

## Article

# Recurrent Overlap Between Tourism Suitability and Ecological Sensitivity in the Yellow River Basin

Bingling Luo <sup>1,\*</sup>, Junyuan Zhao <sup>2,3</sup>, Wanzhen Fu <sup>4</sup> and Jingzi Guo <sup>5</sup> 

<sup>1</sup> School of Management, Zhengzhou College of Finance and Economics, Zhengzhou 450044, China

<sup>2</sup> School of Business, Xinyang College, Xinyang 464000, China

<sup>3</sup> School of Public Management, China University of Mining and Technology, Xuzhou 221116, China

<sup>4</sup> School of Business, Xinyang Normal University, Xinyang 464000, China

<sup>5</sup> Department of Chemistry, College of Chemistry, University of California, Berkeley, CA 94720-1460, USA

\* Correspondence: toug2026@163.com

## Abstract

Large river basins require spatial evidence showing where tourism-support conditions and ecological constraints coincide. Using the Yellow River Basin, we built a reproducible workflow that combines Google Earth Engine preprocessing with local spatial analysis to map tourism development suitability (TDSI), ecological sensitivity (ESI), and conflict intensity on a 1 km equal-area grid in 2013, 2018, and 2023. Annual hotspot shares remained near one-fifth of valid cells, and 153,958 cells (19.80%) entered the hotspot set in at least two benchmark years. Spatially matched reference checks were mixed: official tourism cells showed a positive high-suitability contrast against 50 km block-matched cells (0.778 versus 0.563; empirical  $p = 0.043$ ), whereas OSM POIs, the named-attraction subset, and GBIF cells showed no clear geography-adjusted enrichment. Aggregation from 1 km to 2 km preserved broad structure, but weighting and ecological-constraint choices changed local membership materially. The full XGBoost–SHAP model identified precipitation variability, land-surface thermal change, protected-area proximity, relief, and road-network intensity as leading internal correlates; a strict two-covariate model achieved AUC = 0.680 and F1 = 0.538, limiting external mechanism claims. The products support uncertainty-aware regional screening. Site-specific approval and long-term persistence claims require finer regulatory, field, and temporal evidence.

**Keywords:** Yellow River Basin; tourism–ecology overlap; ecological sensitivity; benchmark-year comparison; recurrent overlap; geospatial screening; environmental planning



Academic Editors: Mark A. Bonn,  
Harry Coccossis and Colin Michael  
Hall

Received: 1 July 2026

Revised: 13 July 2026

Accepted: 7 August 2026

Published: 10 August 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

Mountain-influenced river basins are settings in which development pressure, accessibility, environmental heterogeneity, and ecological fragility interact over short distances. In China, uneven mountainous terrain makes it difficult to infer local development opportunities directly from coarse development statistics [1]. Tourism development in such contexts is also strongly conditioned by landscape sensitivity and ecological thresholds [2].

This challenge is particularly evident in the Yellow River Basin, where scenic mountains, transitional plateaus, dense corridor settlements, and ecologically constrained headwater zones form part of the same hydrological system. Existing tourism studies of the basin still rely heavily on administrative units and macro-level indicators, including tourism resource conversion efficiency and tourism eco-efficiency [3,4]. Related work on tourism

ecological security and tourism-economy coupling has broadened basin-scale comparison. The within-basin geography of co-located tourism-support conditions and ecological constraints remains unresolved [5,6].

This gap has practical planning consequences. Tourism space in the Yellow River Basin follows corridors, heritage landscapes, and terrain transitions that cross county and provincial borders [7,8]. Unit-level summaries flatten this internal geography. Park- or estuary-scale suitability studies provide detailed local evidence, and a basin-wide conflict screen is still needed to connect those local patterns across the full hydrological system [9,10].

Remote sensing makes it possible to replace coarse summaries with spatially continuous observation. Satellite-based land-use and land-cover analysis already provides mature regional change-detection tools [11], and cloud platforms such as Google Earth Engine (GEE) enable such tools to be scaled under consistent preprocessing rules [12]. Comparable workflows have reconstructed annual land dynamics and river planform change, showing that multisource time series can generate repeatable regional products [13,14]. Dense Landsat time series and trajectory-based analyses further indicate that long-term screening can remain temporally comparable when observation logic and spatial grids are fixed in advance [15,16].

Within the Yellow River Basin, remote sensing has documented eco-environmental conditions for more than two decades. Early basin-scale studies monitored evapotranspiration and broader eco-environmental quality from satellite data [17,18]. Subsequent work tracked landscape evolution and land-surface dynamics across the basin, confirming the technical feasibility of consistent observation over broad extents [19,20]. More recent studies have used GEE and comparative land-cover products to strengthen the methodological basis for basin-wide monitoring [21,22]. Hydroclimatic change has been characterized through vegetation drought responses and terrestrial water-storage variation [23,24]. Studies of eco-environmental quality under urbanization and impervious-surface expansion further show that harmonized multisource imagery can recover major spatial gradients across the basin [25,26].

The ecological-sensitivity literature provides a strong parallel foundation. Recent studies have refined basin-wide ecological-quality and vulnerability diagnoses by incorporating desertification and improved remote-sensing ecological indices [27,28]. Other work has identified contributors to ecological vulnerability under land-use change and climatic stress [29,30]. Habitat-quality, restoration, and ecological-security analyses show where protection pressure is concentrated [31,32]. Scenario-based habitat and landscape-fragmentation studies [33,34], ecological-security pattern studies [35,36], and coordinated-development or macro-scale supply–demand assessments [37,38] add further basin context. However, their main products remain ecological diagnoses, and a year-comparable cell-level conflict surface is still missing.

Related literature on tourism suitability and ecotourism mapping offer useful comparisons beyond the basin. Studies of mountain tourism sustainability and ecotourism land-capability evaluation emphasize that tourism development is inseparable from terrain, ecological carrying pressure, and accessibility [39,40]. Recent suitability studies in the Ethiopian highlands and the Darjeeling Himalaya demonstrate that multicriteria screening can be operationalized with geospatial data; their outputs remain local or subregional [41,42]. Machine-learning and entropy-based suitability mapping have increased analytical flexibility, with applications usually centered on scenic areas or protected landscapes [43,44]. Comparable protected-area studies in Qilian and Taihangshan reinforce this point [45,46]. Multimodal ecological-sensitivity evaluations in mountain national parks reach a similar conclusion at site scale [47].

From a methodological perspective, reviews of ecological-vulnerability remote sensing show that indicator selection, scale compatibility, and temporal comparability are core design decisions [48,49]. Long time-series ecological monitoring illustrates how gradual environmental change can be reconstructed consistently at broad spatial scales; this strand usually focuses on ecological state [50]. Studies that integrate tourism supply, demand, and environmental sensitivity move closer to a coupled diagnosis [51]. The remaining methodological need is a multi-year, basin-wide screen within a fixed hydrological framework. Spatially explicit sensitivity analysis underscores the need to embed robustness testing in suitability workflows [52], and land-use conflict research demonstrates the value of comparing suitability dimensions directly [53].

This sustainability-oriented framing is consistent with recent work in Sustainability and related applied geospatial journals. GIS and remote-sensing studies have translated ecological suitability and land-sensitivity evidence into planning-relevant spatial products [54,55]. Related work has mapped ecological sensitivity and environmental quality for decision support in applied settings [56,57]. A GIS-based coastal planning application further shows how such evidence can be converted into explicit use recommendations and spatial constraints [58]. Together, these studies support the present emphasis on transparent indicator design, explicit spatial overlay, and management-scale interpretation.

These strands address different parts of the problem rather than the same question. Administrative tourism studies compare policy units, basin Earth-observation studies map environmental state, and local suitability studies resolve individual parks or scenic areas. The unresolved methodological issue is how to place tourism-support and ecological-sensitivity proxies on one basin grid while reporting how weighting, threshold, conflict formulation, scale, and omitted ecological constraints alter the local cells selected.

Taken together, the literature provides three necessary components for the present problem. Tourism-environment studies explain why basin-scale tourism space matters. Basin-scale Earth observation studies demonstrate that consistent environmental monitoring across the Yellow River Basin is technically feasible. Suitability and conflict studies show that multiple land functions can be compared explicitly. The remaining gap is planning-oriented: a reproducible method is needed to place tourism-support conditions and ecological sensitivity on the same grid, identify recurrent overlap, and translate cell-level conflict into administrative and hydrological reporting units.

This study addresses that gap by integrating cloud-based indicator generation with reproducible local analysis to map tourism development suitability, ecological sensitivity, and overlap intensity across the Yellow River Basin for 2013, 2018, and 2023. Three research questions guide the analysis: (1) Can harmonized geospatial data and fixed-grid comparison generate comparable tourism-support and ecological-sensitivity surfaces across a large mountain–river basin? (2) Which hotspot areas recur across benchmark years and form repeated overlap patterns? (3) How do the mapped boundaries change after aggregation, spatially matched reference checks, alternative weighting and threshold choices, ecological-constraint stress tests, and restricted-feature driver models?

The study makes four methodological contributions to environmental planning and spatial screening. First, it provides a transparent workflow linking GEE indicator generation, local overlap analysis, robustness testing, and multi-scale reporting. Second, it produces annual hotspot maps and a repeated-overlap screening layer on a common 1 km equal-area grid while explicitly limiting temporal inference to the three benchmark years. Third, it translates grid-level evidence into county and sub-basin reporting units with small-sample reliability flags. Fourth, it combines spatially matched reference checks, multi-scenario sensitivity diagnostics, and restricted-feature driver models to expose where

local boundaries are robust or uncertain. The familiar concentration of overlap in corridor and mountain-front settings is treated as a result, not as the novelty claim.

Table 1 positions the study within the main the literature strands and clarifies the methodological gap addressed by the workflow.

**Table 1.** Representative literature strands and remaining methodological gaps.

| Theme                                           | Representative Strand                                                                                                  | Main Limitation                                                                                                                            | Implication for This Study                                                                                                                                |
|-------------------------------------------------|------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------|
| Administrative tourism-environment assessment   | Tourism ecological security, eco-efficiency, and coordination studies based on Yellow River Basin administrative units | Useful for regional comparison; unit-level aggregation is too coarse to resolve internal basin heterogeneity and local conflict locations. | Requires grid-based mapping of tourism-support conditions and ecological constraints.                                                                     |
| Yellow River Basin Earth observation monitoring | Land-cover, ecological quality, urbanization response, habitat quality, and vulnerability monitoring                   | Captures environmental change effectively; joint tourism-development suitability and ecological-sensitivity screening is usually absent.   | Requires a unified remote-sensing workflow that evaluates tourism–ecology overlap directly.                                                               |
| Local suitability and sensitivity mapping       | Protected-area and scenic-area ecotourism suitability or ecological-sensitivity case studies                           | Provides rich local diagnosis with limited transferability to a hydrologically integrated basin with multiple terrain regimes.             | Requires a basin-wide framework that remains reproducible and comparable across years.                                                                    |
| Spatial conflict identification                 | Land-suitability conflict analysis and spatial sensitivity analysis                                                    | Provides explicit comparison logic; local boundaries remain conditional on weights, thresholds, scale, and conflict formulation.           | Requires hotspot screening, repeated-overlap analysis, matched reference checks, and an explicit multi-scenario uncertainty boundary within one workflow. |

The remainder of the paper is organized as follows. Section 2 introduces the study area. Section 3 describes the materials and methods. Section 4 presents the annual patterns, recurrent-overlap structure, multi-scale aggregation, hold-out reference checks, robustness diagnostics, and driver interpretation. Section 5 discusses planning value, interpretation boundaries, and transferability. Section 6 concludes the paper.

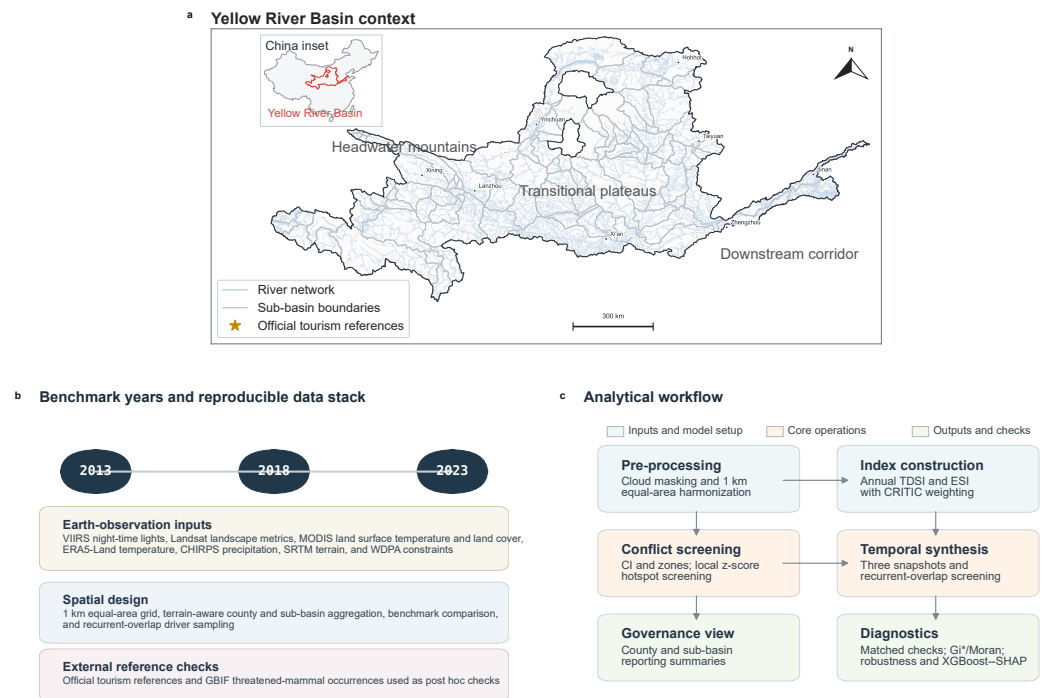
## 2. Study Area

The study-area boundary, sub-basin structure, river network, official tourism references, benchmark years, and analytical workflow are summarized in Figure 1.

