and PLE Land Use Functions

3.1.1. Classification of PLE Land Use Type

Land use classification followed the scheme of the Resource and Environment Science and Data Center (RESDC) of the Chinese Academy of Sciences (CAS) (<https://www.resdc.cn/>, accessed on 20 October 2021). Based on the dominant function of each land use type, a top-down, three-level PLE land use classification system was established (Table 1). The system comprises three primary types (production, living, and ecology land) and eight secondary types. At the secondary level, production land was divided into agricultural and industrial production land; living land into urban living land, rural living land, and other construction land; and ecology land into priority ecology land, ecological restoration land, and general ecology land. The tertiary types correspond directly to the categories of the source land use map. They were consolidated and revised with reference to relevant departmental planning documents, such as established industrial-layout maps and future planning schemes, ultimately yielding the PLE land use distribution map of the study area.

During the actual extraction process, however, “other construction land”, a secondary type consisting mainly of transportation land, encountered resolution-related constraints when the vector base map was rasterized to a uniform 250 m grid. Owing to this resolution limitation, this type was largely assigned to urban living land within built-up areas, whereas across the extensive rural areas it was predominantly assigned to the surrounding production or ecology land, which occupied a larger areal proportion of the raster. Consequently, the adopted extraction scheme no longer treats “other construction land” as a separate type, and living land thus comprises only urban and rural living land.

3.1.2. Spatialization of PLE Land Use Functions

A comprehensive PLE-function evaluation system was constructed based on a multi-source fused dataset, comprising ten indicators: three production functions, three living functions, and four ecology functions (Table S1). All functional indicators were resampled to 250 m resolution raster data. The spatialization methods have been systematically validated in previous work [26,37] and are summarized below.

Production function. The production function comprises three sub-functions: actual grain yield (P1), non-grain agricultural output value (P2), and secondary and tertiary industrial output value (P3). For actual grain yield, cropland net primary productivity (NPP) was first computed using the Thornthwaite Memorial model to represent production potential; a comprehensive cultivation system was then constructed by coupling the grain-planting structure, multiple-cropping index, and crop characteristic parameters, and the potential yield was corrected stepwise to the actual yield, with management factors such as mechanization rate and fertilizer-application intensity incorporated [26]. Non-grain agricultural output value was spatialized separately for county-level forestry and animal husbandry based on MOD17A3 NPP products (merged where forestry and grazing overlapped), whereas fishery output value was distributed evenly across grid cells according to county-level water area. Secondary and tertiary industrial value added was spatialized via three independent pathways (Visible Infrared Imaging Radiometer Suite (VIIRS) nighttime lights, WorldPop population density, and POI kernel density) and, following consistency correction, superimposed with equal weights to enhance robustness [26]. After normalization and spatial overlay, the three sub-functions produced the final production function.

Living function. The living function comprises three indicators: per capita disposable income (L1), residential carrying level (L2), and transport accessibility (L3). Per capita disposable income, without distinguishing urban from rural residents, was derived from

county-level urban and rural per capita disposable incomes and their respective population proportions, weighted by the gross output value of the three industries, and was then spatialized using the industrial value-added base map at the county level. For residential carrying level, all residential-area POIs, the secondary classes under the accommodation-service and commercial-residential primary classes, were selected; a continuous residential-intensity surface was generated through kernel density analysis and corrected with population density to avoid underestimating multi-household residences [26]. Transport accessibility was derived from road-network density and Euclidean distance to roads, both computed on a 250 m grid and combined with equal weights after normalization. After normalization and spatial overlay, the three sub-functions produced the final living function.

Ecology function. The ecology function comprises four indicators: water conservation (E1), soil retention (E2), carbon sequestration (E3), and habitat quality (E4). Water conservation employed an improved precipitation-storage empirical equation with a locally calibrated karst K parameter, thereby capturing the actual conservation capacity under the high-infiltration, thin-soil conditions of karst terrain [26]. Soil retention adopted an improved Revised Universal Soil Loss Equation (RUSLE) model incorporating a bedrock-exposure-rate coefficient; informed by the lithological distribution, the extent of karst landforms, and the rocky-desertification grade, this approach avoided overestimating erosion in rocky-desertified areas [26]. Carbon sequestration followed the vegetation carbon-sequestration formula in the Specifications for Assessment of Forest Ecosystem Services [38,39], using MOD17A3 NPP to estimate annual carbon sequestration at the grid scale. Habitat quality was evaluated with the Habitat Quality module of the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model [40], specifying six stress factors: light rocky desertification, moderate-to-severe rocky desertification, sloping cropland, flat-dam cropland, rural construction land, and urban construction land. After normalization and spatial overlay, the four sub-functions produced the final ecology function.

3.2. Gradient Design

The analysis of PLE-function interactions is, in essence, an examination of the interaction between human activities and the natural environment. From a quasi-experimental standpoint, designing a gradient based on human activity intensity permits clearer identification of factor–function and function–function relationships and enables construction of a PLE-function framework under varying intensities of human influence.

The urban built-up boundary was delineated by combining a Densi-Graph curve—constructed from nighttime-light intensity and the corresponding theoretical closure area—with a triangulated irregular network (TIN) derived from POI data through Delaunay triangulation. With the built-up area as the core, ring buffers were generated at 5 km intervals, along which human activity intensity decreases outward while natural-background constraints progressively strengthen. Buffering to 30 km covered more than 90% of the study area; the remaining fragments were scattered and could be fully enclosed only through repeated buffering, and the resulting samples were too small and too randomly distributed for reliable analysis. The analysis was therefore restricted to within the 30 km buffer, generating six buffers: (0, 5], (5, 10], (10, 15], (15, 20], (20, 25], and (25, 30] km, plus the built-up area (0 km buffer), for a total of seven zones, hereafter referred to as the 0, 5, 10, 15, 20, 25, and 30 km buffers.

3.3. Explanatory Power of Driving Factors for PLE Functions

To characterize the natural and anthropogenic drivers of PLE functions in the karst region as comprehensively as possible, ten indicators were selected from five categories: climate, terrain, soil, land cover, and human activity, to constitute the set of potential driving factors. Data sources and preprocessing are detailed in Table 2.

Table 2. Potential driving factors and their description.

Category	Factor (Abbr.)	Original Resolution	Data Source	Data Processing
Climate	Mean annual temperature, Tem (°C)	-	RESDC, CAS	ANUSPLIN interpolation of meteorological station data
	Annual precipitation, Pre (mm)	-	RESDC, CAS	ANUSPLIN interpolation of meteorological station data
Terrain	Elevation, Ele (m)	30 m	National Earth System Science Data Center	Resampled to 250 m
	Proportion of positive terrain, Pos (%)	30 m	National Earth System Science Data Center	Extracted with the two-level nested (TLN) model [37] and resampled to 250 m
Soil	Soil organic matter, Om (g/kg)	1000 m	RESDC, CAS	Resampled to 250 m
	Silt content, Sil (%)	1000 m	RESDC, CAS	Resampled to 250 m
Land cover	Enhanced Vegetation Index, EVI	250 m	U.S. Geological Survey (USGS) MOD13Q1	Extreme-value and null-value correction
	Rocky desertification grade, KRD	—	Bulletin of Rocky Desertification Status in China	Shapefile to raster, 250 m
Human activity	Population density, Pop (persons/km ²)	1000 m	WorldPop	Resampled to 250 m
	Proportion of construction land, Con (%)	30 m	RESDC, CAS	Resampled to 250 m

Using the Geodetector package in R (R Studio Version 2026.01.2+418), the factor-detection and interaction-detection modules were applied to each PLE function and each potential factor, obtaining for every buffer the explanatory power (*q* value) of individual factors and factor combinations with respect to the spatial differentiation of PLE functions.

Factor detection employs a stratified analysis of variance to quantify the degree to which factor *X* accounts for the spatial differentiation of attribute *Y*. The *q* value is defined as

$$q = 1 - \sum_h N_h \sigma_h^2 / (N \sigma^2), \quad (1)$$

where *h* is the number of factor strata; *N_h* and σ_h^2 denote the number of grid cells and the variance of stratum *h*, respectively; and *N* and σ^2 denote the total number of grid cells and the overall variance of the study area. *q* ∈ [0, 1], with larger values indicating stronger explanatory power [24].

