

Article

Regional Differences in the Potential Drivers of Grassland Degradation from the Perspective of Partial-Order Theory: A Case Study of Ordos

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Abstract

Grassland degradation (GD) varies markedly across space. Identifying potential drivers at the county level enables precise grassland conservation and supports a win–win between economic development and ecological protection. However, most existing studies adopt a single, region-wide lens and lack county-level analyses. Focusing on Ordos, we conduct a county-level assessment and rank potential driver groups using partial-order theory. The results indicated the following: (1) from 2000 to 2020, a total of 6.9% (6026 km²) of grassland was restored, while approximately 5.0% (4372 km²) underwent degradation, with grassland recovery outpacing degradation; (2) urbanisation and economic development were identified as the leading drivers in five counties, followed by human activities and climate (three), and livelihood development (one); and (3) Ordos should adopt county-level differentiated management strategies: controlling urban and industrial expansion in urbanisation and economic-development-dominated counties, regulating grazing and land-use activities in human-activity-dominated counties, implementing dynamic grazing bans and drought preparedness in climate-dominated counties, promoting livelihood diversification in livelihood-development-dominated counties, and applying priority-based integrated governance in multi-driver counties.

Keywords: drivers; Hasse diagram technique; grassland degradation/restoration; policy adoption; partial-order theory



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1. Introduction

Grassland degradation (GD), driven by complex human–environment interactions [1], poses a serious challenge to sustainable land management. Understanding the factors driving this degradation is closely aligned with the Sustainable Development Goals (<https://sdgs.un.org/zh/goals>, URL (accessed on 20 January 2026)) [2]. Inappropriate land-cover changes—such as the expansion of construction sites [3] and an increase in agricultural land [4]—lead to GD. GD refers to the process by which grasslands, originally rich in ecological functions and productivity, gradually lose vegetation cover, soil quality, and biodiversity, thereby impairing ecosystem functions [5]. GD is predominantly driven by changes in land cover [6]. Yanbo et al. indicated that about 50.7% of grassland changes in China are primarily driven by land-use changes, underscoring this as a key factor in GD [7]. Accordingly, monitoring and analysing the potential drivers of GD in land-cover processes is crucial for maintaining ecological balance and sustainable development [8,9]. Identifying

these drivers at the county scale is important because this is the main administrative level for managing ecosystems and implementing policies in China.

Previous studies have identified three primary methods for evaluating *GD*: field monitoring, remote sensing big data, and LUCC-based analysis. Each method has distinct strengths and limitations, catering to different research and management needs. Field monitoring provides high-precision, reliable data for assessing vegetation health and ecological changes [10]. However, this method is labour-intensive, costly, and constrained to small-scale applications. In contrast, remote sensing big data allows for efficient, large-scale monitoring by utilising indicators such as the Normalised Difference Vegetation Index (NDVI) and Net Primary Productivity (NPP). It offers extensive spatial coverage and temporal coherence [11,12], but data processing can be complex, and it often lacks detailed insights into degradation processes. LUCC-based analysis has significant advantages in assessing *GD*. LUCC data effectively capture the spatial and temporal dynamics of land-use changes, supporting systematic and comprehensive monitoring of *GD* and grassland restoration (*GR*) processes [13]. This approach is not only suitable for large-scale evaluations, but it also excels at uncovering the underlying mechanisms of degradation. Moreover, LUCC data can directly reflect the impact of human activities (e.g., agricultural expansion and urbanisation) on grasslands, facilitating correlation analysis with other driving factors such as climate and policy to reveal the intrinsic mechanisms behind grassland changes [7]. Additionally, this method provides accurate, actionable data, enabling local governments to develop targeted strategies for grassland conservation and restoration [13].

Analysis of *GD* drivers faces two main challenges: comprehensively considering the characteristics of factors driving change and selecting appropriate methodologies [14]. The characteristics of the drivers include integration, dynamism, hierarchy, synergy, and spatial heterogeneity [14]. The integration of the driver system reflects the fact that land-cover change results from the combined influence of multiple drivers, rather than the isolated effect of a single driver. The dynamism of drivers refers to their temporal variability. Hierarchy indicates that the combination and interaction of various forces follow certain structures and levels, whereby each major category of driver may include several sub-factors. Synergy refers to the combined effects generated by multiple interacting drivers. Spatial heterogeneity is evident in the visible spatial variability of natural environmental elements within the land-use system.

The second challenge in driver analysis is the research method. A review of the existing literature reveals that commonly used approaches include statistical methods [15], machine learning techniques [16], scenario analysis [17], and field surveys. While these methods have advanced understanding of land-cover drivers, they are often constrained by limitations such as linear assumptions, data dependency, or subjectivity, which reduce their effectiveness in capturing the complex relationships between *GD* and its drivers [18,19].

To address these research gaps, this study employs nonlinear integrated analysis methods that can capture the complex interactions between environmental variables and *GD* processes [20,21]. Specifically, partial-order theory (POT) establishes partial-ordering relationships among elements based on multiple criteria [22]. It does not rely on linear assumptions or specific data distributions, thereby ensuring a more objective, data-driven analysis by avoiding subjective weighting [23]. The Hasse diagram technique (HDT) serves as a visualisation tool for POT, intuitively displaying the hierarchical and relational structure of elements [24]. Together, POT and HDT provide a robust framework for analysing complex systems, offering valuable insights into the dynamics and interactions between various factors.

Based on the preceding analysis, this study employs 14 drivers corresponding to two time points within the same study period (2000–2020) to demonstrate the dynamism of the factors driving change. These factors are categorised into five groups according to their

characteristics. POT and HDT are commonly used approaches for evaluating chemical hazards [25]. The evaluation of ecosystem services under various land management policies [26] and water quality assessments [27]. In this study, POT is applied to rank the potential drivers of *GD* in Ordos from 2000 to 2020 and to map the dominant explanatory factors of *GD* in the various counties of Ordos.