The Yellow River Basin provides a suitable case in which nationally important tourism resources, strong ecological constraints, and sharp terrain gradients occur within a single hydrological system. The basin extends from the high-elevation headwater region on the northeastern Qinghai–Tibet Plateau through the Loess Plateau and middle-basin canyon and valley systems to the lower-basin plain. This sequence creates a compact setting for tourism–ecology screening: cultural heritage corridors, mountain scenic areas, river landscapes, and urban service nodes are embedded within areas affected by slope, local relief, hydroclimatic variability, erosion-prone terrain, protected areas, and habitat constraints.

This spatial structure requires analysis below the county scale. Many tourism corridors and ecological constraints cross administrative boundaries, and some counties contain both low-relief development-support areas and highly sensitive mountain-front or river-valley cells. A fixed 1 km equal-area grid provides a consistent unit for detecting where tourism-support conditions and ecological sensitivity overlap. County and sub-basin aggregation are retained for reporting, with grid-level evidence produced first to preserve recurrent overlap before aggregation.





**Figure 1.** Study-area context and analytical workflow for basin-scale tourism–ecology overlap screening. (a) Yellow River Basin context, China locator inset, sub-basin boundaries, river network, major city labels, official tourism references, north arrow, and scale bar. (b) Benchmark years and reproducible data stack. (c) Analytical workflow distinguishing inputs/model setup, core operations, and outputs/diagnostics. The primary hotspot operation is the local z-score screen; Getis–Ord  $G_i^*$  and local Moran are comparison diagnostics.

### 3. Materials and Methods

#### 3.1. Workflow Overview

The workflow was implemented as a two-stage pipeline governed by a single configuration file (`config/study_config.yaml`). The cloud stage, executed through the Google Earth Engine (GEE) Python API, generated annual indicator stacks in a common projection and at a common spatial resolution. The local stage read those exported stacks and reproduced all downstream analytical products on the same grid: tourism development suitability (TDSI), ecological sensitivity (ESI), conflict intensity (CI), annual hotspot masks, recurrent-overlap rasters, county and sub-basin summary tables, hold-out reference-check tables, robustness diagnostics, and eXtreme Gradient Boosting with Shapley additive explanations (XGBoost–SHAP) driver analysis. All analytical GeoTIFFs used EPSG:3410 at 1000 m, and vectors were reprojected to that grid before sampling or aggregation. The pipeline creates a reproducible planning-support chain for applied spatial screening.

This two-stage design separates the roles of data harmonization and spatial analysis. The cloud stage concentrates sensor harmonization, catalog access, masking, and annual compositing into a transparent export step. The local stage then treats the exported stacks as fixed analytical inputs, allowing conflict mapping, robustness testing, and figure generation to be reproduced without repeated dependence on live cloud execution.

The local pipeline writes year-specific outputs to dedicated folders and cross-year outputs to shared directories. Year-specific folders store annual TDSI, ESI, CI, zone, hotspot, and weighting products; cross-year folders store recurrent-overlap rasters, aggregation tables, robustness diagnostics, and modeling outputs. This file contract allows figures and manuscript tables to be regenerated directly from shared intermediates, creating an audit trail from raw indicator stacks to final submission materials.

The benchmark years 2013, 2018, and 2023 were selected as evenly spaced observation windows compatible with the multisource data configuration. They are three fixed snapshots rather than a dense time series. Temporal interpretation in this paper refers only to repeated relative classification across those benchmark years, not to long-term structural persistence.

### 3.2. Data Sources and Indicator System

All annual indicator stacks were constructed from publicly accessible GEE catalog datasets. The VIIRS monthly nighttime light product (NOAA/VIIRS/DNB/MONTHLY\_V1/VCMSFG) was reduced to the annual mean of `avg_rad` to represent human activity intensity. Landsat surface reflectance was obtained from LANDSAT/LC08/C02/T1\_L2 and, for 2023, the merged LANDSAT/LC09/C02/T1\_L2 archive; scenes were restricted to the warm season (May–September), masked using `QA_PIXEL`, converted with Collection 2 scale and offset terms, and composited using the median reducer. This warm-season restriction reduces cloud contamination and keeps vegetation, water, and thermal signals comparable across years. From this composite, the workflow calculated NDVI, MNDWI, and NDBSI. NDVI and MNDWI entered the final subsystem definitions. NDBSI was retained in the exported stack as an auxiliary land-surface descriptor. ERA5-Land (ECMWF/ERA5\_LAND/DAILY\_AGGR) provided annual mean `temperature_2m`, CHIRPS (UCSB-CHG/CHIRPS/DAILY) provided annual precipitation totals, and MOD11A2 (MODIS/061/MOD11A2) provided annual mean daytime LST after quality masking and scale-factor conversion. SRTM (USGS/SRTMGL1\_003) supplied elevation-derived slope and local relief. Built-up support was represented by the urban-class share from MCD12Q1 (MODIS/061/MCD12Q1), and the ecological protection constraint was represented by distance to current WDPAs (WCMC/WDPAs/current/polygons) transformed into a bounded proximity score.

For reproducibility, negative VIIRS `avg_rad` values were set to zero before annual averaging; the workflow did not filter by `cf_cvg`. Landsat scenes covered 1 May–29 September, masked `QA_PIXEL` bits 1–5, and used the Collection 2 reflectance transform  $DN \times 0.0000275 - 0.2$ . MOD11A2 retained mandatory `QC_Day` codes 0 or 1 and used  $DN \times 0.02 - 273.15$ . Relief was the maximum minus minimum elevation within a 5 km-radius circular neighbourhood; climate comfort was  $\max[0, 1 - |T - 18|/20]$ ; and protected-area proximity was  $\exp(-d/50 \text{ km})$  after capping distance at 250 km. The OSM files were generated on 7 April 2026, and the official-tourism and GBIF extracts were generated on 23 April 2026 [59]. The dynamic WDPAs current asset was used, but its exact monthly vintage was not archived.

The supporting vector package comprised the Yellow River Basin boundary, HydroBASINS sub-basins, county-level administrative units clipped from an open boundary source, an OpenStreetMap (OSM) river network, and an OSM major-road network consisting of motorway, trunk, primary, and secondary classes and their link classes. Tourism hold-out reference candidates were assembled from official Ministry of Culture and Tourism lists (5A scenic areas and national tourist resorts) and the United Nations Educational, Scientific and Cultural Organization (UNESCO) World Heritage list for China. These candidates were geocoded and filtered to point records with sufficient spatial certainty inside the basin; the retained sample used for enrichment testing consisted of 5A scenic areas and UNESCO sites. Ecological hold-out reference checks used Global Biodiversity Information Facility (GBIF) occurrence records for threatened mammals with coordinates inside the basin. These tourism and ecological layers served as post hoc enrichment references. The World Database on Protected Areas (WDPA)-based protection term remained an input to ESI, representing a time-invariant ecological-constraint layer.

The indicator system was structured as a direct comparison between development-support conditions and ecological constraints. TDSI combines proxies for human activity intensity, urban support, vegetation and water attractiveness, temperature-based climate comfort, and terrain feasibility; higher TDSI values are expected where service support, landscape appeal, and buildability co-occur. It is a supply-side support screen and does not measure visitor demand, expenditure, seasonality, congestion, or preference. ESI combines slope, relief, land-surface thermal stress, annual precipitation, vegetation- and water-related ecological importance, and protected-area proximity; it is not a complete soil-loss, desertification, or biodiversity-risk model. This paired structure identifies locations where both dimensions are simultaneously strong on the same grid.

All annual indicators were resampled or aggregated to a common 1 km equal-area grid before normalization. Continuous coarse-resolution climate and thermal layers (ERA5-Land temperature, CHIRPS precipitation, and MOD11A2 LST) were bilinearly resampled to the target grid in GEE. Higher-resolution continuous surfaces and fractional masks (VIIRS radiance, Landsat-derived indices, SRTM elevation, and MCD12Q1 urban fraction) were aggregated to 1 km by mean reduction. The WDPA distance surface was computed directly on the 1 km export grid and then converted to a proximity score before normalization, so that cells near protected areas contributed more strongly to ESI. Each indicator was min-max normalized separately within each benchmark year; constant variables were assigned 0.5, and inverse terrain indicators were sign-adjusted before normalization. Consequently, cross-year recurrence denotes repeated membership in annual relative classes rather than persistence of an absolute index value. The 1 km resolution balances basin-scale tractability with subregional spatial differentiation.

Indicator weights were computed separately for each year using the criteria importance through the inter-criteria correlation (CRITIC) method [60]:  $C_j = \sigma_j \sum_k (1 - r_{jk})$  and  $w_j = C_j / \sum_j C_j$ , with population standard deviation and Pearson correlation. TDSI and ESI were then calculated as weighted linear combinations of their standardized indicators; exact annual weights and median thresholds are supplied in the machine-readable files `data/processed/<year>/weights_<year>.csv`, and the annual CI P80 thresholds were 0.199919, 0.202221, and 0.199507. Annual zone classes were defined from the median values of TDSI and ESI, yielding four descriptive screening states: `priority_development`, `conflict_control`, `ecological_conservation`, and `low_intervention`. Conflict intensity was calculated as the multiplicative interaction of the two subsystem surfaces, so that high values occur where development suitability and ecological sensitivity are simultaneously elevated. This is an operational joint-high screening index rather than an established causal conflict mechanism.

Table 2 summarizes the indicator framework, underlying data sources, and the role of each proxy in the workflow.

**Table 2.** Indicator framework and main data sources.

| Index | Dimension                | Indicator or Proxy                              | Data Source                | Role in Framework                                                      |
|-------|--------------------------|-------------------------------------------------|----------------------------|------------------------------------------------------------------------|
| TDSI  | Human activity           | Annual mean nighttime light radiance            | NOAA VIIRS monthly lights  | Proxy for tourism-related human activity intensity and service support |
| TDSI  | Urban support            | Built-up land proxy (urban_frac, IGBP class 13) | MODIS MCD12Q1              | Proxy for urban support conditions in the final configured workflow    |
| TDSI  | Landscape attractiveness | NDVI; MNDWI                                     | Landsat 8 and Landsat 9 L2 | Vegetation and water attractiveness terms used in the final TDSI       |

Table 2. Cont.

| Index | Dimension             | Indicator or Proxy                                      | Data Source                | Role in Framework                                                 |
|-------|-----------------------|---------------------------------------------------------|----------------------------|-------------------------------------------------------------------|
| TDSI  | Climate comfort       | Temperature-based comfort transform                     | ERA5-Land                  | Outdoor thermal-comfort support for tourism                       |
| TDSI  | Buildability          | Inverse slope; inverse relief                           | SRTM                       | Lower terrain complexity indicates higher development feasibility |
| ESI   | Terrain sensitivity   | Slope; relief                                           | SRTM                       | Terrain-related ecological sensitivity and instability            |
| ESI   | Thermal stress        | Land surface temperature                                | MODIS MOD11A2              | Heat-related ecological stress                                    |
| ESI   | Hydroclimate pressure | Annual precipitation                                    | CHIRPS                     | Hydroclimatic pressure background in the final ESI                |
| ESI   | Ecological importance | NDVI; MNDWI                                             | Landsat 8 and Landsat 9 L2 | Vegetation- and water-related ecological importance               |
| ESI   | Protection constraint | Protected-area proximity transformed from WDPA distance | WDPA current polygons      | Ecological constraint associated with protection status           |

### 3.3. Conflict Mapping and Recurrent-Overlap Screening

Basin-wide spatial clustering was first evaluated using global Moran's  $I$  with raster 8-neighbor adjacency [61]. For a conflict-intensity value  $x_i$  at cell  $i$ , spatial weight  $w_{ij}$ , number of valid cells  $n$ , and  $S_0 = \sum_i \sum_j w_{ij}$ , the statistic was computed as

$$I = \frac{n}{S_0} \frac{\sum_i \sum_j w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2}. \quad (1)$$

A custom raster local z-score hotspot screen was then applied to the same CI surface using a  $3 \times 3$  moving window. For each valid cell, the  $3 \times 3$  neighborhood mean was standardized against the basin-wide mean and standard deviation of CI, converted to a two-sided normal  $p$ -value, and flagged as a significant positive hotspot when the local z-score was positive and  $p \leq 0.05$ . This local screen is computationally transparent for a gridded raster workflow and uses the same immediate-neighborhood support as the 8-neighbor Moran calculation.

To address the hotspot-definition concern, the revision added a formal comparison with Getis–Ord  $G_i^*$  and local Moran high-high clustering [62,63]. Getis–Ord  $G_i^*$  was computed on the same  $3 \times 3$  neighborhood support and screened with a two-sided 95% normal threshold. Local Moran high-high cells were identified where the cell and its spatial lag were both above the basin-wide mean and the local Moran contribution was positive. For comparability with the annual conflict-hotspot definition, both diagnostic alternatives were intersected with the same 80th-percentile top-conflict mask before Jaccard comparison.

Hotspot screening was combined with an annual top-conflict threshold to isolate the most structured conflict cores. For each year, valid CI values were thresholded at the basin-wide 80th percentile to produce a year-specific high-conflict mask. The annual conflict-hotspot raster was then defined as the intersection of that top-conflict mask and the significant local hotspot mask. This intersection selects cells that are both high in magnitude and spatially clustered relative to their surroundings.

Because percentile selection affects the size of the hotspot set, a revision sensitivity test repeated the annual and recurrent hotspot extraction at 70th, 75th, 80th, 85th, and 90th CI percentile thresholds while keeping the same local z-score hotspot screen and two-year recurrence rule. For each threshold, the pipeline reported annual hotspot cell counts, recurrent hotspot counts, recurrent shares, and Jaccard overlap relative to the 80th-percentile baseline.