Interaction detection evaluates whether two factors, *X*₁ and *X*₂, acting jointly, enhance or weaken the explanatory power for a PLE function. By comparing *q* (*X*₁∩*X*₂) with *q* (*X*₁) and *q* (*X*₂), interactions are classified into five types: nonlinear weakening, single-factor nonlinear weakening, two-factor enhancement, independence, and nonlinear enhancement [24].

In this study, the following factor categories were defined (all *q* values were statistically significant at *p* < 0.05):

(1) Core driver: the single factor with the highest explanatory power for a given PLE function.

(2) Paired driver: the factor that, upon interacting with the core driver, produces the highest explanatory power for that function.

(3) Common driver: a factor that serves as the core driver of one function and simultaneously as the core or paired driver of another.

To capture the dynamic effects of drivers, the 2010 built-up area and the seven buffers were taken as the baseline gradient, and the changes in driving factors were analyzed to explain the changes in PLE functions between 2010 and 2019. Of the ten factors, five factors

(Ele, Pos, Om, Sil, and KRD) either remained unchanged or were available for only one time point and were therefore analyzed using their original values, whereas the remaining five were analyzed using the differences between 2019 and 2010.

3.4. Analysis of PLE-Function Interactions and Framework Construction

Within each buffer, Pearson correlation analysis was used to determine the overall direction and intensity of the pairwise relationships among L-P, L-E, and P-E. The Pareto frontier curve was then introduced to characterize the possibility-boundary function between the constraint variable (PLE function a) and the response variable (PLE function b) [29,30].

To extract the Pareto frontier curve, the normalized constraint variable x was first partitioned into 100 equal-interval levels. Within each level, the boundary point of the response variable y was extracted. All boundary points were then fitted with a polynomial. The resulting boundary line is the Pareto frontier curve, also termed the possibility-boundary function curve.

According to its trend, the Pareto curve can be classified as monotonic or non-monotonic, corresponding to the transition between synergy and trade-off. A tipping point is inherent in the transformation between synergy and trade-off. From a spatial perspective, the tipping point at which synergy turns into trade-off marks the highest synergy efficiency, the region with the highest, yet most vulnerable, PLE-function carrying capacity, whereas the tipping point at which trade-off turns into synergy marks the region with the greatest potential for functional improvement. From a temporal perspective, the tipping point of a non-monotonic curve may drift, and a monotonic curve may exhibit drift in the centroid of its boundary points. Both provide key indications of changes in PLE-function carrying capacity.

On this basis, an interaction model was constructed for each buffer, comprising three components: the PLE functions, the driving factors, and the interaction relationships. Production, living, and ecology functions constitute the three key nodes of the framework. Lines connecting the functions denote interactions, with color indicating direction and line style indicating significance. Core drivers point directly to the functions they influence, whereas paired drivers point to the core driver with which they interact.

Several data and methodological considerations bear on the interpretation of these results. On the data side, the PLE-function and driving-factor layers were fused from heterogeneous sources—satellite products, meteorological-station interpolations, vector planning maps, and county statistics—whose native resolutions range from 30 m to 1 km and which were harmonized onto a common 250 m grid; this resampling, together with the downscaling of county-level statistics through nighttime-light, population, and POI proxies, inevitably introduces scale and allocation uncertainty. The most visible instance is the “other construction land” category, whose sub-grid transport features could not be resolved at 250 m and were absorbed into the surrounding dominant types (Section 3.1.1). On the method side, the three tools are complementary but each has limits: the Geodetector requires no linearity assumption and captures single- and paired-factor explanatory power, yet its q value depends on the discretization of continuous factors; Pearson correlation is simple and comparable across buffers but reports only a linear, spatially averaged association; and the Pareto frontier curve recovers the nonlinear response boundary and its tipping points, but is sensitive to the extraction of boundary points and to the order of the fitted polynomial. Reading the three together, rather than in isolation, is precisely what allows the averaged and the structural facets of an interaction to be reconciled.

4. Results

4.1. Spatiotemporal Patterns of PLE Land and Functions Along the Gradient

During the study period, land use change in the Guizhou-Guangxi karst region was characterized by rapid built-up area expansion and the consequent restructuring of land use patterns (Table S2). The built-up area increased 2.44-fold, from 69,694 pixels in 2010 to 170,063 pixels in 2019, with 86.6% of this increment concentrated in the 0–5 km buffer. Within the built-up area, the three major land use categories were substantially reorganized. Beyond the built-up area, the 0–5 km transition belt was the only zone where ecology land experienced a net loss, whereas all buffers farther than 5 km recorded a net gain.

Corresponding to the above land use changes, the living and production functions spatially peaked within the built-up area (approximately 0.36 and 0.05, respectively, in 2019) and exhibited a decaying pattern from the near suburbs to the far suburbs, with a sharp decline over the 0–5 km interval and a leveling-off beyond 5 km (Figure 3). The ecology function, by contrast, showed a monotonically increasing trend, rising from 0.27 and 0.25 at 0 km in 2010 and 2019, respectively, to 0.45 and 0.46 at 30 km, with the growth rate slowing considerably beyond 5 km. The tipping points of the two patterns near 5 km further confirmed the near-suburban belt as the transitional boundary between urban and rural functions.

Temporally, the living function increased most notably within the built-up area (from 0.31 to 0.36, a 16% increase), with smaller increases observed in the other buffers. The production function declined considerably in the urban core but rose slightly outside the built-up area. By 2019, the production function in the 5 km buffer approximated that of the built-up area, suggesting a trend of industrial activity shifting toward the near suburbs. The ecology function declined marginally in the urban core but generally increased across the other buffers. Overall, the gradient differentiation of PLE functions remained broadly stable, although the core area experienced a clear functional transition toward strengthened living functions and weakened production functions.

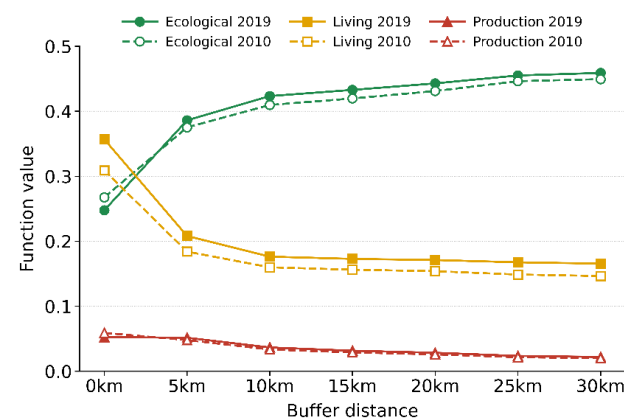


Figure 3. Spatiotemporal changes in PLE functions with increasing buffer distance.

4.2. Identification of Driving Factors

The results of factor detection and interaction detection for the 10 potential driving factors with respect to the spatiotemporal changes in PLE functions across the seven buffers are summarized in Table 3. The explanatory power of the driving factors differed among the three functions, generally following the order: living function > ecology function > production function. The living function exhibited strong coupling with anthropogenic factors and was therefore relatively straightforward to explain. By contrast, the production function, which integrates the output values of three industries and has a complex internal structure, consistently produced low q values.

Table 3. Analysis of the driving factors of PLE functions in each buffer.