The Ordos region possesses substantial natural resources, including high-quality coal, natural gas, and oil reserves. Recently, under China's "Western Development" strategy, Ordos has become a crucial national energy base [28]. This makes studying *GD* in Ordos essential, as intensive resource extraction and energy development have placed significant pressure on its fragile grassland ecosystems. The objectives of this study are as follows: (1) What major changes have occurred in *GD* in Ordos since 2000? (2) What are the potential drivers of *GD* in each county in Ordos from 2000 to 2020? (3) How can POT and the HDT be used to build a framework for identifying key potential driver groups? This study applies POT and the HDT to systematically identify the potential drivers of *GD*, overcoming the limitations of traditional linear and weighted methods. By focusing on county-level analysis and integrating key driver characteristics, this study uncovers the main mechanisms of *GD*. It provides evidence to guide targeted grassland restoration and sustainable land management.

2. Materials and Methods

2.1. Study Area

Ordos is located in the southwest of Inner Mongolia ($37^{\circ}35'–40^{\circ}51' \text{ N}$, $106^{\circ}42'–111^{\circ}27' \text{ E}$), China, covering an area of $8.7 \times 10^4 \text{ km}^2$ [29]. It lies within the northern temperate semi-arid continental climate zone, characterised by distinct seasonal changes and low rainfall levels [30]. The annual mean temperature is between 5.3°C and 8.7°C , and annual precipitation ranges from 300 mm to 400 mm [30]. By the end of 2023, the city's permanent population was 2.2×10^6 [31]. Since the 2000s, Ordos has leveraged its abundant coal resources—which account for one-sixth of the nation's proven reserves—to rapidly develop into a key region in Inner Mongolia, with coal mining as its economic core [32].

Grassland is the dominant land-cover type in Ordos, extending to approximately $5.1 \times 10^4 \text{ km}^2$ and accounting for about 59% of the total study area. It is mainly distributed in the eastern, central, and northern parts of Ordos. From east to west, the grassland landscape shows a clear ecological gradient from typical steppe to desert steppe and further to steppe desert. The grasslands of Ordos constitute a key section of the ecological security barrier in the Yellow River Basin, a core area of the northern sand prevention belt, and an ecologically sensitive transition zone from grassland to desert [33].

This region was selected as a case study primarily due to its achievements in both ecological protection and economic development, particularly after the year 2000 [30]. Counties, as the third-tier administrative units in China, subordinate to provinces and prefectures, have independent administrative functions and thus serve as suitable units for regional land-cover planning research [34]. Analysing drivers of *GD* at the county scale enables local governments to adjust ecological restoration measures and improve land-use policies based on findings from a grassroots perspective. As of 2025, Ordos consists of nine county-level administrative divisions. This study includes eight of them, excluding Kangbashi New District, which was established in 2017 and for which statistical data are unavailable. The abbreviations and corresponding county/banner names are shown in Figure 1.

2.2. Data Collection and Processing

2.2.1. Selection of the Study Period

The years 2000 and 2020 were selected based on both policy relevance and data availability. In the year 2000, several national ecological restoration and grassland management policies were

initiated or widely implemented in Ordos and surrounding regions, such as the Grain for Green Program, the Natural Forest Conservation Program, the Beijing–Tianjin Sand Source Control Engineering Project, grazing prohibition, and rotational grazing [6]. Therefore, 2000 can be regarded as a suitable baseline year for representing the early stage of intensive ecological policy implementation. The year 2020 was selected as the endpoint because it allows the evaluation of *GD* after approximately two decades of policy intervention and regional development. This 20-year period is also appropriate for capturing long-term changes in *GD* and its drivers rather than short-term fluctuations. In addition, the data on *GD* and its driving factors are relatively complete, consistent, and comparable for the period from 2000 to 2020.