Recurrent overlap was defined as membership in the annual conflict-hotspot set in at least two of the three benchmark years. In addition to the binary recurrent-overlap layer, the pipeline wrote a repeated-hotspot count raster and a cross-year mean CI raster. This definition emphasizes repeated relative detection across the fixed benchmark years; it does not by itself establish long-term structural persistence.

### 3.4. Multi-Scale Aggregation

To extend interpretation beyond the grid-cell level, all results were aggregated to county and HydroBASINS sub-basin units using the same fixed raster grid. Polygon layers were reprojected to the raster coordinate reference system before aggregation. For each polygon, the pipeline computed mean CI, maximum CI, high-conflict share, recurrent-overlap share, zone-specific area shares, and the dominant zone. High-conflict share was defined as the proportion of cells exceeding the basin-wide 80th CI percentile for that year, recurrent-overlap share as the proportion belonging to the recurrent-overlap raster, and dominant zone as the zone with the largest within-polygon area share.

County records with fewer than 10 valid raster cells were flagged in the county reliability output and treated as report-only screening records; counties with no valid cells received a separate “no valid cells” flag. These records are retained for auditability but are not used as direct county-level planning evidence (Table 3).

**Table 3.** County records with fewer than 10 valid 1 km cells. These aggregated values are retained for reference only and must not be used as direct evidence for county-level planning decisions.

| County Unit     | Valid Cells | County Unit     | Valid Cells |
|-----------------|-------------|-----------------|-------------|
| Huojia County   | 1           | Siziwang Banner | 2           |
| Ruzhou City     | 1           | Yuanping City   | 2           |
| Xinfu District  | 1           | Barkam County   | 3           |
| Zhashui County  | 1           | Mengyin County  | 4           |
| Changzhi County | 2           | Sishui County   | 4           |
| Foping County   | 2           | Huguan County   | 5           |
| Qingfeng County | 2           | Li County       | 8           |

No-valid-cell records: Erqi District, Pingding County, Pingyi County, Qin County, Qufu City, Shandan County, and Shanyang District. These units received a separate “no valid cells” flag and no county metric.

The dual aggregation strategy serves two interpretive needs. County aggregation translates raster results to an administrative scale familiar for planning and reporting. Sub-basin aggregation retains a hydrological frame closer to the basin’s physical organization. Using both scales makes it possible to assess whether the same underlying grid evidence remains interpretable when the analytical frame shifts from governance units to hydrological units.

### 3.5. Hold-Out Reference Checks, Robustness, and Driver Interpretation

Three diagnostic blocks were applied after the annual rasters had been generated. First, tourism hold-out checks were performed against 2023 suitability. The official tourism lists provide contemporary reference points. Official tourism candidates were assembled from Ministry of Culture and Tourism 5A scenic-area and national tourist resort lists together with UNESCO World Heritage records, then filtered to high-confidence basin point records. The pipeline sampled TDSI values at those retained official tourism references and compared them with equal-sized random samples of valid raster cells. A cell was labeled as high suitability when its TDSI exceeded the basin-wide 66.7th percentile of valid 2023 cells. The revision also examined OpenStreetMap tourism POIs and a named-attraction stratum; the latter is a subset of the OSM layer and is not treated as independent evidence. For the inferential comparison, all point layers were grid-deduplicated and compared with



non-reference cells from the same 50 km blocks over 1000 Monte Carlo iterations (seed 42), preserving the target count within each represented block.

Second, ecological reference checks used the same threshold and spatial-matching logic for ESI. GBIF occurrence records for threatened mammals (IUCN categories VU, EN, or CR) were filtered to study-area coordinates and unique 1 km cells. WDPA-derived ecological polygons were removed from external validation because WDPA proximity is an ESI input. Reporting effort and taxonomic sampling bias make the GBIF analysis a spatial-alignment check rather than an accuracy assessment.

Third, the revision added an ecological-constraint sensitivity analysis for soil erosion sensitivity and desertification risk, two constraints omitted from the primary ESI. These are heuristic stress-test proxies derived mainly from the existing annual indicator stacks, not independent RUSLE soil-loss or official desertification products. The soil-erosion sensitivity layer combined slope, relief, precipitation, bare-soil intensity (NDBSI), and low vegetation cover ( $1 - NDVI$ ) after year-wise 2nd–98th percentile robust scaling. The desertification-risk layer combined low vegetation cover, NDBSI, low precipitation, land-surface temperature, and low water expression ( $1 - MNDWI$ ) using the same scaling rule. The layer construction follows recent Yellow River Basin studies that link desertification and ecological quality to vegetation, dryness or bare-soil expression, thermal conditions, and terrain-hydroclimatic gradients [27,28]. It also aligns with ecological-vulnerability and ecological-sensitivity studies that treat land-use stress, terrain, and ecosystem-service constraints as relevant ecological-risk dimensions [29,36]. High-risk cells were defined as the top 20% of valid basin cells for each layer in each year, and recurrent high-risk cells were defined as high-risk cells in at least two benchmark years. The second step constructed two augmented ESI scenarios and recomputed CI, annual conflict hotspots, and recurrent overlap: a moderate scenario assigning 70% weight to baseline ESI, 15% to soil-erosion sensitivity, and 15% to desertification risk; and a stronger scenario assigning 50%, 25%, and 25%, respectively.

Fourth, robustness was assessed at the weighting, CI-formulation, recurrence-threshold, and scale levels. Weight sensitivity was evaluated by recomputing all annual TDSI, ESI, and CI surfaces with entropy weighting, an equal-priority hierarchical AHP baseline, two deterministic unequal-preference AHP sensitivity scenarios, their element-wise geometric-mean aggregation, a combined CRITIC–entropy scheme, and a combined CRITIC–AHP scheme [64,65]. Preference scenario A emphasizes tourism-planning priorities specified by the authors; scenario B is a documented ordinal 1–5 stress test rather than an expert survey or active AI-generated input. All pairwise matrices had consistency ratios below 0.10. The alternative specifications were compared using the Pearson correlation of CI, mean and median absolute CI difference, top-conflict Jaccard overlap, recurrent-overlap Jaccard overlap, and zone agreement.

The multiplicative CI formulation was evaluated against an additive mean model and a difference-penalized overlap model. The additive model defines conflict as  $(TDSI + ESI)/2$ . The difference-penalized model defines overlap as  $(TDSI + ESI)/2 - |TDSI - ESI|/2$ , equivalent to the lower of the two subsystem scores. Recurrent-overlap sensitivity was then tested under one-year, two-year, and three-year recurrence thresholds. Because only three benchmark years are available, each two-year pair was also intersected and compared with the baseline two-of-three layer; this is a descriptive decomposition of that definition, not independent temporal validation. Scale robustness was evaluated by aggregating the indicator stack from 1 km to 2 km through  $2 \times 2$  block means.

Recurrent-overlap drivers were analyzed using a spatial-block XGBoost classification model [66] with post hoc SHAP attribution [67], built from the 2013–2023 change table. Positive samples were drawn from recurrent-overlap cells and negative samples from other valid cells, targeting 25,000 positives and 50,000 negatives (random seed 42). The final

sampled frame covered 410 spatial blocks, 426 counties, and all 105 sub-basins. The cell-level case-control sample had smaller county coverage than the full county aggregation table used in Section 3.3. Each cell was attributed with slope, relief, protected-area proximity, nighttime-light growth rate, urban expansion, NDVI change, LST change, the coefficient of variation of annual precipitation across the three benchmark years, 5 km-window smoothed road-segment intensity (legacy field name: *road\_density*), distance to river, and polygon labels for county and sub-basin.

Following spatial-resampling principles [68], cross-validation used 50 km blocks derived from gridded coordinates, with five folds through StratifiedGroupKFold or GroupKFold. Before model fitting, predictor multicollinearity was checked with variance inflation factors [69]. The 50 km block size exceeds the 1 km grid and local  $3 \times 3$  hotspot neighborhood, groups nearby cells within the same held-out spatial unit, and preserves enough blocks for five-fold evaluation. The tuning grid comprised 200 or 300 trees, depths of 3 or 5, and learning rates of 0.03 or 0.05, with subsample and column subsample fixed at 0.8. Three-fold tuning and five-fold evaluation used the same sampled frame and were not nested; the reported scores are therefore internal spatial-block cross-validation estimates. A revision diagnostic repeated the model under 25 km, 50 km, 75 km, and 100 km block sizes.

To test how strongly the driver result restated the composite indices, the revision trained a reduced-feature model using nighttime-light growth, urban expansion, NDVI change, LST change, precipitation variability, road-segment intensity, and distance to river, excluding static slope, relief, and protected-area proximity. Because five of these variables are transformations of index inputs, this model only partly limits circularity. A stricter lower-bound model therefore used only road-segment intensity and distance to river, neither of which enters TDSI or ESI. Model performance was reported with AUC, F1, precision, recall, specificity, balanced accuracy, and fold-level confusion matrices at a probability cutoff of 0.5. The stratified case-control design supports discrimination and covariate-association analysis, not basin-wide probability estimation.

This final step is interpretive. The spatial-block design tests whether recurrent overlap is statistically associated with hydroclimatic variability, terrain, accessibility, recent land-surface change, and protection-related covariates while reducing spatial leakage. SHAP describes model attribution rather than causation; dependence-curve uncertainty used 1000 ordinary bootstrap resamples of 3000 sampled observations (16 quantile bins; seed 20260627), not a spatial-block bootstrap. Analyses were rerun under Python 3.13.11 with NumPy 2.2.6, pandas 2.3.3, SciPy 1.17.0, scikit-learn 1.8.0, XGBoost 3.2.0, SHAP 0.51.0, GeoPandas 1.1.2, Rasterio 1.5.0 (GDAL 3.12.1), PyProj 3.7.2 (PROJ 9.5.1), and Shapely 2.1.2 (GEOS 3.13.1); the pinned dependency file is supplied with the code archive.

## 4. Results

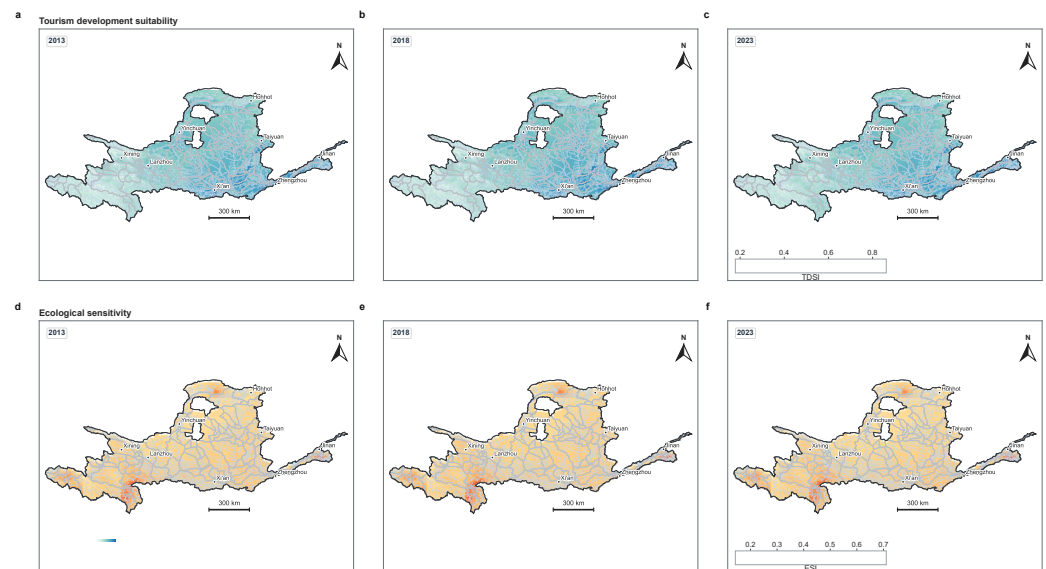
### 4.1. Annual Suitability and Sensitivity Patterns

The annual TDSI and ESI surfaces show similar east–west contrasts across the three benchmark snapshots, together with pronounced local heterogeneity linked to terrain and development corridors. TDSI remains comparatively high in the lower- and middle-basin corridor system. ESI is higher in terrain-constrained and protection-influenced sectors. Annual mean CI values were 0.1659, 0.1706, and 0.1687 in 2013, 2018, and 2023, respectively, indicating modest differences among the selected years.

The panel structure of Figure 2 clarifies this result. Panels (a–c) show that high TDSI values form a broad corridor-oriented pattern, with the most favorable development-support conditions concentrated in the eastern and middle-basin belt and weaker support in terrain-constrained western sectors. Panels (d–f) reveal a contrasting ESI geography,

with sensitivity peaking in mountain-front, relief-dominated, and protected sectors. This comparison identifies the cells where tourism-support conditions and ecological sensitivity overlap strongly.

Figure 2 shows that the broad comparative pattern recurs in the three snapshots while local configurations differ, motivating repeated-classification screening without implying long-term temporal stability.



**Figure 2.** Annual patterns of tourism development suitability (TDSI) and ecological sensitivity (ESI) on the 1 km grid. (a–c) TDSI in 2013, 2018, and 2023. (d–f) ESI in 2013, 2018, and 2023. Color bars show low-to-high index values; TDSI uses a blue-green scale and ESI a yellow-orange scale.

#### 4.2. Conflict Hotspots and Recurrent Overlap Across Benchmark Years

Global Moran's  $I$  remained very high in all three benchmark years (0.9798, 0.9786, and 0.9792), confirming strong spatial clustering of conflict intensity. Annual conflict-hotspot shares were 19.92%, 19.85%, and 19.84% in 2013, 2018, and 2023, respectively. Their similarity is partly constrained by the annual 80th-percentile mask and therefore does not, by itself, demonstrate temporal stability. The hotspot-method comparison supported the use of the raster  $3 \times 3$  screen: after intersection with the same top-conflict mask, the custom hotspot layer and Getis–Ord  $G_i^*$  layer had Jaccard values of 1.000, 1.000, and 1.000 in 2013, 2018, and 2023, respectively, and the local Moran high-high comparison yielded Jaccard values of 0.996, 0.993, and 0.992.