Buffer	Production Function				Living Function				Ecology Function				Common Driver
	Core Factor	Paired Factor	q (Core)	q (Interaction)	Core Factor	Paired Factor	q (Core)	q (Interaction)	Core Factor	Paired Factor	q (Core)	q (Interaction)	
0 km	Con	Tem	0.10	0.20	Pop	Pre	0.54	0.63	Con	Tem	0.17	0.29	Con
5 km	Ele	Pre	0.08	0.16	Pop	Con	0.44	0.49	Ele	Pre	0.16	0.28	Ele
10 km	Ele	Pre	0.08	0.14	Pop	Ele	0.18	0.27	Ele	Pre	0.15	0.30	Ele
15 km	Ele	Pre	0.06	0.14	Pop	Con	0.18	0.27	Ele	Pre	0.13	0.34	Ele
20 km	Ele	Pre	0.05	0.14	Pop	Con	0.19	0.27	Pre	Tem	0.16	0.35	Pre
25 km	Ele	Pre	0.04	0.14	Pop	Tem	0.18	0.36	Pre	Tem	0.17	0.39	Pre
30 km	Ele	Pre	0.04	0.16	Pop	Tem	0.15	0.40	Pre	Tem	0.16	0.41	Pre

[Note] Con, proportion of construction land; Pop, population density; Ele, elevation; Tem, mean annual temperature; Pre, annual precipitation; q, explanatory power derived from the Geodetector.

For the production function, a typical spatiotemporal contrast in driving forces was observed between built-up and non-built-up areas. Within the built-up area, Con was identified as the core driver and, in interaction with Tem, provided the best explanation for the production function. In the six buffers beyond the built-up area, the core driver was Ele and the interaction factor was Pre. Although the explanatory power of the core factor for the production function decreased with increasing buffer distance from the built-up area, the q value remained essentially stable when the interaction with Pre was incorporated.

For the living function, the core driver was consistently Pop across all seven buffers, whereas the paired factor varied considerably. In the built-up area, the paired factor was Pre, and all three PLE functions were best explained by the interaction of anthropogenic factors with climatic factors. Within the 5–20 km range, the paired factor was Con at all distances except 10 km, where it was Ele, which again reflected the strong driving effect of anthropogenic factors on the living function. Beyond 20 km, the driving factors shifted to the combination of Pop and Tem. The q value exhibited a clear gradient pattern: it was very high in the built-up area and the 5 km buffer, and dropped sharply beyond 5 km. Similar to the production function, the explanatory power of the core factor for the living function declined with increasing buffer distance and stabilized beyond 10 km. However, when the interaction factor was considered, the q value followed a U-shaped curve, first decreasing and then increasing with distance.

With increasing buffer distance, the core and interaction factors of the ecology function exhibited a three-stage gradient change. Within the built-up area, Con and Tem constituted the interaction pair. Within the 15 km buffer, the ecology function was jointly driven by Ele and Pre. Beyond 15 km, the interaction pair shifted to Pre and Tem. The explanatory power of the core factor for the ecology function followed a U-shaped pattern. However, once an interaction pair was formed with climatic factors, the q value increased monotonically, demonstrating the important role of climatic factors in shaping the spatiotemporal pattern of the ecology function.

4.3. Analysis of PLE-Function Interactions

4.3.1. Correlation Analysis

The spatiotemporal variations in the PLE-function correlations are presented in Table 4. Spatially, the L-P relationship was a trade-off within the built-up area (0 km) and converted to a relatively strong synergy in all buffers beyond 5 km. This synergy peaked at 0.4725 at 15 km in 2010 and at 0.4713 at 10 km in 2019, and decayed slowly toward the far suburbs, indicating that the coupling between production and living functions was tightest in this region. The P-E interaction exhibited the opposite pattern to L-P. The built-up area showed a weak synergy, whereas beyond it the relationship became a trade-off that was most intense in the 5

km buffer and weakened with increasing distance. The L-E relationship remained a trade-off across all buffers. With increasing buffer distance, the trade-off intensity progressed from weak to strong, peaked at 10 km, and then declined gradually.

Larger differences between the correlation coefficients of the two time points indicate a weakening trade-off or a strengthening synergy. In terms of spatiotemporal change, the PLE-function interactions exhibited a three-stage pattern. In the built-up area, the L-E trade-off strengthened, and the P-E synergy weakened. The 5 km buffer exhibited a similar pattern, though to a lesser degree. Only in the 10 km and 30 km buffers did all three function interactions display a positive trend of weakened trade-offs or strengthened synergies. In the 15–25 km buffers, the L-P synergy weakened to varying degrees, with the correlation coefficient decreasing while still maintaining a relatively strong synergy.

Table 4. Spatial correlation coefficients of the PLE functions.

Buffer\Interaction Interaction	2010			2019			Dif (Higher Is Better)		
	L-P	L-E	P-E	L-P	L-E	P-E	L-P	L-E	P-E
0 km	−0.1824	−0.3219	0.0525	−0.1342	−0.3410	0.0031	0.0482	−0.0192	−0.0494
5 km	0.3897	−0.3627	−0.2808	0.4003	−0.3762	−0.2984	0.0105	−0.0136	−0.0176
10 km	0.4659	−0.4302	−0.2797	0.4713	−0.4124	−0.2750	0.0053	0.0178	0.0046
15 km	0.4725	−0.4241	−0.2708	0.4614	−0.3934	−0.2505	−0.0111	0.0306	0.0203
20 km	0.4552	−0.4051	−0.2636	0.4291	−0.3220	−0.1884	−0.0261	0.0831	0.0752
25 km	0.4383	−0.3763	−0.2527	0.4374	−0.2975	−0.1772	−0.0009	0.0788	0.0756
30 km	0.4292	−0.3566	−0.2478	0.4591	−0.2794	−0.2374	0.0299	0.0772	0.0104

4.3.2. Trend Analysis of Interactions Based on Pareto Curves

To characterize the possibility boundaries of the three function pairs and their spatiotemporal evolution (Figure 4), the Pareto frontier curves of L-P, L-E, and P-E for the seven buffers in 2010 and 2019 were polynomially fitted (the fitting equations and marker points are given in Table S3). For each curve, the former function was taken as the constraint variable x and the latter as the response variable y . The spatial (along the buffer gradient) and temporal (2010–2019) trends were then analyzed with respect to both curve shape and tipping point threshold.

Overall, in terms of curve shape and marker type, the quadratic coefficients of all curves were negative. Consequently, the Pareto frontier curve was uniformly upward-convex within the fitted interval, with its vertex representing the tipping point reported in Table S3. When the tipping point lay inside the function-level interval, the curve was non-monotonic and was marked by the tipping point. When the vertex lay outside the interval, the curve was monotonic, and the centroid was then adopted as the key threshold for analysis. Accordingly, all 21 curves in 2010 were of the tipping-point type. In 2019, three curves, the L-E curves of the 10 km and 15 km buffers and the P-E curve of the 25 km buffer, turned into the centroid type, indicating that the interaction curves of these buffers degenerated from a rise-then-fall shape into a monotonic, declining trade-off. Regarding goodness of fit, the 2019 values were generally lower than those of 2010, with a particularly marked gap beyond the 5 km buffer, reflecting increased dispersion of boundary points and a weakening of the constraint relationship.