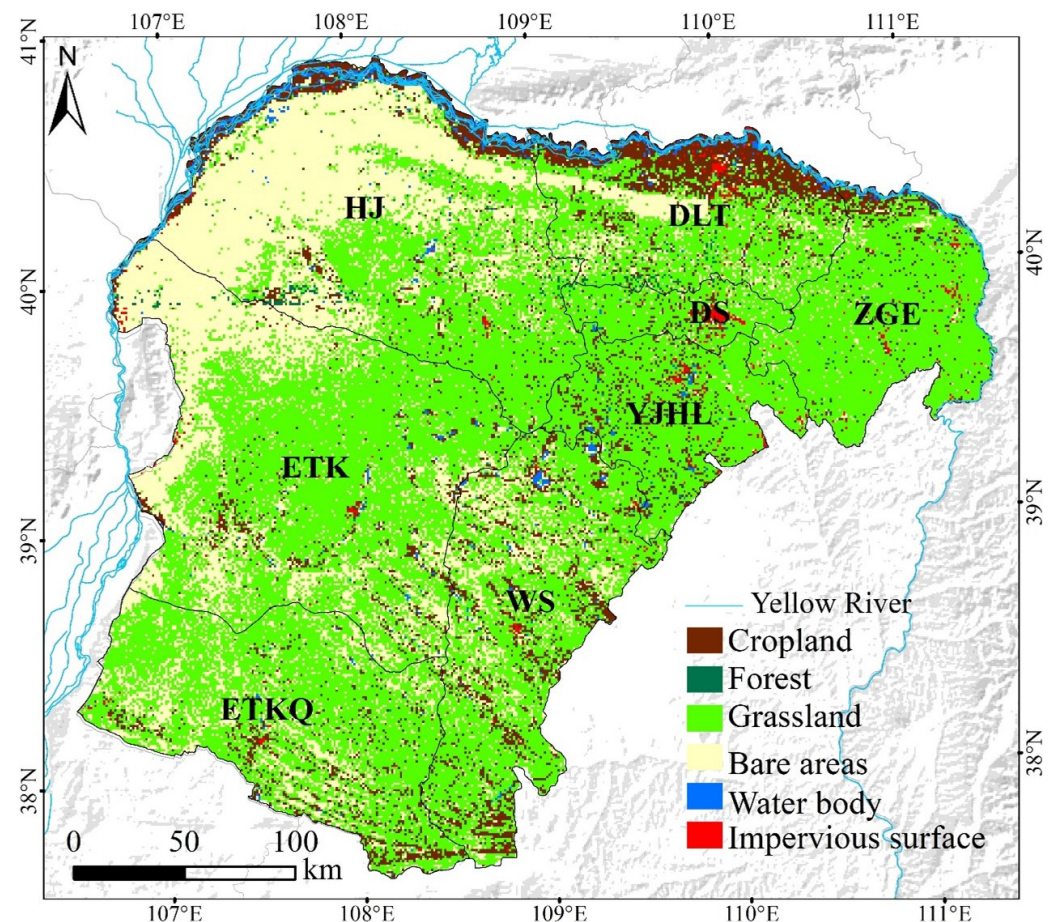


Figure 1. Land use and land cover in Ordos (2020). Note: The abbreviation of the eight counties/banners is listed as follows: HJ = Hangjin; DLT = Dalate; ZGE = Zhungeer; DS = Dongsheng; ETK = Etuoke; YJHL = Yijinhualuo; WS = Wushen; ETKQ = Etuokeqian.

2.2.2. Land-Cover Data and Processing

In this study, land-cover data were obtained from the Global Land-Cover Product with a Fine Classification System at 30 m resolution (GLC_FCS30), accessed via the Earth Big Data Science Engineering and Data Sharing Service System (<https://data.casearth.cn/>, URL (accessed on 15 November 2025)). The dataset spans 1985 to 2020 and is updated every five years, covering a total of eight periods, with a spatial resolution of 30 m. The overall accuracy of GLC_FCS30 is reported to be 84.33% [35,36]. This dataset has been widely used in China, Africa, and other regions worldwide for ecological assessments and decision-making [37,38].

The GLC_FCS30 dataset contains nine primary land-use categories and 18 s-level subcategories. In this study, these were reclassified into six land-use types based on the land-cover characteristics of the study area: cropland, forest, grassland, water body, bare areas, and impervious surfaces (Table 1).

Table 1. Land-use classification and reclassification description.

GLC_FCS30 Level 1 Classes	GLC_FCS30 Level 2 Classes	Description	Merged Category
Cropland	Rainfed cropland Herbaceous cover Irrigated cropland	Land used for cultivating crops.	Cropland
Forest	Closed deciduous broadleaved forest Open evergreen needle-leaved forest Closed evergreen needle-leaved forest Closed deciduous needle-leaved forest	Land covered with trees and with a canopy cover of over 30%.	Forest
Shrubland	Shrubland Deciduous shrubland		
Grassland	Grassland Sparse vegetation	Land covered with natural herbaceous vegetation, with a coverage of more than 10%.	Grassland
Bare areas	Bare areas Unconsolidated bare areas	Natural land with vegetation covers less than 10%.	Bare areas
Water body	Water body	Areas covered by liquid water within terrestrial boundaries.	Water body
Wetlands	Wetlands		
Impervious surfaces	Impervious surfaces	Surface formed by artificial construction activities.	Impervious surfaces
Permanent ice and snow	Permanent ice and snow	This land-cover type does not exist in the Ordos region.	

2.2.3. Identifying Possible Drivers

We collected 14 drivers that could lead to *GD* based on a vast review of the literature [37,39,40]. The selection of these 14 driving factors was guided by two principles: mechanistic relevance and policy/management applicability. Mechanistic relevance refers to whether an indicator has a clear pathway linking it to grassland degradation, such as through climate stress, grazing pressure, land-use change, urban expansion, or socioeconomic development. Policy/management applicability refers to whether the indicator can be measured at the county scale and whether it can support differentiated grassland management and policy interventions. The 14 drivers were further classified into five groups: climate, economic, human activity, livelihood, and urbanisation. Detailed information on the indicators included in each group is provided in Table 2.

All drivers were defined on a 30 × 30 m grid covering the *GD* region. To ensure that the identified potential drivers were specifically associated with grassland degradation rather than reflecting background spatial heterogeneity, a comparative analysis of driving factors between *GD* and non-*GD* areas was conducted. The detailed results of this control analysis are provided in the Supplementary Materials (Figure S1, Table S1). The analysis proceeded as follows. First, statistical indicators from the Inner Mongolia Statistical Yearbook—including primary industry *GDP*, secondary industry *GDP*, tertiary industry *GDP*, per capita *GDP*, and per capita net income of farmers and herdsmen—were processed using inverse distance weighting (IDW) interpolation and then converted to density surfaces. Second, land-cover data from the Chinese Academy of Sciences were used in ArcGIS 10.8 to calculate the Euclidean distance to the nearest pixel classified as urban land (class 51), rural settlements (class 52), or industrial land (class 53).

Table 2. Collection and processing of driver data.

Driver Group	Driver Indicator	Time Series	Data Source	Measure	Description	Unit	Impact Orientation
Climate driver group	Annual precipitation	2000–2020	https://cds.climate.copernicus.eu/ URL (accessed on 25 November 2025)	—	Calculation of temperature and precipitation value for every <i>GD</i> object.	mm	The larger the value, the smaller the impact on <i>GD</i> , normalised to [1, 0].
	Annual average temperature					°C	
Human activity group	Grazing intensity		https://doi.org/10.6084/m9.figshare.26195684 URL (accessed on 3 December 2025)	—	Calculate the grazing intensity in <i>GD</i> object.	Sheep unit/ha	The larger the value, the greater the impact on <i>GD</i> , normalised to [0, 1].
	Population density		http://www.resdc.cn/ URL (accessed on 17 December 2025)			Person/km ²	
Economic driver group	Primary industry GDP Secondary industry GDP Tertiary industry GDP GDP		Inner Mongolia Statistical Yearbook http://tj.nmg.gov.cn/ URL (accessed on 12 December 2025)	IDW interpolation	Calculation of driver’s densities for <i>GD</i> object.	yuan/km ²	
Livelihood group	Per capita GDP Per capita net income of farmers and herdsmen						
Urbanisation group	Urban land		http://www.resdc.cn/ URL (accessed on 17 December 2025)	Euclidean distance	The Euclidean distance from the <i>GD</i> object to the driver object.	m	
	Rural settlements						
	Industrial and Mining land						
	Roads						

2.3. Methodologies

2.3.1. Evaluation of GD and GR

In this study, *GD* and *GR* were assessed based on land-cover transition processes from 2000 to 2020, following the methodology of Hu and Batunacun [41]. *GD* was defined as the conversion of grassland into other land-cover types, including cropland, forest, water bodies, and bare land. In contrast, *GR* referred to the transformation of cropland, forest, water bodies, bare land, or impervious surfaces back into grassland. In addition, non-degraded grassland (non-*GD*) was defined as areas that underwent neither *GD* nor *GR* during the study period.