Recurrent overlap was also substantial. Across 777,607 valid grid cells, 153,958 cells reappeared as conflict hotspots in at least two benchmark years, equivalent to 19.80% of the valid basin area. These cells are concentrated in middle- and lower-basin corridor sectors and selected transitional mountain-front settings, indicating repeated relative high-conflict classification within the three-year benchmark design.

Figure 3 makes the hotspot logic visible. Panels (a–c) show elongated clusters of high CI values in the basin corridor and selected mountain-front segments. Panels (d–f) show how the combined upper-quantile and local-hotspot filter narrows these broad high-CI areas into statistically concentrated annual hotspot cores. The inset shares confirm that hotspot extent remained nearly unchanged across benchmark years, even though exact local configurations differed.

The transition structure complements the hotspot maps. The largest diagonal terms in the zone-transition matrix remained within the same zone between 2013 and 2023, especially for conflict\_control and ecological\_conservation. Substantial exchanges also

occurred among *priority\_development*, *low\_intervention*, and *conflict\_control*. The annual products differ locally, and the broad geography of conflict recurs strongly enough to justify a repeated-hotspot definition. The repeated-hotspot count and relief profile further show that recurrent overlap is disproportionately concentrated outside the flattest parts of the basin: the share was lowest in the 0–50 m class, increased sharply in the 50–200 m and 200–400 m classes, and then remained elevated above 400 m.

Figure 4 brings these cross-year relationships together. Panel (a) links recurrent-overlap cells to the mean conflict field, panel (b) separates one-, two-, and three-year recurrence, panel (c) summarizes inter-zone transitions, and panel (d) shows the fixed local-relief profile across 0–50 m, 50–200 m, 200–400 m, and >400 m classes.



**Figure 3.** Annual conflict intensity and hotspot patterns. (a–c) CI surfaces in 2013, 2018, and 2023. (d–f) Significant conflict hotspots in 2013, 2018, and 2023, with inset text reporting the hotspot share of valid cells for each benchmark year. CI is shown from light to dark purple, while significant hotspots are magenta against a gray background.

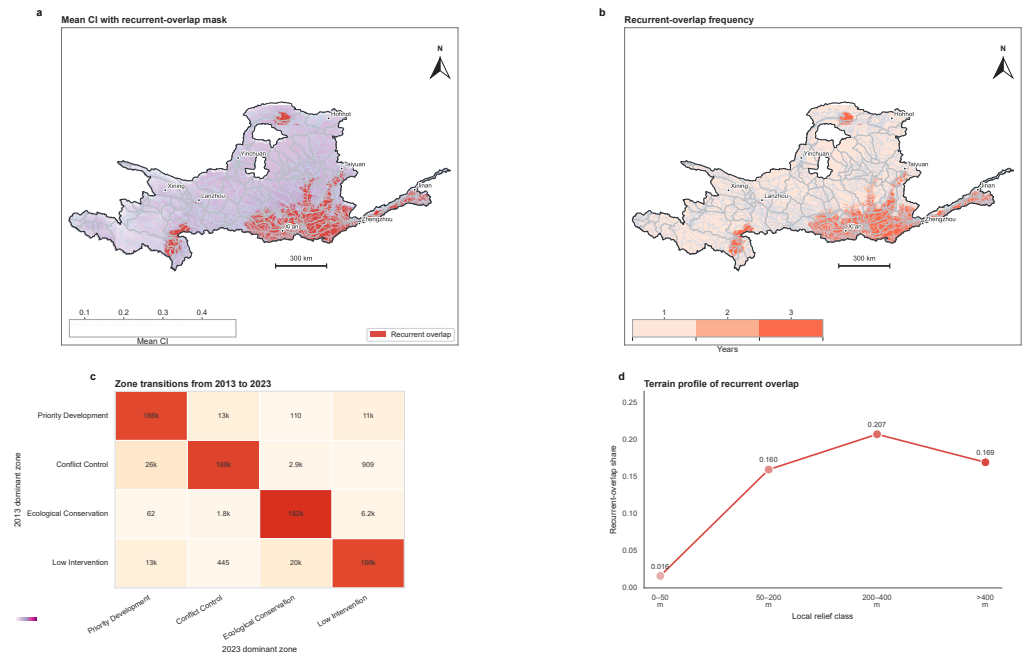
#### 4.3. County and Sub-Basin Application Patterns

The grid-based conflict pattern remains interpretable after aggregation to counties and sub-basins. Across the 436 counties with valid county-level metrics in the 2023 aggregation, *conflict\_control* was the most frequent dominant zone (180 counties), followed by *priority\_development* (100), *low\_intervention* (80), and *ecological\_conservation* (76). Seven counties had no valid grid cells after clipping to the valid basin grid and were left without a dominant-zone label. At the sub-basin scale, the distribution was more balanced: 32 *priority\_development* units, 25 *low\_intervention* units, and 24 units each for *conflict\_control* and *ecological\_conservation*.

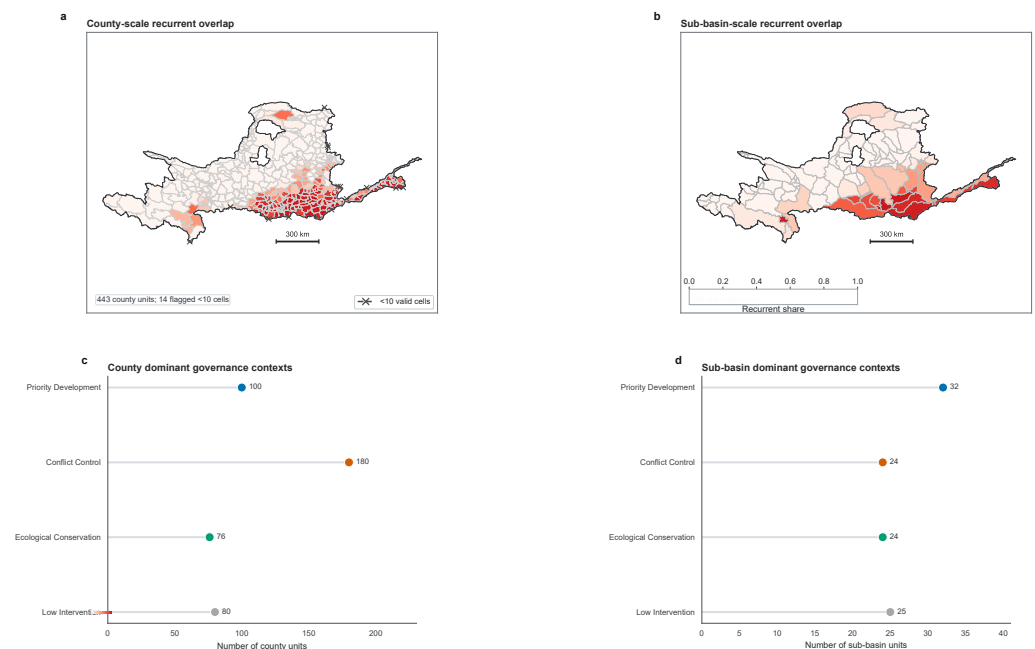
Several county-sized units in the middle-basin corridor reached recurrent-overlap shares near 1.0, and the sub-basins with the highest shares were overwhelmingly classified as *conflict\_control*. This result requires scale-aware interpretation: 14 county records contained fewer than 10 valid cells and are report-only values, not direct planning evidence; 7 additional counties had no valid cells (Table 3). More broadly, the aggregated pattern identifies corridor and transition-zone settings where recurrent overlap occupies a large share of analysis cells. Counties indicate where overlap may warrant administrative follow-up. Sub-basins show how the same hotspots are embedded within the basin’s hydrological structure.

Figure 5 should be read in two parts. Panels (a) and (b) show where recurrent overlap concentrates after aggregation. Panels (c) and (d) summarize how aggregated units are clas-

sified by dominant management state. The main corridor pattern is preserved at both scales, and the balance among dominant zones becomes more even under the hydrological frame.



**Figure 4.** Cross-year recurrent-overlap and transition characteristics. (a) Mean CI with the recurrent-overlap overlay. (b) Recurrence frequency map summarizing cells identified in one, two, or three benchmark years. (c) Zone-transition matrix from 2013 to 2023. (d) Recurrent-overlap share across fixed local-relief classes (0–50 m, 50–200 m, 200–400 m, and >400 m). In panel a, darker purple indicates higher mean CI and red marks recurrent overlap; in panel b, orange to red denotes increasing frequency; in panel c, darker cells denote larger transition counts; and in panel d, the red line shows recurrent share.

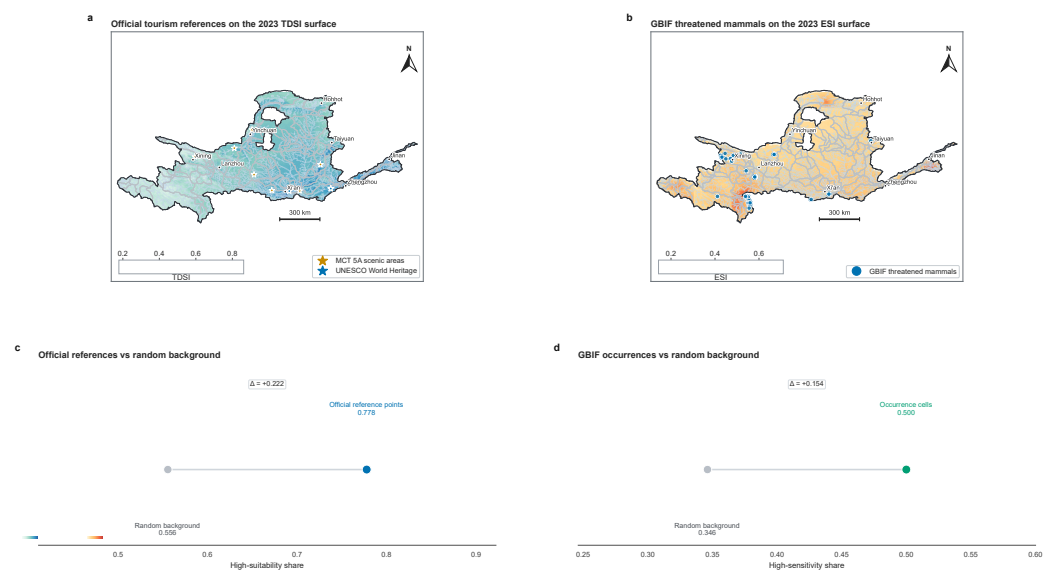


**Figure 5.** Multi-scale aggregation of recurrent-overlap patterns. (a) County-level recurrent-overlap share; county units with fewer than 10 valid grid cells are marked and should be treated as reference-only screening records. (b) Sub-basin recurrent-overlap share. (c) Dominant-zone distribution across counties. (d) Dominant-zone distribution across sub-basins.



#### 4.4. Hold-Out Reference Checks and Robustness

The unadjusted hold-out reference checks provide descriptive plausibility checks for the mapped 2023 surfaces. For the nine retained official tourism reference cells, the share located in high-suitability cells reached 0.778, compared with 0.556 for an equal-size basin-wide random background. Within this small sample, the retained Ministry of Culture and Tourism 5A sites had a high-suitability share of 0.750, and the retained UNESCO World Heritage sites had a share of 1.000. On the ecological side, 26 grid-deduplicated GBIF threatened-mammal cells had a high-sensitivity share of 0.500, compared with 0.346 for an equal-size basin-wide random background and 0.333 for the valid-cell ESI background. Figure 6 maps these layers and reports the unadjusted contrasts; the spatially matched tests follow below.

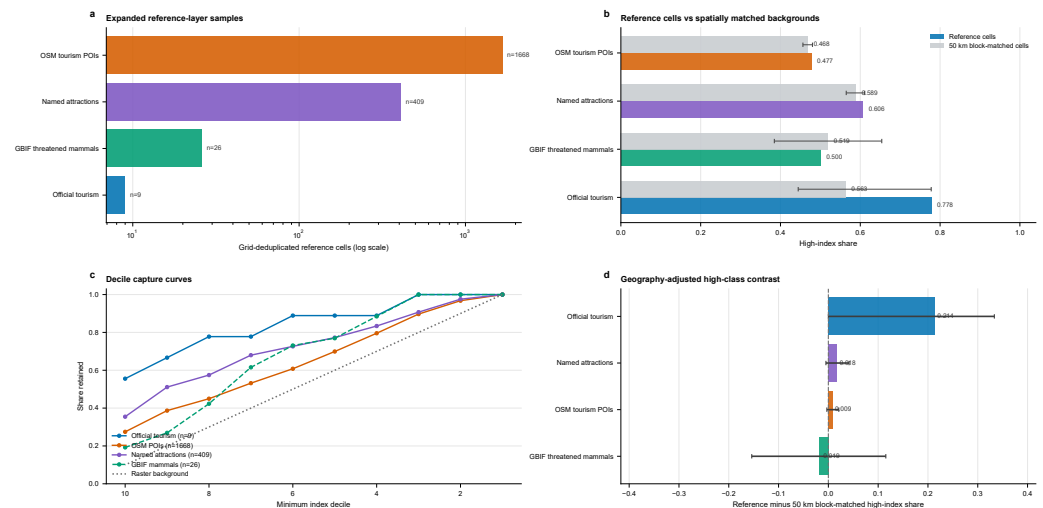


**Figure 6.** Unadjusted descriptive reference checks for the mapped suitability and sensitivity surfaces. Panels (a,b) map 10 official source points and 44 retained GBIF occurrence records before 1 km cell deduplication. Panels (c,d) report high-class shares for 9 and 26 unique valid 1 km cells, respectively, against equal-size basin-wide random backgrounds; the spatially matched checks are reported in Figure 7. Color bars show low-to-high index values; TDSI uses blue-green and ESI yellow-orange, colored symbols denote reference records, and gray bars denote random backgrounds.