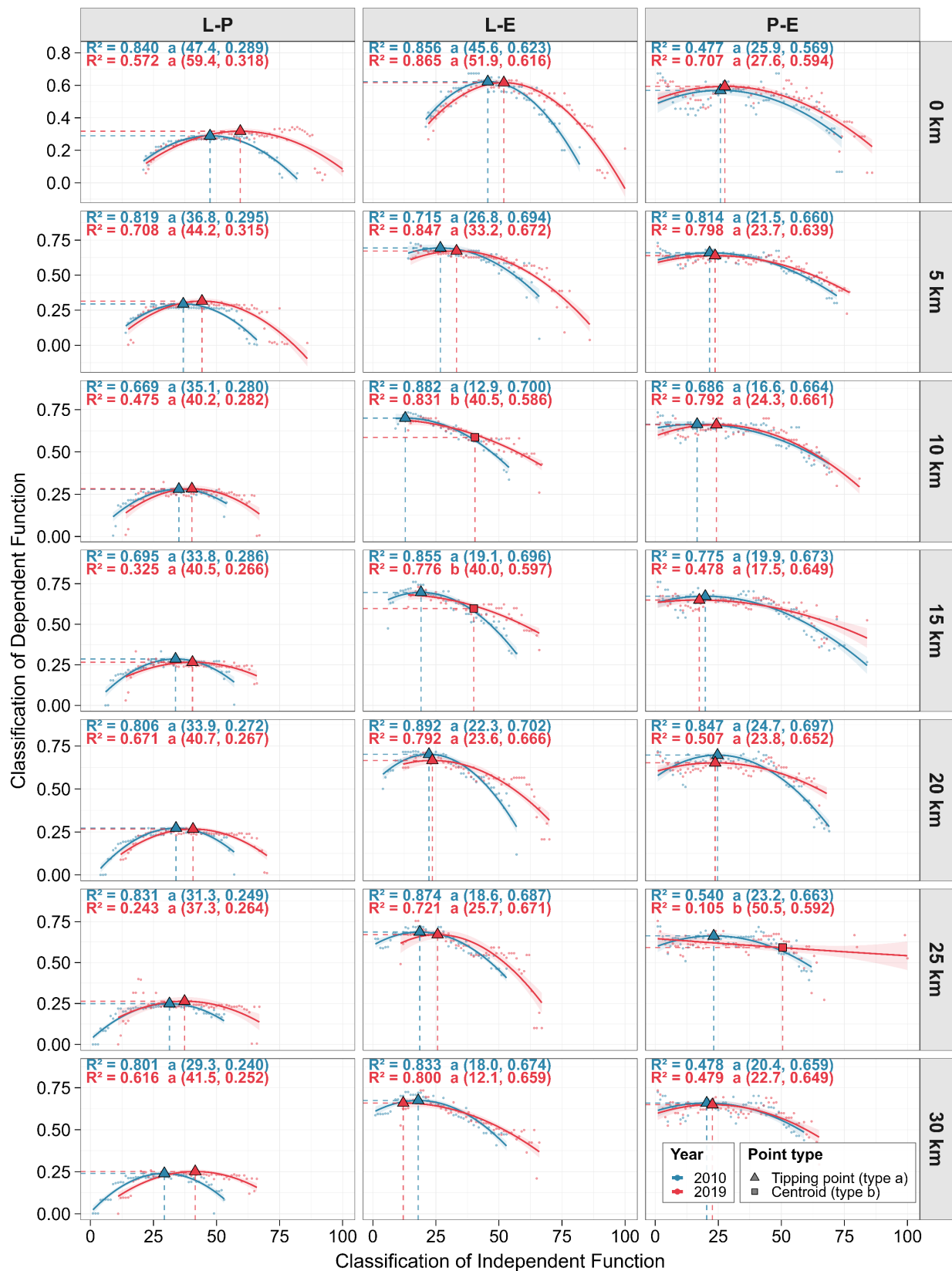


Figure 4. Pareto frontier curves of PLE-function interactions (Note: For every subplot, the coefficient of determination (R^2) of the polynomial fit and the coordinates of the tipping point (type a) or boundary centroid (type b) are annotated on the panel, and all textual elements have been enlarged for legibility; the complete fitting equations and marker coordinates are provided in Table S3).

Although the L-P goodness of fit in 2019 was generally low, the L-P curves for all buffers were upward-convex. The production function increased as the living-function level rose, peaked at the tipping point, and then declined. The tipping point represented the point of highest synergy efficiency between the two functions. Spatially, in 2010, the living-function level corresponding to the tipping point decreased from level 47 within the built-up area to level 29 at 30 km, and the peak production function decreased correspondingly from 0.29 to 0.24. That is, with increasing buffer distance, the synergy peak occurred at a lower living level and at a reduced height. The same gradient-decreasing pattern was maintained in 2019. Temporally, the living-function level corresponding to the tipping point shifted uniformly to the right in each buffer. The peak production function rose considerably in the built-up area and the 5 km near suburbs, remained essentially flat at 10 km, and fell slightly at 15–20 km. Overall, this reflected an upper-right translation of the curve accompanied by a rise in the vertex, most substantially in the 0–5 km buffer.

The L-E curves were the steepest of the three function pairs. The ecology function peaked at a relatively low living-function level and then decreased at an accelerating rate as the living function rose, constituting a typical trade-off. Spatially, in 2010, the living-function level corresponding to the tipping point was highest in the built-up area and dropped rapidly beyond 5 km, indicating that beyond the near suburbs the trade-off was triggered at a lower living level. The peak ecology function rose from 0.62 in the built-up area to approximately 0.70 at 5–20 km and then fell slightly toward the far suburbs, consistent with the low-near and high-far suburban pattern of the ecology function. Temporally, the peak ecology function decreased in every buffer. As noted above, the 10 km and 15 km buffer curves degenerated from the tipping-point type to the centroid type, turning from a rise-then-fall shape into an approximately monotonic declining trade-off, with the trade-off becoming pervasive across the entire range.

The P-E curves were likewise upward-convex rather than monotonically declining. The ecology function rose slightly as the production-function level increased, peaked at the tipping point, and then turned to decline, with an overall steepness that was smaller than that of L-E. Spatially, in 2010, the peak ecology function rose from 0.57 in the built-up area to 0.70 at 20 km and was approximately 0.66 in the other buffers. Temporally, the peak ecology function decreased in most buffers, most substantially at 20 km (from 0.70 to 0.65). It rose only in the built-up area and remained essentially flat at 10 km. The production-function level corresponding to the tipping point shifted mostly to the right, with a slight leftward shift at 15 and 20 km. In the 25 km buffer, the 2019 curve degenerated into an approximately linear form, indicating that P-E in this region tended toward a trade-off across the entire range.

4.4. Framework of PLE-Function Interactions

In this section, the individual elements presented above were integrated along the human activity gradient, unifying the PLE functions, driving factors, and interaction relationships within an integrated framework (Figure 5). The spatiotemporal changes in the interaction framework for each buffer are analyzed below.

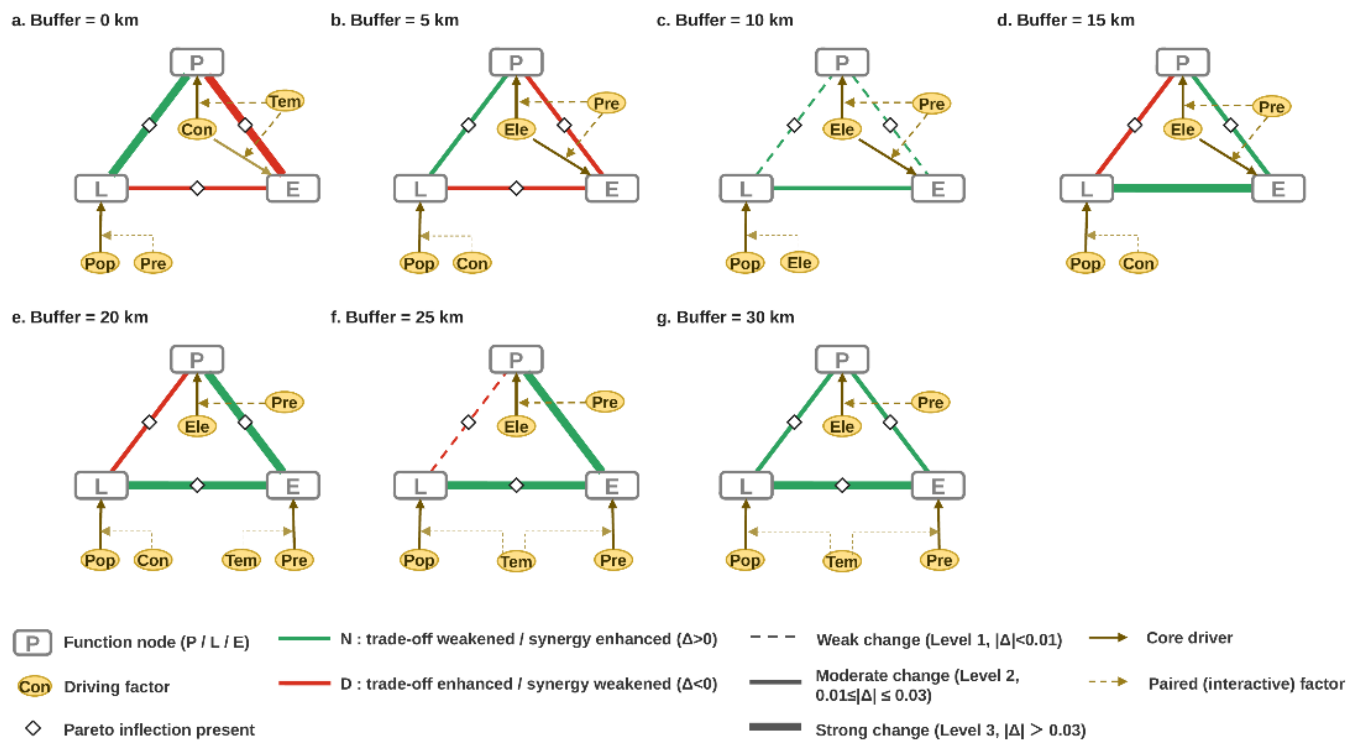


Figure 5. Framework of PLE-function interactions (Note: Con, construction land; Pop, population density; Ele, elevation; Tem, mean annual temperature; Pre, annual precipitation; P, production function; L, living function; E, ecology function).