To further quantify the dynamics of *GD* and *GR*, we calculated both their proportions and annual rates of change. The formulas are presented as follows:

$$R_{GD} = \frac{A_{GD}}{A_{tot}} \times 100 \quad (1)$$

$$R_{GR} = \frac{A_{GR}}{A_{tot}} \times 100 \quad (2)$$

$$r_{GD} = \frac{R_{GD}}{\Delta t} \quad (3)$$

$$r_{GR} = \frac{R_{GR}}{\Delta t} \quad (4)$$

where A_{GD} and A_{GR} are the areas of *GD* and *GR* (unit: km²); A_{tot} is the total area of the study region (unit: km²); R_{GD} and R_{GR} are the proportions of *GD* and *GR* (unit: %); Δt is the study period length (unit: year); and r_{GD} and r_{GR} are the annual rates of *GD* and *GR* (unit: %·year^{−1}).

2.3.2. Integrating POT and HDT for Multicriteria Ranking

This study integrates POT and the HDT to rank the multidimensional potential drivers of *GD* across the eight counties of Ordos. POT is a non-compensatory, multi-indicator ranking method that establishes partial-order relationships without assigning subjective weights. Unlike conventional statistical tests, it does not provide *p*-values, confidence intervals, or effect sizes; instead, it identifies relative dominance and incomparability among objects while preserving information contained in multiple indicators [22]. HDT visualises these relationships through hierarchical levels, chains, and incomparable elements [24]. In this study, POT-HDT is used to compare the relative influence of different driver groups on *GD* across counties.

Step 1: Establishing the POT structure.

Let a finite set be denoted as $X = \{a, b, c, \dots\}$, where each element $a, b, c \in X$ can be compared. In this study, X is the set of counties in Ordos, and each element (e.g., HJ, DLT, ZGE, ETK, DS, WS, ETKQ, and YJHL) denotes an individual county. A partial-order relation in POT has three properties: reflexivity, antisymmetry, and transitivity [42].

Step 2: Visualising relationships using HDT.

The Hasse diagram encompasses several conceptual elements. Based on its application in this study, the following key concepts are used to rank the primary drivers of *GD* in Ordos, as detailed below [26,42]:

Maximum element: The element typically located at the top of the HDT (e.g., ETK and ETKQ in Figure 2).

Minimum element: The element typically located at the bottom of the HDT (e.g., DLT, ZGE, DS, and YJHL in Figure 2).

Isolate element: An element that is not comparable with any other elements. It is also referred to as an element that simultaneously satisfies the conditions of both a maximum and a minimum element (e.g., HJ in Figure 2).

Level: A group of targets positioned at the same horizontal level in the HDT. These targets represent a layer of comparable ranking (e.g., three levels are shown in Figure 2).

Chain: In a partially ordered set, if every pair of elements is comparable, they form a chain. Chains are used to examine the relative influence of the same drivers across multiple counties (e.g., DLT → WS → ETK in Figure 2).

Step 3: Defining dominance relations.

In this study, we used a dominance rule to rank counties based on driver values. A county is said to dominate another if its values are greater than or equal to the other county in all indicators and strictly greater in at least one. Counties that are not dominated by any others are assigned to Level 1. After removing these, the next set of undominated counties forms Level 2, and the process continues until all counties are assigned a level. This method allows us to rank counties according to the relative influence of each driver group on *GD*.

Step 4: Data processing and integration procedure.

For the Hasse diagram analysis, the procedure consisted of four main steps. (1) All driver data were rasterised and spatially matched with *GD* data. (2) To ensure comparability across different units and scales, all driver values were normalised to a range of 0–1. (3) Because different drivers may influence *GD* in different directions, selected variables were reoriented to maintain consistency. For example, normalised precipitation values were transformed into $1 - \text{precipitation}$, because higher precipitation generally promotes grassland recovery. Similarly, the orientations of distance to urban areas, rural settlements, roads, and industrial and mining areas were also adjusted. (4) Based on the processed dataset, POT was applied to establish ranking relationships, and HDT was used to visualise the hierarchical structure of these relationships (Figure 2).

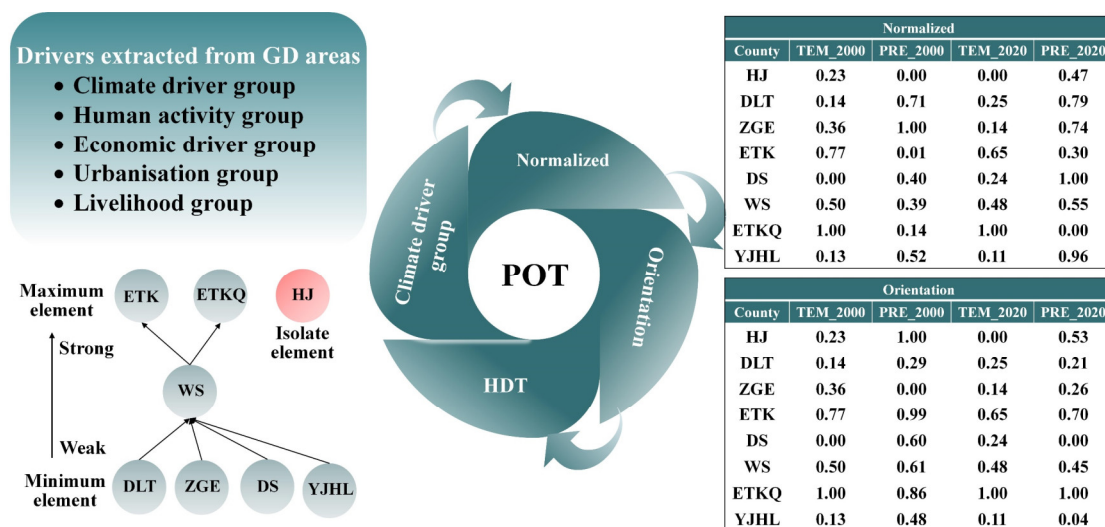


Figure 2. Application examples of POT and HDT.