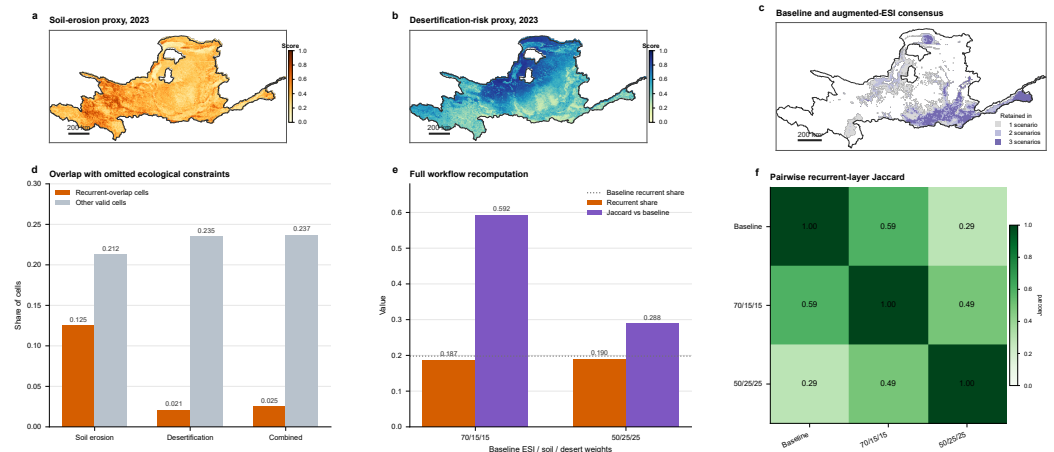
The expanded, grid-deduplicated checks were compared with non-reference cells from the same 50 km blocks. Official tourism cells had a high-suitability share of 0.778 versus a matched mean of 0.563 (95% interval 0.444–0.778; empirical  $p = 0.043$ ). The corresponding contrasts were 0.477 versus 0.468 for OSM tourism POIs ( $n = 1668$ ,  $p = 0.075$ ), 0.606 versus 0.589 for the named-attraction subset ( $n = 409$ ,  $p = 0.072$ ), and 0.500 versus 0.519 for GBIF cells ( $n = 26$ ,  $p = 0.683$ ). Thus, only the small official-tourism sample showed a clear positive geography-adjusted contrast at the 0.05 level. The named-attraction layer is an OSM subset, and GBIF remains a sampling-biased alignment check. Figure 7 reports these matched contrasts together with descriptive decile-capture diagnostics; no WDPA-derived polygon was used as external validation.

The added ecological-constraint sensitivity analysis tests how heuristic soil-erosion and desertification proxies change the recurrent-overlap product. Recurrent-overlap cells intersected recurrent high soil-erosion screening areas at a lower share than the non-recurrent background: 12.48% versus 21.24% (enrichment ratio = 0.59; Jaccard = 0.067). The desertification-risk proxy showed weaker spatial alignment: 2.10% of recurrent-overlap cells versus 23.46% of background cells (enrichment ratio = 0.09; Jaccard = 0.011). When these proxies were inserted into ESI and the full CI-hotspot workflow was recomputed,

the 70/15/15 scenario produced a recurrent-overlap share of 18.66% and a Jaccard of 0.592 against the baseline layer. The 50/25/25 scenario produced a similar share of 18.96% but a lower Jaccard of 0.288. Figure 8 therefore shows similar aggregate extent but materially different local membership; the proxies reuse the existing indicator stack and are not substitutes for independent RUSLE or official desertification products.



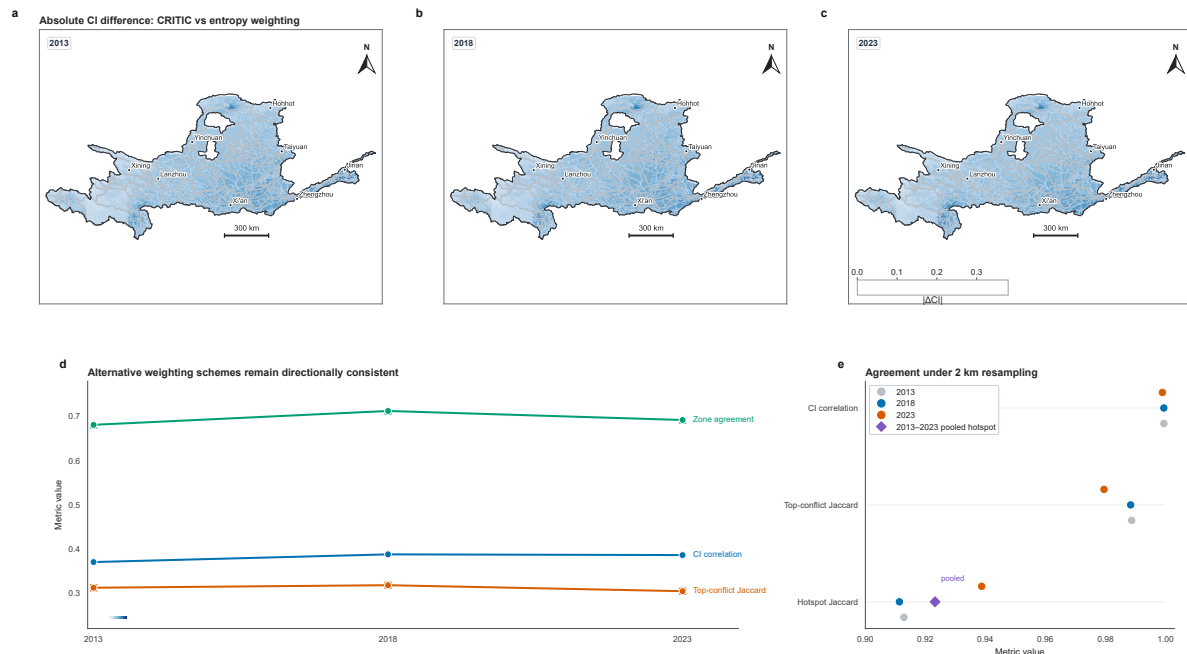
**Figure 7.** Expanded reference-alignment diagnostics. (a) Grid-deduplicated reference-cell counts by layer, shown on a log scale. (b) High-index share of each reference layer compared with a 50 km block-matched background. (c) Descriptive decile-capture curves for the TDSI- and ESI-based checks; the dotted gray curve shows the valid-raster background share. (d) Descriptive top-decile enrichment ratios, with the dashed vertical line marking no enrichment relative to that background.



**Figure 8.** Additional ecological-constraint and augmented-ESI sensitivity diagnostics. (a) Soil-erosion screening layer in 2023. (b) Desertification-risk screening layer in 2023. (c) Consensus membership across the baseline recurrent-overlap layer and two augmented-ESI recurrent layers. (d) Overlap between recurrent-overlap cells and omitted ecological-constraint screening layers compared with other valid cells. (e) Recurrent-share and Jaccard response after inserting soil-erosion and desertification screening layers into ESI. (f) Pairwise Jaccard overlap among baseline and augmented recurrent layers.

The robustness diagnostics produced a clear uncertainty hierarchy. Entropy weighting changed local CI values substantially: substituting entropy weighting for CRITIC yielded year-specific CI correlations of 0.371, 0.388, and 0.386, and zone agreement of 0.681, 0.713, and 0.692. Its recurrent-overlap share was 4.91%, with Jaccard 0.173 relative to CRITIC. The equal-priority AHP specification produced a recurrent-overlap share of 19.62% and Jaccard 0.849; preference scenarios A and B produced shares of 18.21% and 17.79%, and the

geometric-mean aggregation produced 19.52%. The combined CRITIC–AHP specification produced a share of 19.84% and Jaccard 0.906, whereas combined CRITIC–entropy produced 12.43%. Only 21,820 cells (2.81% of the valid domain) were retained by all eight weighting specifications; this is a strict agreement subset, not a statistical confidence region. Figure 9 locates weighting differences and contrasts them with 1 km to 2 km scale transfer; Figure 10 maps cross-scenario membership.



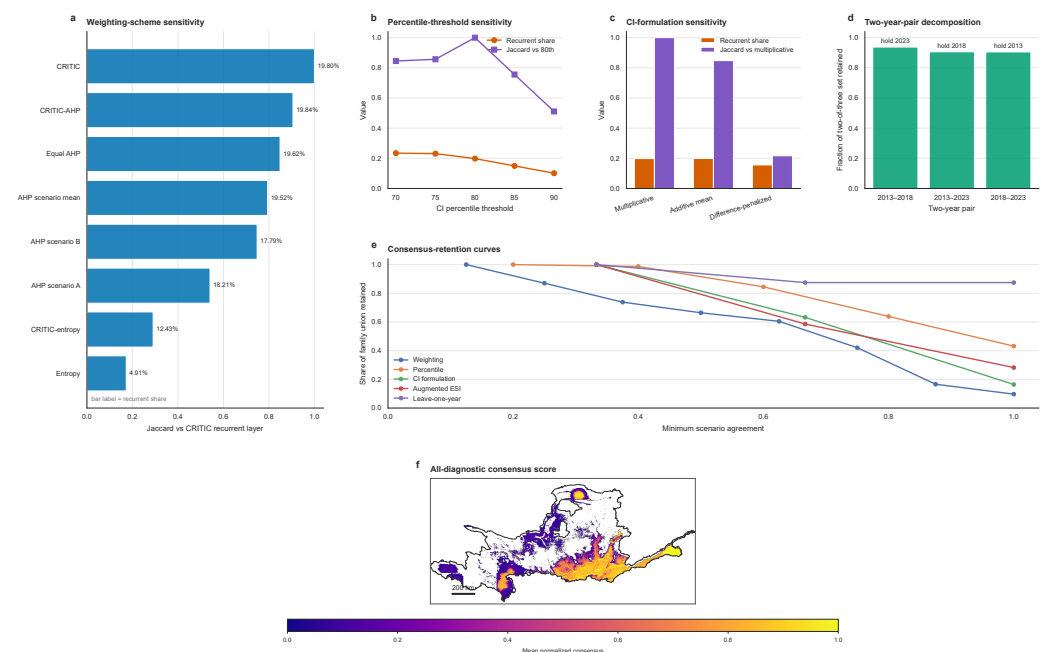
**Figure 9.** Robustness diagnostics for weighting and spatial scale. (a–c) Absolute CI differences between the CRITIC and entropy-weighting schemes in 2013, 2018, and 2023. (d) Cross-year robustness metrics under alternative weighting. (e) Scale-transfer metrics comparing the 2 km and 1 km outputs. Darker blue denotes larger absolute CI differences; blue, orange, and green identify the metrics in panel (d), while the legend in panel (e) identifies year colors and the purple pooled estimate.

The CI formulation, recurrence-threshold, and percentile-threshold tests further bound the main conclusion. Under the baseline multiplicative model, recurrent-overlap shares were 22.50%, 19.80%, and 17.32% for one-, two-, and three-year thresholds, respectively. The additive mean model gave a two-year share of 19.88% and a Jaccard of 0.848 against the baseline two-year recurrent layer. The difference-penalized model was more restrictive, producing a two-year recurrent share of 15.60% and a Jaccard of 0.217. Exact local boundaries therefore depend on whether conflict is defined as joint intensity or strict subsystem balance. When the CI percentile cutoff varied from 70% to 90%, two-year recurrent shares decreased from 23.43% and 23.12% at the 70th and 75th percentiles to 14.96% and 10.11% at the 85th and 90th percentiles. Jaccard overlap relative to the 80th-percentile baseline was 0.845, 0.857, 0.755, and 0.511 for the 70th, 75th, 85th, and 90th percentile alternatives; Table 4 reports the requested annual and recurrent cell counts. The two-year pair decompositions retained 90.5–93.8% Jaccard overlap with the two-of-three layer, with pairwise shares of 17.92–18.56%; however, they are deterministic subsets of the same three snapshots rather than independent temporal validation. Figure 10 summarizes scenario membership; because percentile sets are nested, stricter agreement identifies smaller retained subsets rather than independently validated confidence regions.

**Table 4.** Hotspot cell-count sensitivity to the annual CI percentile cutoff. Recurrent counts use the same two-of-three benchmark-year rule; Jaccard is relative to the 80th-percentile recurrent layer.

| CI Cutoff | 2013 Cells | 2018 Cells | 2023 Cells | Recurrent Cells | Recurrent Share | Jaccard |
|-----------|------------|------------|------------|-----------------|-----------------|---------|
| 70th      | 193,093    | 180,813    | 167,889    | 182,171         | 23.43%          | 0.845   |
| 75th      | 188,772    | 178,675    | 167,597    | 179,749         | 23.12%          | 0.857   |
| 80th      | 154,886    | 154,356    | 154,289    | 153,958         | 19.80%          | 1.000   |
| 85th      | 116,458    | 116,311    | 116,460    | 116,312         | 14.96%          | 0.755   |
| 90th      | 77,701     | 77,682     | 77,745     | 78,614          | 10.11%          | 0.511   |

Table 5 compiles the core recurrent-overlap, hold-out reference-check, robustness, and model-performance metrics reported throughout the manuscript.