Spatially, the framework exhibited a structure in which the succession of core drivers and the transformation of interactions were highly synchronized along the gradient. With increasing buffer distance, the dominant driver shifted from the anthropogenic factor Con in the built-up area, through the terrain factor Ele, to the climatic factor Pre. Among the three functions, the core driver of the production function changed from Con to Ele and then remained stable in the periphery. The core driver of the ecology function shifted over further from Ele to Pre, whereas the living function retained Pop as its core throughout. Correspondingly, L-P changed from a weak trade-off in the built-up area to a relatively strong synergy beyond the near suburbs and decayed slowly toward the far suburbs. P-E changed from a weak synergy in the built-up area to a trade-off in the periphery, peaking at 5 km and weakening with distance. L-E remained a trade-off in all buffers, reaching its maximum intensity at 10 km and then weakening gradually. The succession of the driving-factor structure and the transformation in the direction and intensity of the three relationships thus corresponded to one another segment by segment along the gradient.

Temporally, the interaction framework revealed a directional reorganization of PLE-function coupling between 2010 and 2019, generally manifested as a differentiation in which the core area fluctuated while the periphery improved. The built-up area and the near suburbs (0–5 km) were the only zones in the entire region where ecology-related coupling deteriorated, with P-E synergy weakening and the L-E trade-off strengthening. Beyond 10 km, the situation generally turned to improvement, with the L-E and P-E trade-offs weakening and weakening most substantially in the middle-to-far suburbs (20–25 km). Only L-P showed a slight decline in synergy in the middle section (15–25 km). The framework further marked the change in the nature of the coupling through the change in tipping points. As detailed in Section 4.3.2, tipping points disappeared for L-E at 10–15 km and for P-E at 25 km, where curves shifted from non-monotonic to monotonic trade-offs.

Combining the spatial pattern with the temporal change, the seven buffers were grouped into three coupling patterns. (a) Human-driven core zone (the 0 km buffer). Production and ecology were both core-driven by Con and living by Pop, presenting a weak L-P trade-off, a weak P-E synergy, and a moderate L-E trade-off. Temporally, the L-P trade-off weakened, the P-E synergy weakened, and the L-E trade-off strengthened, reflecting the core-area feature of living-function strengthening alongside ecology-related coupling under pressure. (b) Terrain-constrained steady-state zone (5–15 km). Production and ecology were jointly driven by Ele and living by Pop, presenting a combination of pronounced L-P synergy with moderate-to-strong P-E and L-E trade-offs, in which P-E varied gently along the gradient while L-P and L-E tended to stabilize toward the near-suburban periphery. Year on year, improvement began at 10 km, with the L-E and P-E trade-offs weakening. (c) Climate-background-dominated zone (20–30 km). The core driver of ecology shifted to Pre while production remained driven by Ele, and the explanatory power of climatic factors increased with distance, presenting a far-suburban synergy-potential pattern in which the L-P synergy was maintained and the P-E and L-E trade-offs weakened considerably. The improvement of L-E reached its maximum at 20–30 km and that of P-E at 20–25 km.

5. Discussion

5.1. Integrating Drivers, Interactions, and Their Dynamics Within a Framework

Prior studies have examined driving factors, interaction directions and intensities, and nonlinear thresholds largely in isolation, leaving the correspondence between drivers and interaction patterns unestablished [23,41]. This study uses the human activity intensity gradient as a unified coordinate within which the direction and intensity of interactions, the nonlinear thresholds, the core drivers, and their interannual changes are integrated. In this way, previously isolated statistical results were linked into a continuous, interpretable driver-response process.

The integrated PLE-function interaction framework reveals that the succession of core drivers and the transformation of interaction patterns are highly synchronized along the gradient and can be understood as two responses to the same underlying gradient. At the same time, the direction-intensity and the Pareto tipping point are placed on the same connecting line, allowing the “average association” and the “critical structure” of a relationship to be read together. The disappearance of a tipping point in certain buffers is therefore no longer a slight fluctuation of the correlation coefficient but can be identified as a state transition in the nature of the relationship. The analytic framework could be applied to other ecologically fragile regions where a human-activity gradient can be defined, and it could be extended to explore coupling evolution under alternative future scenarios.

5.2. Control Handover as the Mechanism of Coupling Reorganization Along the Urban–Rural Gradient

The coupling reorganization revealed by the framework can be attributed, at the mechanistic level, to an orderly handover of functional control along the gradient, consistent with critical transition theory [28,42]. For the production and ecology functions constrained by the natural background, their dominant drivers succeed along the gradient from construction land in the built-up area through elevation to precipitation. Production stops at elevation because arable land in this karst region is concentrated in valley basins and intermontane flats whose extent is set by terrain, as ecosystem-service bundles in karst landscapes have been shown to be primarily determined by landforms and topography [43]. Ecology hands over further to precipitation because on the highly permeable karst substrate soil moisture rather than relief governs vegetation, and soil moisture lim-

itation in karst areas has been identified as a key constraint on vegetation growth [44], with precipitation driving water yield in the South China karst [34]. In this way, control is transferred stepwise from human construction to terrain constraints and the climatic background [27,45]. The living function, centered on human habitation, is by contrast dominated by population throughout and is relatively independent of this succession of natural elements.

The transformation of the three function relationships is the coupled response to this transfer of control, and geomorphic and land-use characteristics specific to the Guizhou-Guangxi karst determine its local form. In the built-up cores, production and living land are confined to a few valley basins and intermontane flats, so the 2.44-fold expansion of construction land competed directly with the scarce cropland and the surrounding ecological land; core-zone coupling is therefore governed by anthropogenic pressure rather than by any natural factor, yielding a weak L-P trade-off, an L-E trade-off and a barely synergistic P-E. Moving outward, the fragmented peak-cluster and peak-forest terrain confines settlement and cultivation to the same limited pockets of workable land and the slopes immediately above them: scattered hamlets sit adjacent to the sloped plots they work, so living and production co-occur in space and L-P turns from a trade-off into a significant synergy; the same sloped cultivation encroaches on thin-soil ecological land, which is why L-E remains a trade-off and P-E turns into one, both peaking in the 5–10 km belt. In the far suburbs, where settlements thin out and disturbance is weak, the near-uniform climatic background—chiefly precipitation on the high-infiltration karst substrate—regulates the ecological process, so trade-offs relax across the board. The gradient divergence of PLE interactions is thus not merely a statistical gradient but the spatial expression of how fragmented topography, scattered rural settlement, sloped farming, and spatially uneven urban expansion successively cede control from human to terrain to climatic forcing.

In this sequence, the living function, by virtue of its stable population driving, consistently acts as the link of pattern transformation. It turns from competition to synergy with production while maintaining a long-term trade-off with ecology, which exactly explains why L-P synergy reaches its maximum in the near-to-middle suburbs. Existing studies of ecosystem-service trade-offs mostly attribute trade-offs and synergies to differences in land-management modes or biophysical backgrounds [5,7,9], with biodiversity-driven provisioning further modulating service interactions in karst landscapes [46]; similar urban–rural gradient effects of construction-land expansion on land-use-function trade-offs have been reported for rapidly urbanizing basins outside the karst [31], and grid-scale coupling studies in neighboring karst river basins and the Guangxi karst–Beibu Gulf likewise find socioeconomic drivers overtaking natural constraints as development intensifies [47,48]. What the present framework adds is that the driving structure and the interaction pattern are not independent of each other but co-evolve along the gradient, and that this correspondence extends to the structural state of the interaction—the presence or loss of a Pareto tipping point—not only to its averaged direction and intensity; neither link has been explicitly characterized in previous trade-off/synergy studies, and together they imply differentiated management tailored to the control structure of each zone.