2.3.3. Framework

In the present study, the application of POT and the HDT comprises three main components: data collection and processing; land-cover and *GD* analysis; and ranking of key drivers.

Step 1: Data collection and processing. Land-cover data for the years 2000 and 2020 were processed through projection, clipping, and resampling to ensure spatial consistency and compatibility. Concurrently, drivers were classified into five categories—climate, economy, human activity, livelihood, and urbanisation—based on attributes such as integrity, dynamism, hierarchy, synergy, and spatial heterogeneity. These processed datasets provided a robust foundation for spatiotemporal analysis and the identification of relevant driving forces.

Step 2: Land-cover and *GD* analysis. The spatiotemporal patterns of land cover and *GD* from 2000 to 2020 were analysed to identify dynamic trends and spatial variations. Land-cover analysis was used to explore conversion rates, directions, and spatial differentiation to uncover land-use dynamics. *GD* analysis assessed the spatial variability and severity of *GD*, emphasising regional disparities and the extent of degradation.

Step 3: Ranking of potential drivers. Potential drivers influencing *GD* at the county level were identified and ranked. POT was used to quantify and prioritise these drivers, while HDT was applied to visualise their hierarchical relationships. This approach highlighted the relative importance of the drivers, providing a scientific basis for regional comparative analysis and the formulation of targeted management strategies (Figure 3).

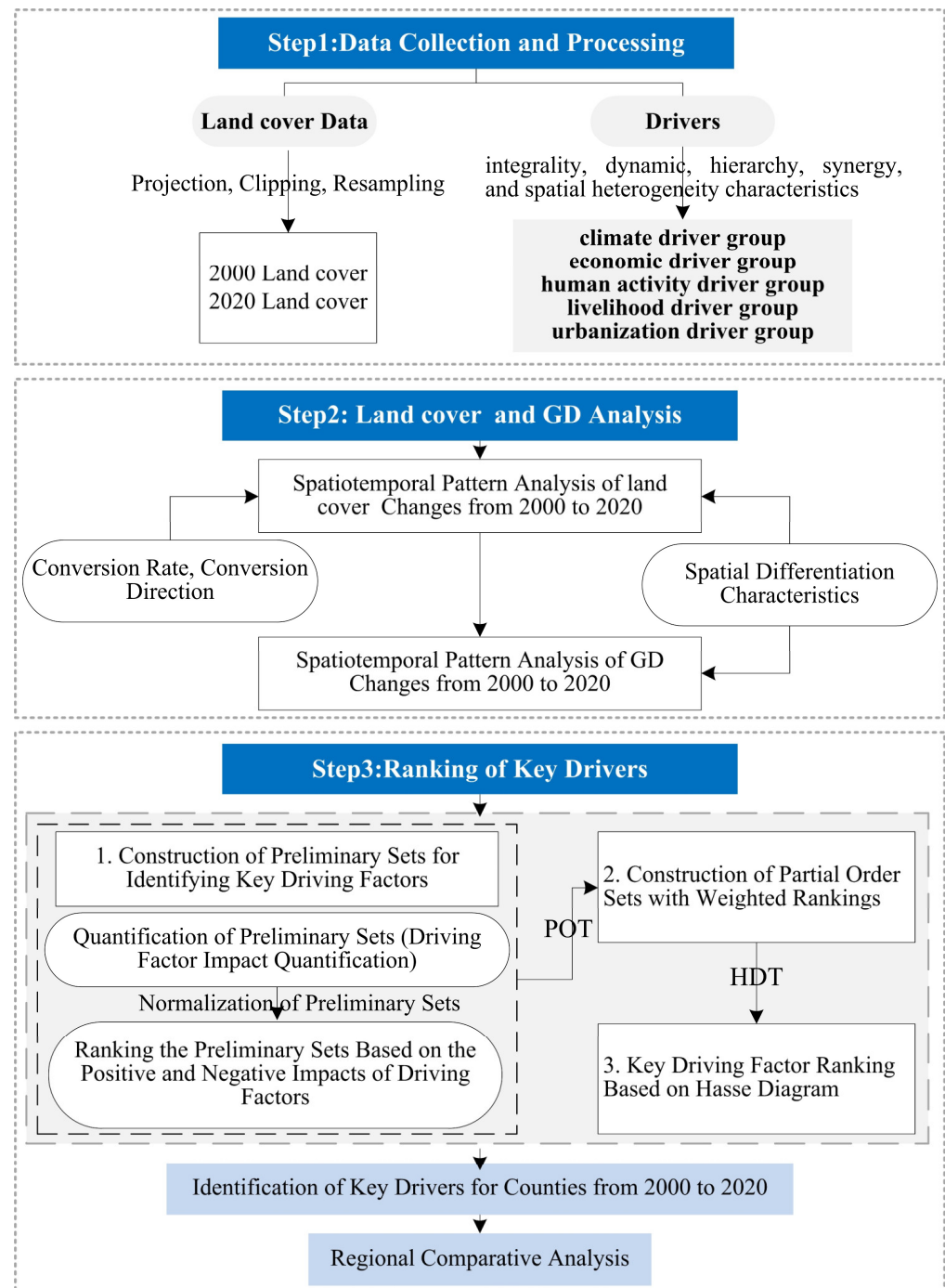


Figure 3. Study framework.