**Figure 10.** Multi-scenario recurrent-overlap consensus diagnostics. (a) Weighting-scheme sensitivity, with bar labels reporting recurrent-overlap share. (b) Percentile-threshold sensitivity. (c) CI-formulation sensitivity. (d) Leave-one-year recurrence stability for the three two-year pairs. (e) Consensus-retention curves showing the share of each diagnostic-family union retained as scenario agreement becomes stricter. (f) All-diagnostic consensus score map.**Table 5.** Core recurrent-overlap, hold-out reference-check, robustness, and model-performance diagnostics.

| Category                 | Metric                                                               | Value                             |
|--------------------------|----------------------------------------------------------------------|-----------------------------------|
| Recurrent overlap        | Valid grid cells                                                     | 777,607                           |
| Recurrent overlap        | Recurrent-overlap grid cells                                         | 153,958                           |
| Recurrent overlap        | Recurrent-overlap share                                              | 19.80%                            |
| Hotspot evolution        | Hotspot share in 2013                                                | 19.92%                            |
| Hotspot evolution        | Hotspot share in 2018                                                | 19.85%                            |
| Hotspot evolution        | Hotspot share in 2023                                                | 19.84%                            |
| Matched reference check  | Official tourism high-suitability share vs. 50 km block-matched mean | 0.7778 vs. 0.5633 ( $p = 0.043$ ) |
| Matched reference check  | OSM tourism POI high-suitability share vs. matched mean              | 0.4772 vs. 0.4685 ( $p = 0.075$ ) |
| Matched reference check  | Named-attraction high-suitability share vs. matched mean             | 0.6064 vs. 0.5886 ( $p = 0.072$ ) |
| Matched reference check  | GBIF high-sensitivity share vs. matched mean                         | 0.5000 vs. 0.5190 ( $p = 0.683$ ) |
| Reference check          | Official tourism; OSM POI; named-attraction; GBIF unique cells       | 9; 1668; 409; 26                  |
| Hold-out reference check | GBIF threatened-mammal species                                       | 11                                |

Table 5. Cont.

| Category                               | Metric                                                                                                        | Value                                                                         |
|----------------------------------------|---------------------------------------------------------------------------------------------------------------|-------------------------------------------------------------------------------|
| Additional ecological-constraint check | Recurrent-overlap cells intersecting recurrent high soil-erosion screening layer                              | 12.48%                                                                        |
| Additional ecological-constraint check | Recurrent-overlap cells intersecting recurrent high desertification-risk screening layer                      | 2.10%                                                                         |
| Additional ecological-constraint check | Jaccard with recurrent high soil-erosion; desertification layer                                               | 0.067; 0.011                                                                  |
| Augmented ESI sensitivity              | Recurrent share under 70/15/15 and 50/25/25 ESI/soil/desert scenarios                                         | 18.66%; 18.96%                                                                |
| Augmented ESI sensitivity              | Recurrent Jaccard vs. baseline under 70/15/15 and 50/25/25 scenarios                                          | 0.592; 0.288                                                                  |
| Weight robustness                      | CI correlation (CRITIC vs. entropy), 2013–2023                                                                | 0.3706; 0.3880; 0.3864                                                        |
| Weight robustness                      | Entropy recurrent share; Jaccard vs. CRITIC                                                                   | 4.91%; 0.173                                                                  |
| Weight robustness                      | Recurrent share under equal AHP; preference scenario A; preference scenario B; group AHP; combined CRITIC–AHP | 19.62%; 18.21%; 17.79%; 19.52%; 19.84%                                        |
| Weight robustness                      | Cells retained by all eight weighting specifications                                                          | 21,820 (2.81% of valid cells)                                                 |
| Percentile-threshold robustness        | Two-year recurrent share at 70th; 75th; 80th; 85th; 90th CI percentiles                                       | 23.43%; 23.12%; 19.80%; 14.96%; 10.11%                                        |
| Percentile-threshold robustness        | Jaccard vs. 80th-percentile recurrent layer at 70th; 75th; 85th; 90th percentiles                             | 0.845; 0.857; 0.755; 0.511                                                    |
| Leave-one-year recurrence              | Pairwise recurrent share, 2013–2018; 2013–2023; 2018–2023                                                     | 18.56%; 17.94%; 17.92%                                                        |
| Leave-one-year recurrence              | Jaccard vs. three-year two-of-three recurrent layer                                                           | 0.938; 0.906; 0.905                                                           |
| Hotspot method check                   | Jaccard, custom screen vs. Getis–Ord Gi*, 2013–2023                                                           | 1.000; 1.000; 1.000                                                           |
| Hotspot method check                   | Jaccard, custom screen vs. local Moran high-high, 2013–2023                                                   | 0.996; 0.993; 0.992                                                           |
| CI formulation                         | Two-year recurrent share, multiplicative; additive; difference-penalized                                      | 19.80%; 19.88%; 15.60%                                                        |
| Scale robustness                       | CI correlation (2 km vs. 1 km), 2013–2023                                                                     | 0.9995; 0.9994; 0.9990                                                        |
| Scale robustness                       | Recurrent-hotspot Jaccard                                                                                     | 0.9232                                                                        |
| Internal full-model performance        | Mean AUC; F1; precision; recall                                                                               | 0.9421; 0.8074; 0.7633; 0.8591                                                |
| Reduced-feature model                  | Mean AUC; F1; precision; recall                                                                               | 0.8661; 0.6956; 0.6621; 0.7385                                                |
| Reduced-feature model                  | Leading permutation-importance AUC drops                                                                      | Precipitation variability = 0.185; LST change = 0.082; road intensity = 0.044 |
| Strict external-covariate model        | Mean AUC; F1                                                                                                  | 0.6799; 0.5378                                                                |
| Driver importance                      | Top SHAP features                                                                                             | Precipitation variability; LST change; protected-area proximity               |

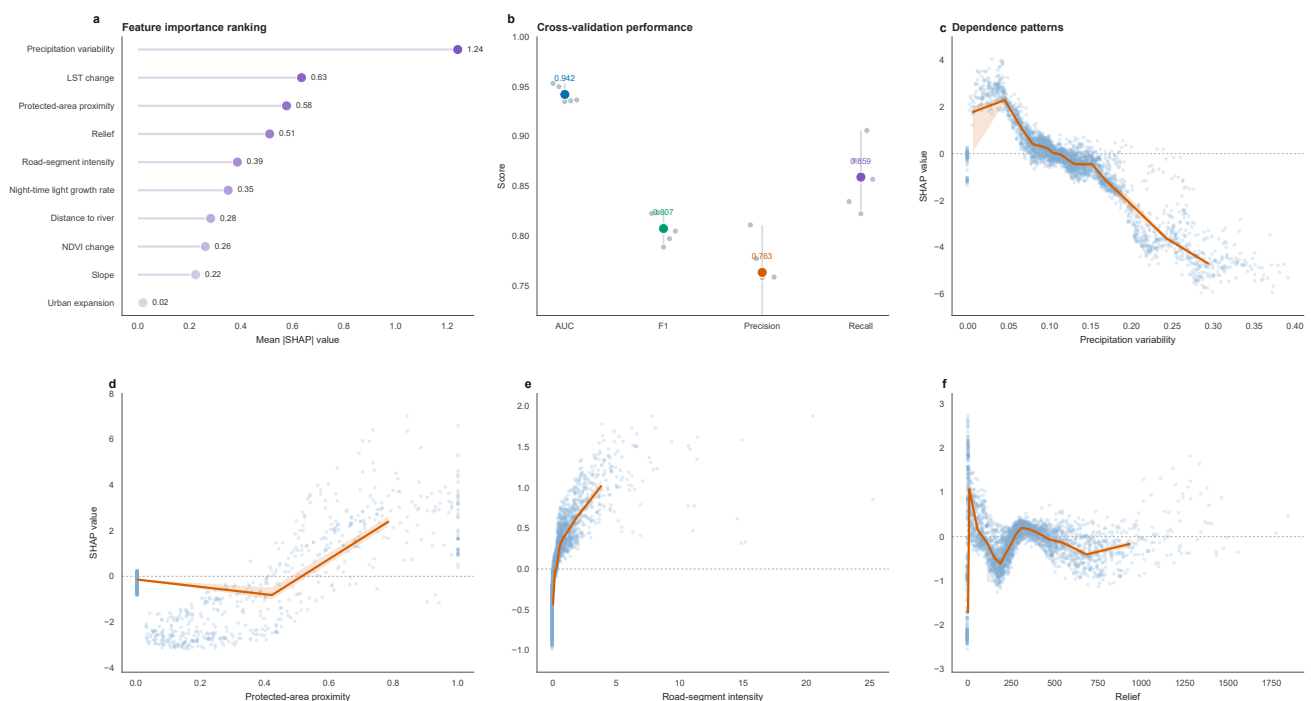
#### 4.5. Spatial-Block Driver Interpretation

The full spatial-block XGBoost classifier distinguished recurrent-overlap cells from other sampled valid cells with mean scores of AUC = 0.942, F1 = 0.807, precision = 0.763, and recall = 0.859 across five folds. These are internal, non-nested spatial-block cross-validation scores for a case-control sample, not external generalization or calibrated basin-wide probabilities. Multicollinearity was low: the largest VIF was 2.62 for relief, followed by 2.56 for slope, and all remaining predictors were below 1.20. The grid selected 300 estimators, maximum depth 5, learning rate 0.05, subsample 0.8, and column subsample 0.8. At the 50 km block size, the five fold-level confusion matrices (TN, FP, FN, TP) were (8978, 972, 827, 4170), (8746, 1250, 618, 4360), (8750, 1323, 896, 4143), (8180, 1828, 469, 4515), and (8609, 1364, 716, 4286). Mean AUC declined from 0.951 at 25 km to 0.942 at 50 km, 0.934 at 75 km, and 0.926 at 100 km; mean F1 remained between 0.777 and 0.822. Figure 11 presents the resulting covariate-association diagnostics.



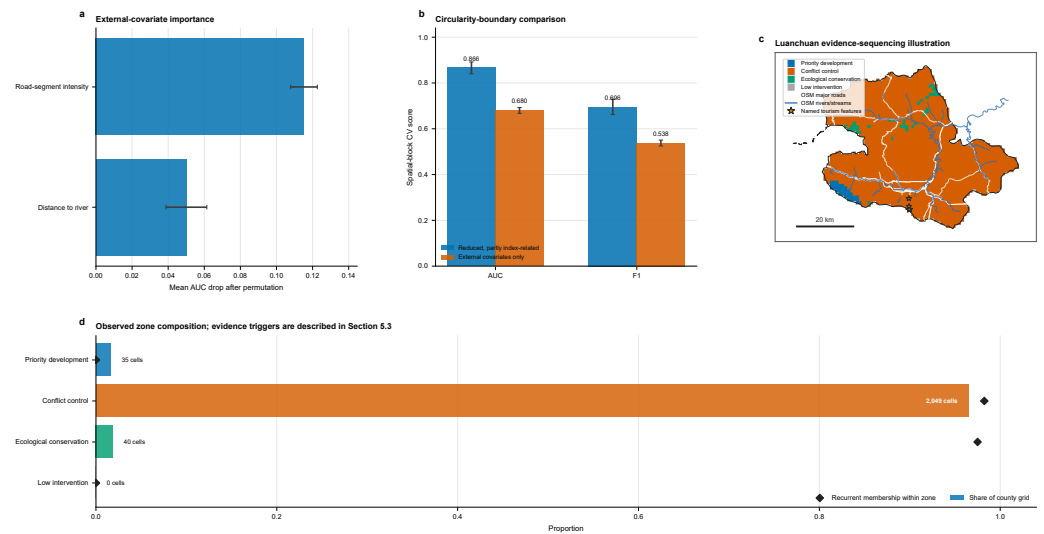
SHAP ranked precipitation variability (*precip\_cv*), land-surface thermal change (*lst\_change*), protected-area proximity (*protected\_proximity*), relief, and road-segment intensity as the leading variables in the fitted full model. Hydroclimatic variability produced the largest mean absolute SHAP values, followed by thermal change and protection proximity. These are model-attribution rankings for the sampled covariates, not causal effects.

The dependence plots show a negative association for precipitation variability. Lower *precip\_cv* values had positive SHAP contributions, and recurrent-overlap share in the sampled frame declined from 0.596 in the lowest *precip\_cv* quintile to 0.086 in the highest quintile. Protected-area proximity and road-segment intensity showed increasingly positive fitted contributions toward the upper ends of their observed ranges. In 2023, the 200–400 m relief class had the highest recurrent-overlap share (0.218), with mean TDSI of 0.553 and mean ESI of 0.319. These patterns describe the classifier and do not establish hydroclimatic, access, or terrain mechanisms.



**Figure 11.** Internal spatial-block driver interpretation based on XGBoost-SHAP. (a) Mean absolute SHAP feature importance. (b) Cross-fold model performance. (c–f) Dependence relationships for precipitation variability, protected-area proximity, 5 km-window road-segment intensity, and relief, respectively. Gray dots in panel b show individual folds and larger colored dots show metric means; light-blue dots in the dependence panels show cell-level SHAP values. Orange lines indicate binned median SHAP values; shaded bands are ordinary-bootstrap 95% intervals for the binned medians and are not spatial uncertainty intervals.

The reduced-feature model achieved mean AUC = 0.866 and mean F1 = 0.696 across five 50 km folds; however, five predictors remained transformations of index inputs. The stricter model using only road-segment intensity and distance to river achieved AUC = 0.680 and F1 = 0.538, providing a more appropriate lower-bound circularity check. Figure 12 compares these models and presents Luanchuan County only as a model-based evidence-sequencing illustration.



**Figure 12.** Circularity-boundary checks and a county-level illustration. (a) Permutation importance for the strict model using only road-segment intensity and distance to river. (b) Internal spatial-block cross-validation scores for the partly index-related reduced model and the strict two-covariate model. (c) Model-derived 2023 zones in Luanchuan County with OSM roads, rivers, and named tourism features. (d) Zone shares and recurrent membership; conditional evidence triggers are described in Section 5.3. The county panels illustrate evidence sequencing and have not been validated against a local statutory plan or field survey.

## 5. Discussion

### 5.1. Why a Grid-Based Conflict Workflow Matters

The central value of this study lies in its planning-oriented integration of familiar data streams. The Yellow River Basin already has a substantial literature on tourism, ecology, and spatial planning. The missing applied step is to place tourism-support conditions and ecological sensitivity on the same grid and compare their overlap across benchmark years. The workflow converts multisource observation and contextual data into annual gridded products, derives hotspot and recurrent-overlap layers, and reports the same evidence at county and sub-basin scales.