This local reading also indicates where structural degradation concentrates. In the built-up core and near suburbs (0–5 km), the abrupt encroachment of expanding built-up land on thin-soil ecological land degrades the averaged L-E and P-E coupling directly, making these the only zones in which ecology-related coupling deteriorated; farther out, where averaged intensities do ease, repeated sloped cultivation and afforestation on an already fragile substrate flatten the response boundary and erode the win-win tipping point. The two signals therefore need to be read together.

5.3. Quantitative Relief Versus Structural Rigidification: A Hidden Pathway of Coupling Degradation

The most notable finding is the divergence between quantitative and structural aspects of coupling evolution. We set it out in four steps: what the two measures show, what the loss of a tipping point means, why an averaged association cannot reveal it, and why the divergence is consequential in fragile karst terrain. Although trade-off intensities ease beyond 10 km, three Pareto frontier curves—L-E at 10 km and 15 km, and P-E at 25 km—degenerated over the same period from a rise-then-fall form into a monotonic decline and lost their tipping points, while the goodness of fit of the 2019 curves fell generally beyond the 5 km buffer. Improvement in intensity and loss of structure thus occur in the same buffers.

What disappears is not a numerical margin but an operating range. The tipping point marks the carrying-capacity buffer within which win-win is still attainable, a property consistent with the critical-threshold concept in ecosystem-service trade-offs [42]. Once it vanishes, the functions enter a locked-in trade-off in which a gain for one side must come at the cost of continuous loss for the other. In critical-transition theory, such loss of a tipping point is interpreted as a narrowing of the system's safe operating boundary [28], a signal that the system is losing its capacity to recover from disturbance [49].

An averaged association cannot report that contraction. Pearson correlation summarizes a linear relationship across all pixels of a buffer, so it captures the typical direction and strength of a pairing but is indifferent to the shape of the boundary that limits it. A weakening trade-off and a vanishing tipping point are therefore not conflicting readings of the same data but answers to different questions: the coefficient can move in the reassuring direction precisely while the boundary flattens. The improvement suggested by the correlation coefficient must therefore be interpreted with caution.

This quantity-quality divergence has practical implications in fragile karst regions. The study area has thin soils, prominent rocky desertification, and extremely limited production and living land, so its system resilience is inherently low [19,33,50]. A contracted carrying-capacity buffer therefore leaves little margin for recovery. Yet the core area and near suburbs (0–5 km), which absorbed 86.6% of the newly added construction land, showed a counter-trend deterioration of ecology-related coupling against the background of overall improvement. Correlation-based monitoring alone would have registered regional improvement while missing both the structural loss beyond 10 km and this counter-trend deterioration in the core; early warning therefore requires structural indicators derived from Pareto-based diagnostics to be read alongside the averaged association.

5.4. Policy Implications and Management Countermeasures

At the application level, diagnosis along the human activity gradient provides a mechanistic basis for differentiated territorial-space governance [8,13,41]. The framework reveals that the three coupling zones differ in their crux and potential. The appropriate intervention in each follows from the driver that controls it and from the structural state of its interactions, so the priority, the instrument and the early-warning trigger are set out zone by zone below.

In the human-driven core zone (0 km), where construction land dominates both production and ecology, excessive concentration of anthropogenic pressure is the primary challenge. Strict control of construction-land expansion [51] and enforcement of the ecological-protection redline [52] should take priority, coupled with compact, infill-oriented urban growth that spares the scarce valley cropland and the adjacent ecological land. Because the core and its immediate surroundings (0–5 km) were the only part of the region where ecology-related coupling deteriorated, performance here should be judged on that coupling rather than on aggregate coordination indices.

The terrain-constrained steady-state zone (5–15 km) is the pivot at which trade-offs convert into synergies, and it is also where structural erosion has advanced furthest: two of the three curves that lost their tipping points lie here (L-E at 10 km and 15 km), and the L-P synergy already weakens from 15 km outward. Consolidating slope cropland into terraced systems [53] and stabilizing Grain-for-Green plots [54] would lock in the L-P synergy that the co-occurrence of settlement and cultivation sustains here. Because the tipping points of this zone have already been lost, intervention should not wait for the correlation coefficient to deteriorate.

The climate-background-dominated zone (20–30 km) retains the highest synergy potential, the L-E and P-E trade-offs weakening most markedly here, yet the P-E curve at 25 km lost its tipping point even as its averaged trade-off eased. Protecting what remains of the nonlinear carrying-capacity buffer is therefore the priority: a moratorium on further conversion of ecological land and priority investment in rocky-desertification control [35,39] are the appropriate instruments, and the disappearance of a Pareto tipping point should serve as the operational trigger for degradation early warning.

Across all three zones, monitoring should pair the averaged correlation with Pareto-derived structural indicators so that counter-trend degradation is caught early. Compared with conventional zoning approaches, this refined gradient-based framework can more effectively direct limited governance resources toward the most critical buffers.

5.5. Limitations and Future Directions

This study still has aspects that could be improved in terms of the temporal and spatial scales of the data. On the temporal side, the analysis is based on two time points (2010 and 2019). Although these are sufficient to reveal the overall direction of PLE-function coupling evolution, they cannot characterize its continuous trajectory. The drift of tipping points among buffers can only be inferred from the two endpoints, and interannual fluctuations are difficult to distinguish from long-term trends. On the spatial side, the concentric ring buffers constructed at 5 km intervals are a spatial approximation of the human activity intensity gradient. They may be confounded by directional heterogeneity and by factors such as terrain and administrative boundaries and therefore do not constitute a strictly controlled variable. These limitations suggest that future research should be extended along both temporal and spatial dimensions. The 250 m grid resolution, while sufficient for capturing gradient-scale patterns, may smooth over fine-grained heterogeneity within each buffer.

At the research level, the framework should be advanced from characterizing correspondences to revealing causal mechanisms. Supported by multi-temporal, long-series data, interpretable causal and mechanistic models need to be developed to clarify how driving factors affect inter-function relationships, and their generality should be tested across different karst and other ecologically fragile regions through multi-regional comparisons [23]. The structural indicators derived from Pareto-based diagnostics also warrant further development and validation as complementary monitoring tools for early warning systems. From a policy standpoint, the framework's sensitivity to structural degradation gives it important early-warning value: the counter-trend deterioration of the core area against a background of overall improvement, and the narrowing of the safe operating boundary signaled by the disappearance of peripheral tipping points, often precede the deterioration of aggregate indicators and can thus serve as early signals for identifying potential ecological risks and preventing irreversible degradation. On the decision-making front, the framework offers a basis for zoned and graded differentiated management in karst regions, supports dynamic supervision and evaluation of ecological-restoration projects, and enables scenario-based analysis of coupling evolution under different

development and protection pathways, thereby strengthening sustainable land-use and ecological-security decisions in fragile regions and beyond.

6. Conclusions

This study constructed an integrated framework that unifies driving factors, interaction dynamics, and nonlinear thresholds along a human activity intensity gradient, applied to the Guizhou-Guangxi karst region (2010–2019). Spatially, the core drivers of production and ecology functions shifted along the gradient from construction land through elevation to precipitation, whereas living function remained consistently driven by population. Synchronized with this driver succession, the direction and intensity of the three pairwise interactions transformed accordingly, allowing the study area to be partitioned into three internally consistent coupling domains: a human-driven core zone (0 km), a terrain-constrained steady-state zone (5–15 km), and a climate-background-dominated zone (20–30 km). Temporally, coupling fluctuated in the core but improved in the periphery, with a notable divergence of quantitative relief and qualitative degradation: trade-off intensities eased beyond 10 km, yet several Pareto frontier curves degenerated from nonlinear rise-then-fall forms into monotonic trade-offs, with tipping points disappearing and signaling the erosion of carrying-capacity buffers where win-win synergies remained attainable.