3. Results

3.1. Spatiotemporal Analysis of GD from 2000 to 2020

Between 2000 and 2020, approximately 14.5% of Ordos (12,637 km²) underwent land-cover change (Figure S2), mainly characterised by reductions in bare areas and increases in cropland, grassland, and impervious surfaces (Figures 4 and S3).

Figure 5 shows that over the past two decades, both the area and proportion of GR exceeded those of GD. Approximately 5.01% of the total land area (4372 km²) experienced GD, equivalent to an average annual degradation rate of 0.25%. This was mainly concentrated in WS and ETKQ. GD was primarily associated with the conversion of grassland to cropland and bare land. Simultaneously, approximately 6.90% of the total land area (6026 km²) underwent GR, equivalent to an average annual recovery rate of 0.35%. This was mainly concentrated in ETK and HJ. GR was mainly caused by the conversion of bare land and cropland to grassland. Overall, the greater extent of GR compared to GD indicates a net improvement in grassland conditions in Ordos (Figures 5 and S4).

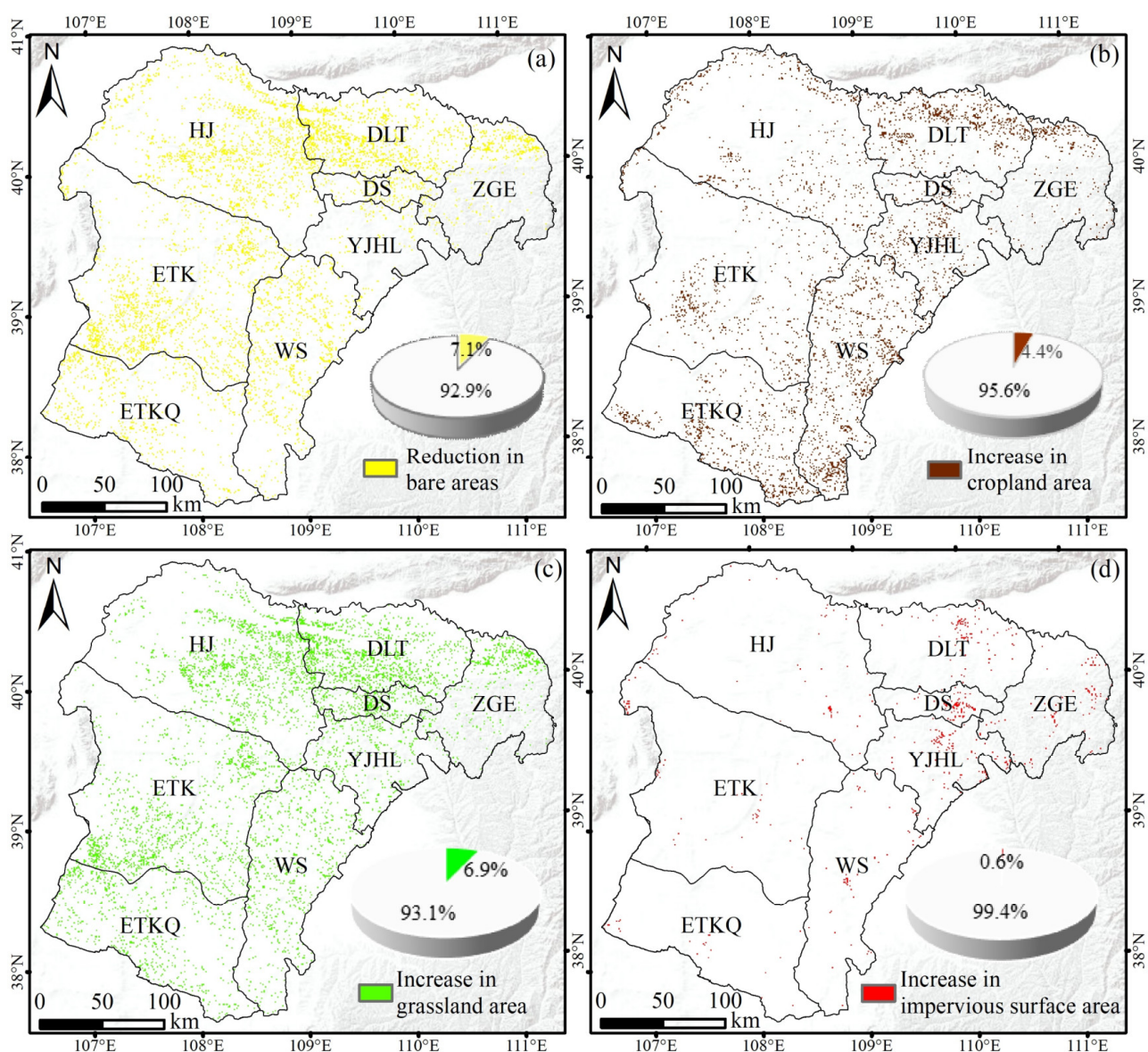


Figure 4. Land-cover change in Ordos. (a) Reduction in bare areas. (b) Increase in cropland area. (c) Increase in grassland area. (d) Increase in impervious surface area.