Administrative tourism studies typically ask where development performance differs across policy units. Ecological monitoring studies ask where environmental conditions vary or change. The present workflow asks where tourism-support conditions and ecological constraints coexist strongly enough to warrant planning attention. Its contribution is integrative, operational, and application-oriented: it harmonizes multisource observation, fixed-grid comparison, recurrent-overlap screening, and multi-scale reporting within a reproducible assessment chain.

### 5.2. What Recurrent-Overlap Screening Adds Beyond Annual Mapping

A key contribution of the results is the distinction between an annual hotspot and repeated membership across the three snapshots. A single-year high-conflict map can reflect environmental conditions, compositing artifacts, and development signals specific to that benchmark year. The recurrent-overlap map identifies cells that re-enter annual relative hotspot sets; it is a repeated-classification screening product, not evidence of long-term structural persistence.

The multi-scale results reinforce this interpretation. Counties and sub-basins with high recurrent-overlap shares remain concentrated in corridor and transition settings that are plausible in both governance and hydrological terms. This feature gives the

workflow applied value: it carries gridded evidence into units that can be interpreted within planning systems.

### 5.3. Planning and Management Implications

The 19.80% recurrent-overlap share is a screening layer for differentiated follow-up. Priority\_development cells combine high TDSI with comparatively low ESI and may be prioritized for finer assessment of service upgrading or visitor-flow improvement. Conflict\_control cells combine high TDSI and high ESI and identify locations where project review should examine development intensity, visitor capacity, ecological compensation, restoration obligations, and monitoring before approval.

Ecological\_conservation cells combine high ESI with lower TDSI and flag protection or restoration questions for detailed review. Low\_intervention cells have lower relative values on both axes and may be monitored where accessibility or land-use pressure changes. These four model-derived categories are screening prompts rather than legal zoning or a binary go/no-go decision.

Luanchuan County provides a model-based illustration of this evidence-sequencing logic, not a validated local implementation case. Of 2124 valid cells, 2049 (96.47%) were classified as conflict\_control; 2013 of those cells (98.24%) also belonged to the recurrent layer. The resulting dominance is useful for showing where finer evidence would be requested, but it does not demonstrate that local authorities adopted the zones or that proposed actions are feasible. The model classes therefore serve only as conditional triggers for parcel-level ecological survey, statutory red-line review, visitor-capacity analysis, erosion-control design, or monitoring rather than prescribing an action from the raster alone.

### 5.4. Interpretation Boundary of the Hold-Out Reference Checks

The reference checks support plausibility only within a specific evidence boundary. The tourism analysis uses a small official sample plus larger OSM tourism POI and named-attraction layers; the latter is a subset of OSM rather than independent evidence. The ecological check uses GBIF threatened-mammal occurrences, which reflect reporting effort, accessibility bias, and taxonomic incompleteness. WDPA-derived polygons were excluded because WDPA proximity enters ESI.

The 50 km block-matched results were mixed: only the nine-cell official-tourism sample showed a positive contrast at  $p < 0.05$ , whereas OSM, named-attraction, and GBIF contrasts were not clear. These are reference-alignment checks, not external accuracy validation; ground-truth assessment needs denser independent field or management data.

The next evaluation step needs denser official tourism inventories with time stamps, additional biodiversity or habitat layers, and independent field or management datasets outside the current indicator construction. This evidence base is required for stricter and more temporally explicit testing of the screening products.

### 5.5. Robustness, Limitations, and Transferability

The robustness results reveal a useful uncertainty hierarchy. Entropy weighting retained only 4.91% of valid cells as recurrent overlap and had Jaccard of 0.173 against CRITIC, whereas the 1 km to 2 km recurrent-hotspot Jaccard was 0.923. The difference-penalized CI definition also changed local membership materially (Jaccard 0.217), and the 90th-percentile cutoff identified a smaller 10.11% recurrent subset. The two-year pair results decompose the selected three-year rule but do not constitute independent temporal validation. The augmented-ESI proxies yielded similar recurrent shares but Jaccard values of only 0.592 and 0.288. Accordingly, multi-scenario retention can identify a conservative agreement subset, while single-weight or single-formulation local rankings remain exploratory; agreement counts are not probabilities or confidence regions.

Several data boundaries guide interpretation. First, the ESI indicator system emphasizes terrain, thermal stress, hydroclimate, vegetation and water importance, and protected-area proximity. The added soil-erosion and desertification layers are heuristic recombinations of much of the same indicator stack; their similar aggregate shares do not validate ecological completeness, and their lower local Jaccard values expose construction sensitivity. Full RUSLE-based soil-loss products, official desertification and ecological-red-line boundaries, and species-distribution or habitat models are needed for a stronger ecological assessment. The GBIF result is a sampling-biased spatial-alignment check, not an independent ESI accuracy test.

Second, the protection-related ecological constraint uses a dynamic WDPA “current” asset whose exact monthly vintage was not archived; historically varying boundaries are needed for temporal interpretation. The VIIRS workflow did not use the `cf_cvg` coverage band, MOD11A2 accepted mandatory-QA codes 0 and 1, and the 2023 MCD12Q1 proxy should be interpreted cautiously. Exact OSM replication metadata and the county-boundary source/version remain provenance gaps. Third, consistently gridded multi-year visitor volume, market accessibility, seasonality, and expenditure data are needed to represent tourism demand. Fourth, the three benchmark snapshots do not support climate-trend or long-term persistence inference.

Additional data and modeling choices define use conditions for the outputs. The official-tourism reference set is authoritative but very small; OSM adds coverage with volunteer-data heterogeneity. The accessibility term is a smoothed road-segment count/intensity rather than road length per square kilometre. The 14 counties with fewer than 10 valid cells are report-only, and 7 counties have no valid cells. SHAP explains the fitted stratified classifier. The seven-variable reduced model still contains five transformations of index inputs; the strict two-covariate model lowers AUC to 0.680 and F1 to 0.538. Neither model supports causal inference or calibrated basin-wide probabilities, and both require genuinely independent covariates and external validation for stronger mechanism claims.

The outputs support regional prioritization before project-level evaluation. A 1 km cell can contain mixed land uses, small protected features, slope breaks, settlement patches, and visitor facilities that exceed the spatial detail of the basin-scale raster. The annual indicator stack is based on remote-sensing composites and generalized contextual layers. Project approval requires parcel-level surveys, legal red-line checks, engineering constraints, cultural-resource assessment, field-verified habitat inventories, environmental impact assessment, and stakeholder review. The contribution of the present workflow is to identify where those detailed evaluations should be directed first.

Together, these boundaries position the workflow as a reproducible planning-support tool for regional screening, relative comparison, and pattern diagnosis. Within that boundary, the approach should be transferable to other large river basins or mountain-front tourism regions that require harmonized benchmark-year products, explicit overlap analysis, and consistent translation from grid evidence to management units. The clearest extensions are denser benchmark years, historically varying protection constraints, broader official tourism inventories, and additional external ecological reference layers.

## 6. Conclusions

This study developed a GEE-supported geospatial screening workflow for mapping tourism development suitability, ecological sensitivity, and their overlap across the Yellow River Basin in 2013, 2018, and 2023. The resulting TDSI, ESI, and CI products show strong spatial clustering, and 153,958 cells (19.80% of the valid domain) entered the annual relative hotspot set in at least two benchmark years. This result identifies repeated classification in the selected snapshots, not long-term structural persistence.

The mapped pattern remains interpretable after county and sub-basin aggregation, but the evidential checks set clear limits. The 50 km matched reference results were mixed; scale aggregation preserved broad geography, whereas weighting, CI formulation, percentile cutoff, and augmented ecological constraints changed local membership materially. Cells retained across several scenarios provide a conservative follow-up subset, not a statistical confidence region.

For environmental planning and natural-resource management, the main contribution is a reproducible applied-science workflow linking multisource geospatial evidence, fixed-grid overlap analysis, recurrent-hotspot screening, and multi-scale interpretation. The outputs are most appropriate for regional screening and follow-up prioritization. Site-specific planning or project approval should be supported by field investigation, official tourism-resource inventories, and independent ecological evidence.

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

**Funding:** This work was supported by the General Program of Philosophy and Social Science Planning of Henan Province (grant number: 2022BJJ092). The funder had no role in study design, data collection, analysis, interpretation, manuscript preparation, or the decision to submit.

**Institutional Review Board Statement:** Not applicable.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** The data and code supporting this study are available in Zenodo at <https://doi.org/10.5281/zenodo.21095087>. Reused public datasets remain available from their original providers, including Google Earth Engine catalog datasets, Ministry of Culture and Tourism data services, UNESCO World Heritage records, GBIF [59], OpenStreetMap, HydroBASINS, and WDPA. The GBIF derived dataset is registered at <https://doi.org/10.15468/dd.ktrrcx>. The underlying extract was generated on 23 April 2026 UTC and retained 44 occurrence records representing 13 species before basin-grid filtering (26 unique valid grid cells).

**Acknowledgments:** The authors thank the data communities and platform providers whose datasets and tools supported the geospatial workflow, including Google Earth Engine, Landsat, VIIRS, MODIS, CHIRPS, ERA5-Land, SRTM, the Ministry of Culture and Tourism of the People's Republic of China data service, the UNESCO World Heritage Centre, GBIF, OpenStreetMap, HydroBASINS, and WDPA. Gemini 3.1 Pro was used solely for text polishing.

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

## References

1. Fang, Y.; Ying, B. Spatial distribution of mountainous regions and classifications of economic development in China. *J. Mt. Sci.* **2016**, *13*, 1120–1138. [CrossRef]
2. Jennings, S. Landscape Sensitivity and Tourism Development. *J. Sustain. Tour.* **2004**, *12*, 271–288. [CrossRef]
3. Hao, M.; Li, G.; Chen, C.; Liang, L. A Coupling Relationship between New-Type Urbanization and Tourism Resource Conversion Efficiency: A Case Study of the Yellow River Basin in China. *Sustainability* **2022**, *14*, 14007. [CrossRef]
4. Zhang, W.; Zhan, Y.; Yin, R.; Yuan, X. The Tourism Eco-Efficiency Measurement and Its Influencing Factors in the Yellow River Basin. *Sustainability* **2022**, *14*, 15654. [CrossRef]
5. He, X.; Cai, C.; Shi, J. Evaluation of Tourism Ecological Security and Its Driving Mechanism in the Yellow River Basin, China: Based on Open Systems Theory and DPSIR Model. *Systems* **2023**, *11*, 336. [CrossRef]
6. Lu, F.; Yoon, S.J. Spatiotemporal Evolution and Spillover Effects of Tourism Industry and Inclusive Green Growth Coordination in the Yellow River Basin: Toward Sustainable Development. *Sustainability* **2025**, *17*, 11372. [CrossRef]