Theoretically, the results show that the driving structure and the interaction pattern of PLE functions are not independent but co-evolve along the human-activity gradient, so that trade-off/synergy relations are better understood as the coupled response to an orderly handover of functional control than as fixed properties of a place; this reframing extends critical-transition and early-warning thinking from single variables to the structure of function interactions. Methodologically, jointly reading an averaged association together with a nonlinear response boundary exposes a quantity–quality divergence that either measure alone would miss, offering a transferable diagnostic for coupled human–natural systems. expanded from that motivated this study. The observed driver succession along the gradient—the core driver of production shifting from construction land to elevation and that of ecology from elevation to precipitation, while living remained population-driven throughout—supports the hypothesis that the dominant drivers of the natural-background functions hand over in an orderly sequence from anthropogenic to terrain and then climatic factors. The synchronized transformation of the three pairwise interactions with this succession—L-P shifting from a weak trade-off in the built-up area to a strong synergy in the near-to-middle suburbs and then decaying, P-E shifting from weak synergy to a trade-off peaking at 5 km, and L-E remaining a trade-off reaching its maximum at 10 km—is consistent with the hypothesis that the direction and intensity of the three interactions reorganize in step with the driver succession. The coexistence of two signals in the same buffers—trade-off intensities easing beyond 10 km while three Pareto frontier curves (L-E at 10 and 15 km and P-E at 25 km) degenerated from non-monotonic to monotonic forms and lost their tipping points, which averaged correlation coefficients alone did not reveal—provides evidence for the hypothesis that an apparent easing of trade-off intensity may coexist with a degradation of interaction structure. These findings provide a diagnostic and early-warning basis for differentiated, zone-specific management in karst and other ecologically fragile regions, and invite validation with longer time series and across additional karst settings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15081336/s1>, Table S1: Datasets used in research and their attributes; Table S2: Production-living-ecology (PLE) land use transition matrix; Table S3: Fitting results of L-P, L-E, and P-E Pareto frontier curves in 2010 and 2019.

Author Contributions: J.L.: conceptualization, methodology, validation, writing—original draft preparation, writing—review and editing, and funding acquisition; Z.H.: conceptualization, methodology, software, writing—review and editing, funding acquisition, and supervision; Z.Z.: data curation, methodology, validation, investigation, funding acquisition, and writing—review and editing; S.L.: methodology and writing—review and editing, supervision. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 42401341; National Natural Science Foundation of China, grant number 72304263; Hebei Natural Science Foundation, grant number D2024205040.

Data Availability Statement: The data are available from the authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Jing, W.; Yu, K.; Wu, L.; Luo, P. Potential land use conflict identification based on improved multi-objective suitability evaluation. *Remote Sens.* **2021**, *13*, 2416.
2. Chen, W.; Zhang, X.; Huang, Y. Spatial and temporal changes in ecosystem service values in karst areas in southwestern China based on land use changes. *Environ. Sci. Pollut. Res.* **2021**, *28*, 45724–45738.
3. Zeng, L.; Li, J.; Zhou, Z.; Yu, Y. Optimizing land use patterns for the Grain for Green Project based on the efficiency of ecosystem services under different objectives. *Ecol. Indic.* **2020**, *114*, 106347.
4. Zhang, Z.; Wang, X.; Zhang, Y.; Gao, Y.; Liu, Y.; Sun, X.; Zhi, J.; Yin, S. Simulating land use change for sustainable land management in rapid urbanization regions: A case study of the Yangtze River Delta region, China. *Landsc. Ecol.* **2023**, *38*, 1807–1830.
5. Bennett, E.M.; Peterson, G.D.; Gordon, L.J. Understanding relationships among multiple ecosystem services. *Ecol. Lett.* **2009**, *12*, 1394–1404.
6. Lu, Z.; Wei, Y.; Xiao, H.; Zou, S.; Ren, J.; Lyle, C. Trade-offs between midstream agricultural production and downstream ecological sustainability in the Heihe River basin in the past half century. *Agric. Water Manag.* **2015**, *152*, 233–242.
7. Rodríguez, J.P.; Beard, T.D., Jr.; Bennett, E.M.; Cumming, G.S.; Cork, S.J.; Agard, J.; Dobson, A.P.; Peterson, G.D. Trade-offs across space, time, and ecosystem services. *Ecol. Soc.* **2006**, *11*, 28.
8. Zhang, J.; Li, S.; Lin, N.; Lin, Y.; Yuan, S.; Zhang, L.; Zhu, J.; Wang, K.; Gan, M.; Zhu, C. Spatial identification and trade-off analysis of land use functions improve spatial zoning management in rapid urbanized areas, China. *Land Use Policy* **2022**, *116*, 106058.
9. Yuan, S.; Mei, Z.; Zhu, C.; Cao, R.; Li, S.; Yang, L.; Su, Y.; Li, W. Investigating the spatio-temporal interactive relationship between land use structure and ecosystem services in urbanizing China. *Ecol. Indic.* **2024**, *158*, 111315.
10. Hegwood, M.; Langendorf, R.E.; Burgess, M.G. Why win–wins are rare in complex environmental management. *Nat. Sustain.* **2022**, *5*, 674–680.
11. Chen, L.; Cai, H. Study on land use conflict identification and territorial spatial zoning control in Rao River Basin, Jiangxi Province, China. *Ecol. Indic.* **2022**, *145*, 109594.
12. Chen, L.; Zhang, A. Identification of land use conflicts and dynamic response analysis of natural–social factors in rapidly urbanizing areas: A case study of the urban agglomeration in the middle reaches of the Yangtze River. *Ecol. Indic.* **2024**, *161*, 112009.
13. Zong, S.; Xu, S.; Huang, J.; Ren, Y.; Song, C. Distribution patterns and driving mechanisms of land use spatial conflicts: Empirical analysis from counties in China. *Habitat Int.* **2025**, *156*, 103268.
14. Li, W.; Kang, J.; Wang, Y. Land use conflicts identification and multi-scenario simulation in mountain cities, Southwest China: A coupled structural and functional perspective. *Land Degrad. Dev.* **2025**, *36*, 1492–1512.
15. Liu, C.; Xu, Y.; Huang, A.; Liu, Y.; Wang, H.; Lu, L.; Sun, P.; Zheng, W. Spatial identification of land use multifunctionality at grid scale in farming-pastoral area: A case study of Zhangjiakou City, China. *Habitat Int.* **2018**, *76*, 48–61.
16. Zhou, D.; Xu, J.; Lin, Z. Conflict or coordination? Assessing land use multi-functionalization using production-living-ecology analysis. *Sci. Total Environ.* **2017**, *577*, 136–147.
17. Liu, C.; Wang, C.; Li, Y.; Wang, Y. Spatiotemporal differentiation and geographic detection mechanism of ecological security in Chongqing, China. *Glob. Ecol. Conserv.* **2022**, *35*, e02072.