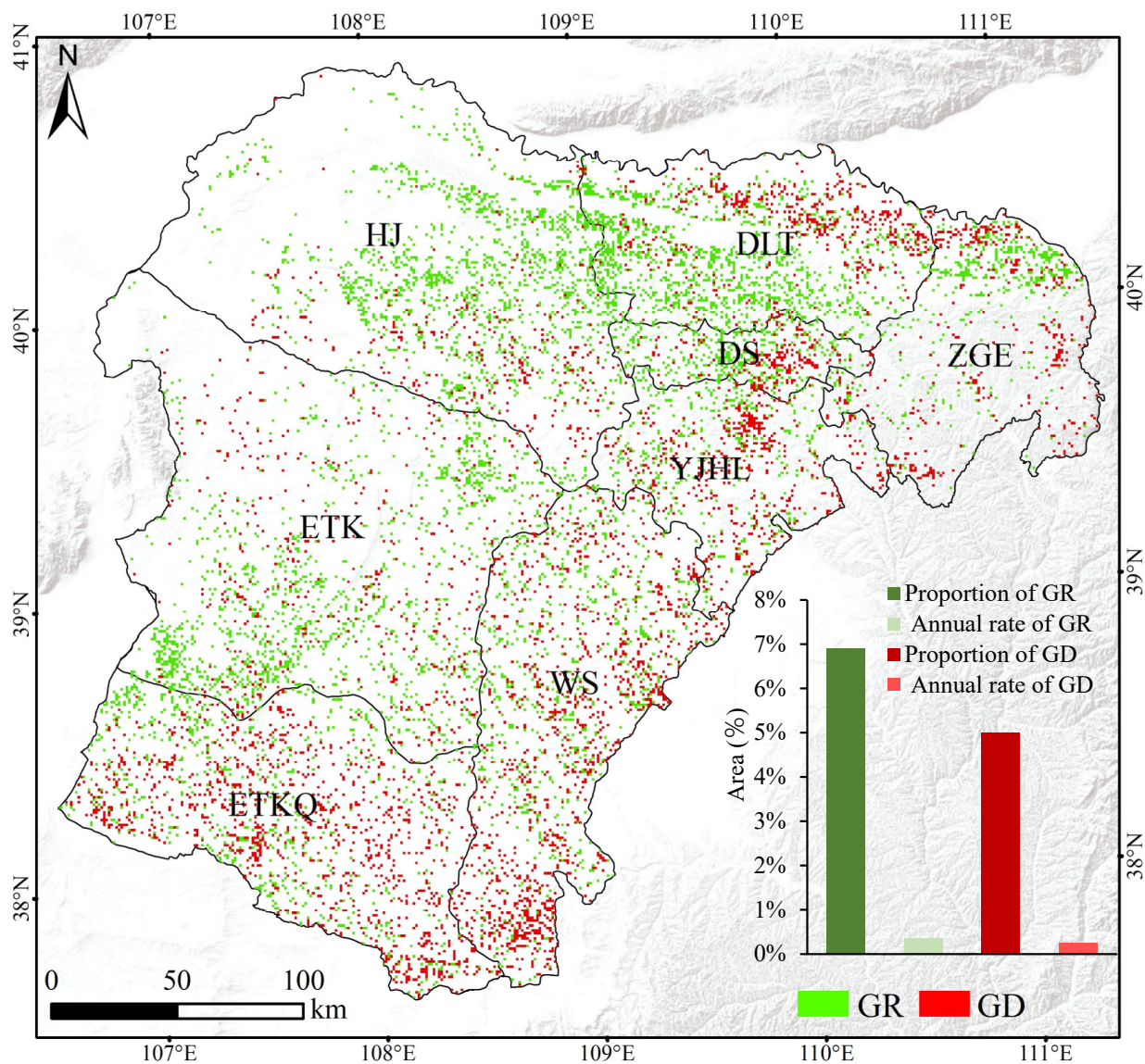


Figure 5. Schematic diagram of GD and GR analysis.

3.2. Partial-Order Analysis of GD Potential Drivers for Each County

To identify the potential driver group contributing to GD, we analysed the levels, chains, and structure of the Hasse diagram in this section. For the climate driver group, three hierarchical levels were identified (Figure 6a, Table S2a). Figure 6a indicates that ETK and ETKQ experienced the strongest relative influence from climate-related drivers. By contrast, climate had the least effect on DLT, ZGE, DS, and YJHL. Spatially, the influence of climate drivers was greater in four western counties than in the eastern counties (Figure 6a).

Figure 6b indicates that HJ, DS, and ETKQ experienced the strongest influence from the human activities driver group. In contrast, human activities had the weakest influence on ETK. DLT, ZGE, YJHL, and WS were identified as isolated factors, indicating that the human activities driver group had no clear dominance or comparability in these counties.

Figure 6c shows that the influence of economic drivers has distinct spatial variation. Economic drivers had a greater impact on GD for the following eastern counties: DLT, ZGE, DS, and YJHL. Among these, the primary industry GDP indicator had a more pronounced effect on GD in HJ, DLT, WS, and ETKQ (Table S2c, highlighted in yellow). The related chains {HJ → DLT}, {ETKQ → DLT}, and {HJ → WS} were defined as “primary industry GDP chains”, highlighting the increasing influence of primary industry GDP along these chains.

Urbanisation exhibited a similarly pronounced effect on *GD* in Ordos. Two hierarchical levels were identified for this driver group (Figure 6d). The spatial characteristics of urbanisation effects mirrored those of economic development, with the four eastern counties experiencing the most substantial impact, and the four western counties experiencing a comparatively limited impact.