7. Li, X.; Zhu, R.; Shi, C.; Yang, X.; Chen, J.; Wei, K. Research on the construction of intangible cultural heritage corridors in the Yellow River Basin based on geographic information system (GIS) technology and the minimum cumulative resistance (MCR) model. *Herit. Sci.* **2024**, *12*, 2711. [[CrossRef](#)]
8. Zhang, Z.; Li, Q.; Hu, S. Intangible Cultural Heritage in the Yellow River Basin: Its Spatial-Temporal Distribution Characteristics and Differentiation Causes. *Sustainability* **2022**, *14*, 11073. [[CrossRef](#)]
9. Wang, H.; Zhang, Y.; Wang, Q.; Yu, J.; Yuan, C. Spatial Assessment of Ecotourism Development Suitability Incorporating Carrying Capacity in the Yellow River Estuary National Park. *Sustainability* **2025**, *17*, 8449. [[CrossRef](#)]
10. Zhao, D.; Liang, Y.; Li, L.; Ma, Y.; Xiao, G. Spatio-Temporal Differentiation and Enhancement Path of Tourism Eco-Efficiency in the Yellow River Basin Under the “Dual Carbon” Goals. *Sustainability* **2025**, *17*, 7827. [[CrossRef](#)]
11. Chen, Z.; Wang, J. Land use and land cover change detection using satellite remote sensing techniques in the mountainous Three Gorges Area, China. *Int. J. Remote Sens.* **2010**, *31*, 1519–1542. [[CrossRef](#)]
12. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sens. Environ.* **2017**, *202*, 18–27. [[CrossRef](#)]
13. Jin, Y.; Liu, X.; Yao, J.; Zhang, X.; Zhang, H. Mapping the annual dynamics of cultivated land in typical area of the Middle-lower Yangtze plain using long time-series of Landsat images based on Google Earth Engine. *Int. J. Remote Sens.* **2020**, *41*, 1625–1644. [[CrossRef](#)]
14. Tobon-Marin, A.; Canon Barriga, J. Analysis of changes in rivers planforms using google earth engine. *Int. J. Remote Sens.* **2020**, *41*, 8654–8681. [[CrossRef](#)]
15. Zhang, M.; Gong, P.; Qi, S.; Liu, C.; Xiong, T. Mapping bamboo with regional phenological characteristics derived from dense Landsat time series using Google Earth Engine. *Int. J. Remote Sens.* **2019**, *40*, 9541–9555. [[CrossRef](#)]
16. Zhou, Q.; Li, B.; Kurban, A. Spatial pattern analysis of land cover change trajectories in Tarim Basin, northwest China. *Int. J. Remote Sens.* **2008**, *29*, 5495–5509. [[CrossRef](#)]
17. Sun, R.; Gao, X.; Liu, C.-M.; Li, X.-W. Evapotranspiration estimation in the Yellow River Basin, China using integrated NDVI data. *Int. J. Remote Sens.* **2004**, *25*, 2523–2534. [[CrossRef](#)]
18. Wang, X.; Ren, Z.; Tan, K. Eco-environmental evaluation with remote sensing in the middle and upper areas of the Yellow River drainage basin. *Int. J. Remote Sens.* **2007**, *28*, 3937–3951. [[CrossRef](#)]
19. Wang, S.; Ding, C.; Liu, J. Landscape evolution in the Yellow River Basin using satellite remote sensing and GIS during the past decade. *Int. J. Remote Sens.* **2009**, *30*, 5573–5591. [[CrossRef](#)]
20. Wohlfart, C.; Liu, G.; Huang, C.; Kuenzer, C. A River Basin over the Course of Time: Multi-Temporal Analyses of Land Surface Dynamics in the Yellow River Basin (China) Based on Medium Resolution Remote Sensing Data. *Remote Sens.* **2016**, *8*, 186. [[CrossRef](#)]
21. Ji, Q.; Liang, W.; Fu, B.; Zhang, W.; Yan, J.; Lu, Y.; Yue, C.; Jin, Z.; Lan, Z.; Li, S.; et al. Mapping Land Use/Cover Dynamics of the Yellow River Basin from 1986 to 2018 Supported by Google Earth Engine. *Remote Sens.* **2021**, *13*, 1299. [[CrossRef](#)]
22. Liu, B.; Zhang, Z.; Pan, L.; Sun, Y.; Ji, S.; Guan, X.; Li, J.; Xu, M. Comparison of Various Annual Land Cover Datasets in the Yellow River Basin. *Remote Sens.* **2023**, *15*, 2539. [[CrossRef](#)]
23. Jiang, W.; Niu, Z.; Wang, L.; Yao, R.; Gui, X.; Xiang, F.; Ji, Y. Impacts of Drought and Climatic Factors on Vegetation Dynamics in the Yellow River Basin and Yangtze River Basin, China. *Remote Sens.* **2022**, *14*, 930. [[CrossRef](#)]
24. Zhou, M.; Wang, X.; Sun, L.; Luo, Y. Spatial Variations in Terrestrial Water Storage with Variable Forces across the Yellow River Basin. *Remote Sens.* **2021**, *13*, 3416. [[CrossRef](#)]
25. Wang, X.; Zhang, S.; Zhao, X.; Shi, S.; Xu, L. Exploring the Relationship between the Eco-Environmental Quality and Urbanization by Utilizing Sentinel and Landsat Data: A Case Study of the Yellow River Basin. *Remote Sens.* **2023**, *15*, 743. [[CrossRef](#)]
26. Zhang, J.; Du, J.; Fang, S.; Sheng, Z.; Zhang, Y.; Sun, B.; Mao, J.; Li, L. Dynamic Changes, Spatiotemporal Differences, and Ecological Effects of Impervious Surfaces in the Yellow River Basin, 1986–2020. *Remote Sens.* **2023**, *15*, 268. [[CrossRef](#)]
27. An, M.; Meng, F.; He, W.; Xue, F.; Song, M.; Xie, P.; Wang, B. Assessment on eco-environmental quality of the Yellow River Basin by considering desertification index. *J. Mt. Sci.* **2024**, *21*, 3275–3292. [[CrossRef](#)]
28. Yang, H.; Hou, S.; Yan, K.; Qiu, J.; Wang, D. Assessment of Ecological Environment Quality in the Yellow River Basin Based on the Improved Remote Sensing Ecological Index. *Remote Sens.* **2026**, *18*, 617. [[CrossRef](#)]
29. Feng, Z.; Yang, X.; Li, S. New insights of eco-environmental vulnerability in China’s Yellow River Basin: Spatio-temporal pattern and contributor identification. *Ecol. Indic.* **2024**, *167*, 112655. [[CrossRef](#)]
30. Niu, H.; Xiu, Z.; Xiao, D. Impact of land-use change on ecological vulnerability in the Yellow River Basin based on a complex network model. *Ecol. Indic.* **2024**, *166*, 112212. [[CrossRef](#)]
31. Ji, X.; Sun, Y.; Guo, W.; Zhao, C.; Li, K. Land use and habitat quality change in the Yellow River Basin: A perspective with different CMIP6-based scenarios and multiple scales. *J. Environ. Manag.* **2023**, *345*, 118729. [[CrossRef](#)] [[PubMed](#)]
32. Jian, S.; Zhu, T.; Hu, C. Integrating potential distribution of dominant vegetation and land use into ecological restoration in the Yellow River Basin, China. *J. Mt. Sci.* **2022**, *19*, 2886–2904. [[CrossRef](#)]

33. Fu, C.; Liu, Y.; Chen, Y.; Li, F.; Huang, J.; Huang, H. Simulation of Land Use Change and Habitat Quality in the Yellow River Basin under Multiple Scenarios. *Water* **2022**, *14*, 3767. [\[CrossRef\]](#)
34. Zheng, L.; Wang, Y.; Li, J. Quantifying the spatial impact of landscape fragmentation on habitat quality: A multi-temporal dimensional comparison between the Yangtze River Economic Belt and Yellow River Basin of China. *Land Use Policy* **2023**, *125*, 106463. [\[CrossRef\]](#)
35. Wang, B.; Fu, S.; Hao, Z.; Zhen, Z. Ecological security pattern based on remote sensing ecological index and circuit theory in the Shanxi section of the Yellow River Basin. *Ecol. Indic.* **2024**, *166*, 112382. [\[CrossRef\]](#)
36. Wei, W.; Liu, C.; Ma, L.; Xie, B.; Zhou, J.; Nan, S. Optimization strategies of ecological security patterns through importance of ecosystem services and ecological sensitivity-A case study in the Yellow River Basin. *Land Degrad. Dev.* **2024**, *35*, 985–1001. [\[CrossRef\]](#)
37. Wang, M.; Wang, X. A study of eco-culture-tourism coupling and coordinated development and influencing mechanism in the Yellow River Basin based on spatial production theory. *Ecol. Indic.* **2025**, *176*, 113689. [\[CrossRef\]](#)
38. Wang, C.; Chang, Y.; Guo, B.; Liu, P. Forecasting and Evaluation of Ecosystem Services Supply-Demand Under SSP-RCP Scenarios in the Henan Segment of the Yellow River Basin, China. *Remote Sens.* **2025**, *17*, 1067. [\[CrossRef\]](#)
39. Milicevic, S.; Boskovic, N.; Lakicevic, M. Sustainable tourism development in mountain areas in Šumadija and Western Serbia. *J. Mt. Sci.* **2021**, *18*, 735–748. [\[CrossRef\]](#)
40. Jozi, S.A.; Majd, N.M. Ecological Land Capability Evaluation of Dehloran County in Order to Ecotourism Development. *J. Indian Soc. Remote Sens.* **2015**, *43*, 571–581. [\[CrossRef\]](#)
41. Gidey, E.; Mhangara, P.; Birhane, E.; Dikinya, O.; Lottering, R.; Hishe, S.; Zenebe, A.; Girma, A.; Nasir, J.; Addisu, A.; et al. Ecotourism suitability mapping and analysis in Tigray-Northern Ethiopian highlands. *J. Ecotour.* **2025**, *24*, 288–306. [\[CrossRef\]](#)
42. Roy, D.; Kundu, P.; Paul, S.; Sarkar, B.C. Potential suitability mapping evaluation for ecotourism development in Darjeeling Himalayan region of India. *J. Ecotour.* **2024**, *23*, 414–435. [\[CrossRef\]](#)
43. Huang, Q.; Zhou, C.; Li, M.; Ma, Y.; Hua, S. An Approach for Mapping Ecotourism Suitability Using Machine Learning: A Case Study of Zhangjiajie, China. *Land* **2024**, *13*, 1188. [\[CrossRef\]](#)
44. Quan, Q.; Wu, Y. Integrating Entropy Weight and MaxEnt Models for Ecotourism Suitability Assessment in Northeast China Tiger and Leopard National Park. *Land* **2024**, *13*, 1269. [\[CrossRef\]](#)
45. Huang, S.; Sheng, D.; Wang, P.; Xiao, J.; Li, Q.; Liu, H. Assessment of ecotourism suitability in Qilian mountain National park. *Sci. Rep.* **2025**, *15*, 19529. [\[CrossRef\]](#) [\[PubMed\]](#)
46. Zhu, Q.; Wang, Z.; Umer, M. The Suitability of Developing Ecotourism in the Shanxi Area of Taihangshan National Park, a Candidate Area for National Parks in China. *Sustainability* **2025**, *17*, 841. [\[CrossRef\]](#)
47. Zhou, X.; Huang, H.; Dai, S.; Zheng, D.; Zhao, J. Research on an Ecological Sensitivity Evaluation of Mountain-Type National Parks Under Multi-Modal Optimization: A Case Study of Shennongjia, China. *Land* **2025**, *14*, 923. [\[CrossRef\]](#)
48. Kamran, M.; Yamamoto, K. Evolution and use of remote sensing in ecological vulnerability assessment: A review. *Ecol. Indic.* **2023**, *148*, 110099. [\[CrossRef\]](#)
49. Shi, H.; Shi, T.; Liu, Q.; Wang, Z. Ecological Vulnerability of Tourism Scenic Spots: Based on Remote Sensing Ecological Index. *Pol. J. Environ. Stud.* **2021**, *30*, 3231–3248. [\[CrossRef\]](#) [\[PubMed\]](#)
50. Zhang, K.; Zhang, Q.; Singh, V.P. Temporal Dynamics of Fractional Vegetation Cover in the Yellow River Basin: A Comprehensive Analysis. *Remote Sens.* **2024**, *16*, 2991. [\[CrossRef\]](#)
51. Li, L.; Feng, R.; Hou, G.; Xi, J.; Gao, P.; Jiang, X. Integrating tourism supply-demand and environmental sensitivity into the tourism network identification of ecological functional zone. *Ecol. Indic.* **2024**, *158*, 111505. [\[CrossRef\]](#)
52. Xu, E.; Zhang, H. Spatially-explicit sensitivity analysis for land suitability evaluation. *Appl. Geogr.* **2013**, *45*, 1–9. [\[CrossRef\]](#)
53. Dong, G.; Ge, Y.; Jia, H.; Sun, C.; Pan, S. Land Use Multi-Suitability, Land Resource Scarcity and Diversity of Human Needs: A New Framework for Land Use Conflict Identification. *Land* **2021**, *10*, 1003. [\[CrossRef\]](#)
54. Ly, T.D.; Ongsomwang, S. Ecological Suitability Evaluation for Conservation and Development in Bac Kan Province, Vietnam. *Appl. Sci.* **2019**, *9*, 5351. [\[CrossRef\]](#)
55. Alexakis, D.E.; Bathrellos, G.D.; Skilodimou, H.D.; Gamvroula, D.E. Land Suitability Mapping Using Geochemical and Spatial Analysis Methods. *Appl. Sci.* **2021**, *11*, 5404. [\[CrossRef\]](#)
56. Feng, H.; Zhang, X.; Nan, Y.; Zhang, D.; Sun, Y. Ecological Sensitivity Assessment and Spatial Pattern Analysis of Land Resources in Tumen River Basin, China. *Appl. Sci.* **2023**, *13*, 4197. [\[CrossRef\]](#)
57. Huo, Q.; Cheng, X.; Du, W.; Zhang, H.; Han, R. Remote Sensing Evaluation and Monitoring of Spatial and Temporal Changes in Ecological Environmental Quality in Coal Mining-Intensive Cities. *Appl. Sci.* **2024**, *14*, 8814. [\[CrossRef\]](#)
58. Nieto, C.E.; Martínez-Graña, A.M.; Merchán, L.; Valencia Ortiz, J.A. A GIS-Based Approach for Use Recommendations and Limitations in Sustainable Coastal Planning in the Southeastern Margin of the Ría de Arosa (Pontevedra, Spain). *Appl. Sci.* **2025**, *15*, 4582. [\[CrossRef\]](#)

59. GBIF.org. Filtered Export of GBIF Occurrence Data. Derived Dataset. 23 April 2026. Available online: <https://doi.org/10.15468/dd.ktrrcx> (accessed on 23 April 2026). [\[CrossRef\]](#)
60. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining objective weights in multiple criteria problems: The CRITIC method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [\[CrossRef\]](#)
61. Moran, P.A.P. Notes on Continuous Stochastic Phenomena. *Biometrika* **1950**, *37*, 17–23. [\[CrossRef\]](#)
62. Getis, A.; Ord, J.K. The Analysis of Spatial Association by Use of Distance Statistics. *Geogr. Anal.* **1992**, *24*, 189–206. [\[CrossRef\]](#)
63. Anselin, L. Local Indicators of Spatial Association–LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [\[CrossRef\]](#)
64. Saaty, T.L. Decision making with the analytic hierarchy process. *Int. J. Serv. Sci.* **2008**, *1*, 83–98. [\[CrossRef\]](#)
65. Aczel, J.; Saaty, T.L. Procedures for synthesizing ratio judgements. *J. Math. Psychol.* **1983**, *27*, 93–102. [\[CrossRef\]](#)
66. Chen, T.; Guestrin, C. XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining, San Francisco, CA, USA, 13–17 August 2016; pp. 785–794. [\[CrossRef\]](#)
67. Lundberg, S.M.; Erion, G.; Chen, H.; DeGrave, A.; Prutkin, J.M.; Nair, B.; Katz, R.; Himmelfarb, J.; Bansal, N.; Lee, S.-I. From local explanations to global understanding with explainable AI for trees. *Nat. Mach. Intell.* **2020**, *2*, 56–67. [\[CrossRef\]](#) [\[PubMed\]](#)
68. Roberts, D.R.; Bahn, V.; Ciuti, S.; Boyce, M.S.; Elith, J.; Guillera-Arroita, G.; Hauenstein, S.; Lahoz-Monfort, J.J.; Schroder, B.; Thuiller, W.; et al. Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* **2017**, *40*, 913–929. [\[CrossRef\]](#)
69. O'Brien, R.M. A caution regarding rules of thumb for variance inflation factors. *Qual. Quant.* **2007**, *41*, 673–690. [\[CrossRef\]](#)

**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.