18. Gao, J.; Zuo, L.; Liu, W. Environmental determinants impacting the spatial heterogeneity of karst ecosystem services in Southwest China. *Land Degrad. Dev.* **2020**, *32*, 1718–1731.
19. Xu, E.; Zhang, H. A spatial simulation model for karst rocky desertification combining top-down and bottom-up approaches. *Land Degrad. Dev.* **2018**, *9*, 3390–3404.
20. Li, K.; Zhao, J.; Li, Y.; Lin, Y. Identifying trade-offs and synergies among land use functions using an XGBoost–SHAP model: A case study of Kunming, China. *Ecol. Indic.* **2025**, *172*, 113330.
21. Chen, M.; Lu, Y.; Ling, L.; Wan, Y.; Luo, Z.; Huang, H. Drivers of changes in ecosystem service values in Ganjiang upstream watershed. *Land Use Policy* **2015**, *47*, 247–252.
22. Jiang, C.; Zhang, H.Y.; Zhang, Z.D. Spatially explicit assessment of ecosystem services in China's Loess Plateau: Patterns, interactions, drivers, and implications. *Glob. Planet. Change* **2018**, *161*, 41–52.
23. Gao, C.; Hu, B.; Wang, Z.; Huang, S.; Zhang, L. Study on spatiotemporal changes of ecosystem service trade-offs/synergies and driving mechanisms in the key zone of mountain–river–sea coupling: A case study of the southwest Guangxi Karst–Beibu Gulf. *Ecol. Indic.* **2024**, *169*, 112892.
24. Wang, J.F.; Xu, C.D. Geodetector: Principle and prospective. *Acta Geogr. Sin.* **2017**, *72*, 116–134. (In Chinese)
25. Wu, Y.M.; Zhang, Y. Study on the coupling and coordinated development between regional economic growth and the environment in China. *Resour. Sci.* **2008**, *30*, 25–30. (In Chinese)
26. Li, J.; Zhang, H.; Xu, E. Quantifying production-living-ecology functions with spatial detail using big data fusion and mining approaches: A case study of a typical karst region in Southwest China. *Ecol. Indic.* **2022**, *142*, 109210.
27. Lyu, R.; Zhang, J.; Xu, M.; Li, J. Impacts of urbanization on ecosystem services and their temporal relations: A case study in Northern Ningxia, China. *Land Use Policy* **2018**, *77*, 163–173.
28. Scheffer, M.; Bascompte, J.; Brock, W.A.; Brovkin, V.; Carpenter, S.R.; Dakos, V.; Held, H.; van Nes, E.H.; Rietkerk, M.; Sugihara, G. Early-warning signals for critical transitions. *Nature* **2009**, *461*, 53–59.
29. Hao, R.; Yu, D.; Wu, J. Relationship between paired ecosystem services in the grassland and agro-pastoral transitional zone of China using the constraint line method. *Agric. Ecosyst. Environ.* **2017**, *240*, 171–181.
30. Li, J.; Xu, E.; Li, S.; Liu, M. Relationships and driving factors of the explicit and implicit land use conflicts in the karst regions, Southwest China. *Ecosyst. Health Sustain.* **2026**, *12*, 0525.
31. Li, S.; Zhu, C.; Deng, X. Exploring the urban–rural gradient effects of construction land expansion processes on land use function trade-off/synergy in rapidly urbanizing areas. *Land Degrad. Dev.* **2024**, *35*, 46–61.
32. Ju, H.; Zhang, Z.; Zhao, X.; Wang, X.; Wu, W.; Yi, L.; Wen, Q.; Liu, F.; Xu, J.; Hu, S.; et al. The changing patterns of cropland conversion to built-up land in China from 1987 to 2010. *J. Geogr. Sci.* **2018**, *28*, 1595–1610.
33. Tian, Y.; Wang, S.; Bai, X.; Luo, G.; Xu, Y. Trade-offs among ecosystem services in a typical karst watershed, SW China. *Sci. Total Environ.* **2016**, *566–567*, 1297–1308.
34. Zhang, S.; Xiong, K.; Qin, Y.; Min, X.; Xiao, J. Evolution and determinants of ecosystem services: Insights from South China karst. *Ecol. Indic.* **2021**, *133*, 108437.
35. Xiao, J.; Xiong, K.N. A review of agroforestry ecosystem services and its enlightenment on the ecosystem improvement of rocky desertification control. *Sci. Total Environ.* **2022**, *856*, 158538.
36. Xiong, K.; He, C.; Zhang, M.; Pu, J. A new advance on the improvement of forest ecosystem functions in the karst desertification control. *Forests* **2023**, *14*, 2115.
37. Li, J.; Zhang, H.; Xu, E. A two-level nested model for extracting positive and negative terrains combining morphology and visualization indicators. *Ecol. Indic.* **2020**, *109*, 105842.
38. State Forestry Administration of China. *Specifications for Assessment of Forest Ecosystem Services (LY/T 1721–2008)*; China Standards Press: Beijing, China, 2008. (In Chinese)
39. Luo, D.; Zhou, Z.; Zhang, L.; Chen, Q.; Huang, D.; Feng, Q.; Wu, T.; Wu, L. Evolution and driver analysis of forest carbon stocks in karst mountainous areas of Southwest China in the context of rocky desertification management. *Catena* **2024**, *246*, 108335.
40. Deng, G.; Jiang, H.; Ma, S.; He, C.; Sheng, L.; Wen, Y. Revealing the impacts of different urban development on habitat quality: A case study of the Changchun–Jilin region of China. *J. Clean. Prod.* **2025**, *511*, 145661.
41. Zhang, Z.; Tong, Z.; Zhang, L.; Liu, Y. What are the dominant factors and optimal driving threshold for the synergies and trade-off between ecosystem services, from a nonlinear coupling perspective? *J. Clean. Prod.* **2023**, *422*, 138609.
42. Hong, G.; Liu, S.; Liu, W.; Wu, X. Nonlinear trade-off relationship and critical threshold between ecosystem services and climate resilience for sustainable urban development. *Sustain. Cities Soc.* **2024**, *103*, 105253.

43. Peng, J.; Meersmans, J.; Qiu, S.; Liu, H.; Wang, F. Understanding the relationships between ecosystem services and associated social-ecological factors in karst landscapes. *Ecosyst. Serv.* **2024**, *67*, 101634.
44. Jiao, L.; Zhang, W.; Zheng, H.; Li, Y.; Fu, B. EEMD disentangles climate-NPP dynamics in southwest China's karst area: Soil moisture overtakes precipitation as a key driver of afforestation-induced carbon sinks. *Ecol. Indic.* **2025**, *158*, 111315.
45. Ran, Z.; Gao, S.; Zhang, B.; Guo, C.; Ouyang, X.; Gao, J. Non-linear effects of multi-dimensional urbanization on ecosystem services in mega-urban agglomerations and its threshold identification. *Ecol. Indic.* **2023**, *154*, 110846.
46. Yang, Y.L.; Xiong, K.N.; Xiao, J. A review of agroforestry biodiversity-driven provision of ecosystem services and implications for karst desertification control. *Ecosyst. Serv.* **2024**, *67*, 101634.
47. Sun, J.; Min, X.; Luo, J.; Yang, F.; Deng, L.; Chen, X.; Huang, S.; Wang, Y. Coupling and coordination of production–living–ecological space in the karst plateau basin, China: A combined spatiotemporal differentiation and impact mechanisms perspective. *Land* **2026**, *15*, 229.
48. Feng, T.; Wu, D.; Yu, X.; Zhang, M.; Dong, R.; Chen, S. Evaluation and influencing factors of coupling coordination of “production–living–ecological” functions based on grid scale: Empirical experience of karst Beibu Gulf in southwest Guangxi, China. *Land* **2025**, *14*, 614.
49. Fan, Y.; Wei, G. Assessment of ecological resilience and its response mechanism to land spatial structure conflicts in China's southeast coastal areas. *Ecol. Indic.* **2025**, *170*, 112980.
50. Xiong, K.; Deng, X.; Zhang, S.; Zhang, Y.; Kong, L. Forest ecosystem service trade-offs/synergies and system function optimization in karst desertification control. *Plants* **2023**, *12*, 2376.
51. Li, W.; Cui, Y.; Qin, Y. Construction land allocation in Beijing-Tianjin-Hebei and Yangtze River Delta urban agglomerations. *Land Use Policy* **2025**, *137*, 107203.
52. Guo, X.; Zhao, T.; Wu, J.; Li, C. How does ecological protection redline policy affect regional land use and ecosystem services? *Environ. Impact Assess. Rev.* **2023**, *102*, 107062.
53. Wang, Q.; Xu, Y.; Zhu, G.; Zhao, L.; Li, R. Terraced fields increased soil organic carbon content in croplands of the loess plateau. *Catena* **2025**, *248*, 108335.
54. Wang, X.; Zhang, X.; Feng, X.; Liu, S.; Yin, L.; Chen, Y. Trade-offs and Synergies of Ecosystem Services in Karst Area of China Driven by Grain-for-Green Program. *Chin. Geogr. Sci.* **2020**, *30*, 94–110.

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.