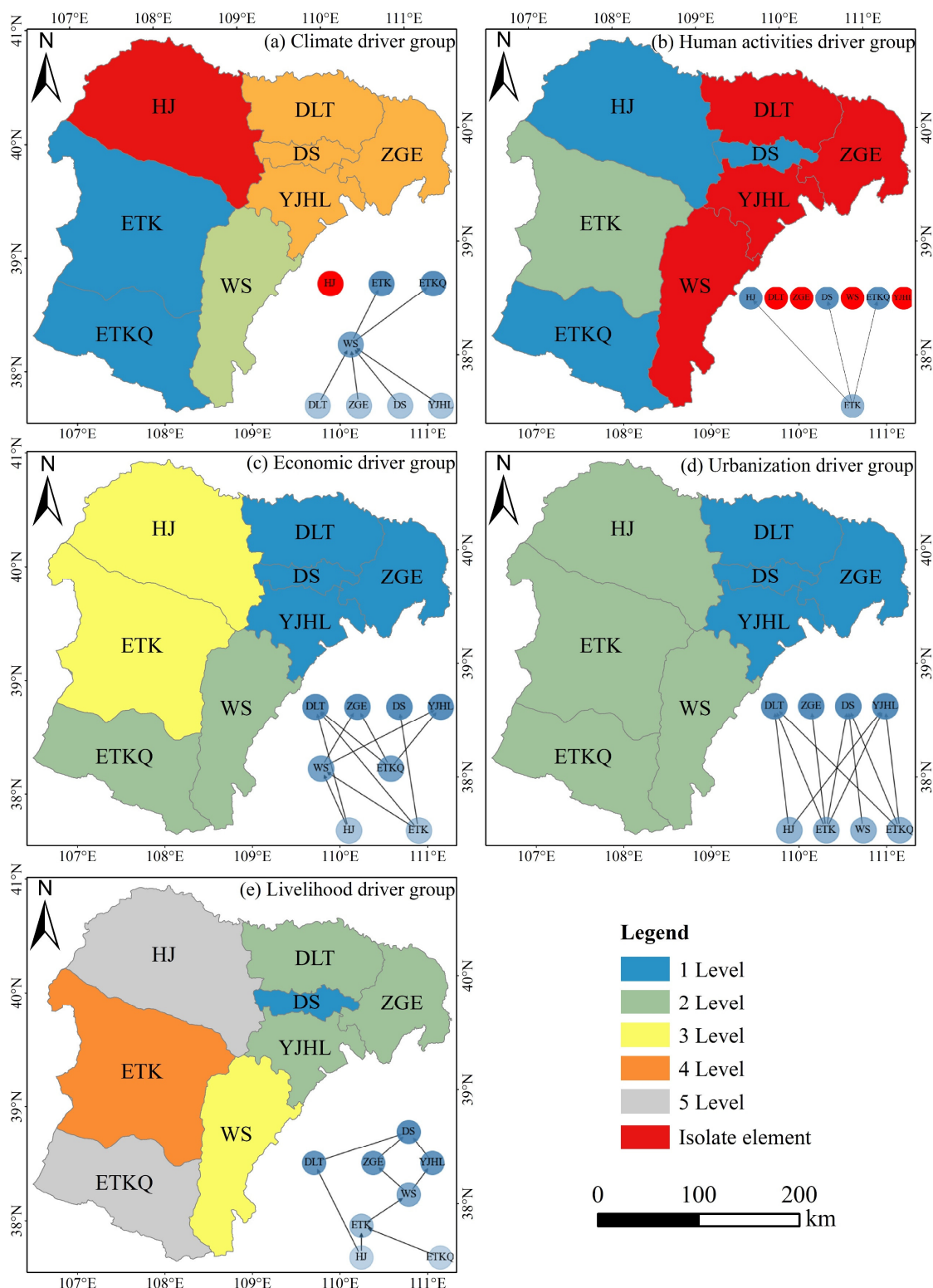


Figure 6. Hasse diagrams for 2000 to 2020. (a) Climate driver group. (b) Human activities driver group. (c) Economic driver group. (d) Urbanisation driver group. (e) Livelihood driver group.

Four levels were identified for the livelihood driver group. Overall, the impact of livelihood development was greater on the eastern four counties than on the western counties. DS, DLT, ZGE, and YJHL were located within the top two levels (Figure 6e).

In summary, economic development, urbanisation, and livelihood development exerted a greater influence on *GD* in the eastern four counties; by contrast, the climate driver group had an opposite trend, with a stronger effect in the western counties.

Details of the changes in *GD* drivers in Ordos are provided in the Supplementary Information (Figure S5).

3.3. Identifying the Potential Drivers of *GD* for Each County

In this section, we compare levels across all driver groups to identify the dominant driver for each county. Figure 6 indicates that urbanisation and economic development were the dominant driver groups in five out of eight counties—DLT, ZGE, DS, WS, and YJHL. Among these, the greatest influence of urbanisation and economic development was observed for DLT, ZGE, DS, and YJHL, followed by WS.

Human activities and climate were the second most influential driver group. Human activities were dominant in three counties, including ETKQ, HJ, and DS, while climate emerged as a key driver in three counties: ETK, ETKQ, and WS. Finally, livelihood development was identified as the primary driver of *GD* in DS.

The overall ranking of driver groups, in terms of their influence on *GD*, is as follows: urbanisation = economic development > human activities = climate > livelihood development (Figures 7 and 8).

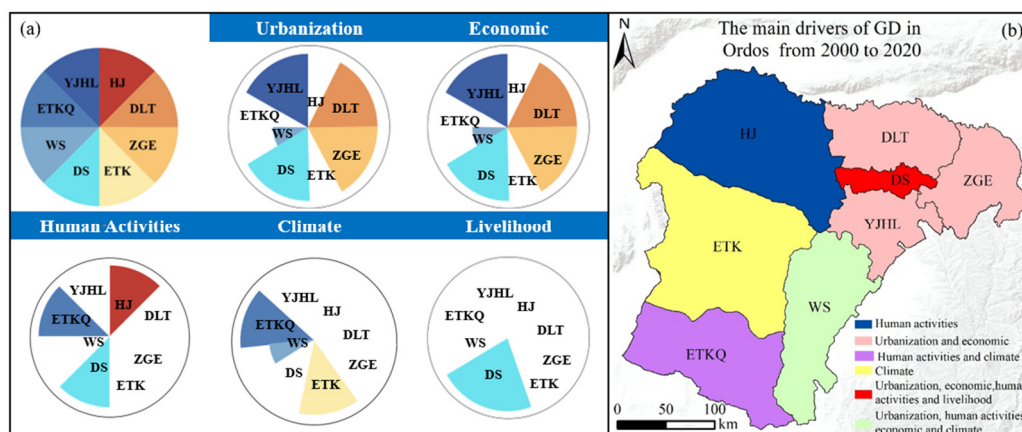


Figure 7. Potential drivers of *GD* in Ordos. (a) Key drivers and their ranking for *GD*. (b) Spatial distribution of potential drivers of *GD* from 2000 to 2020.

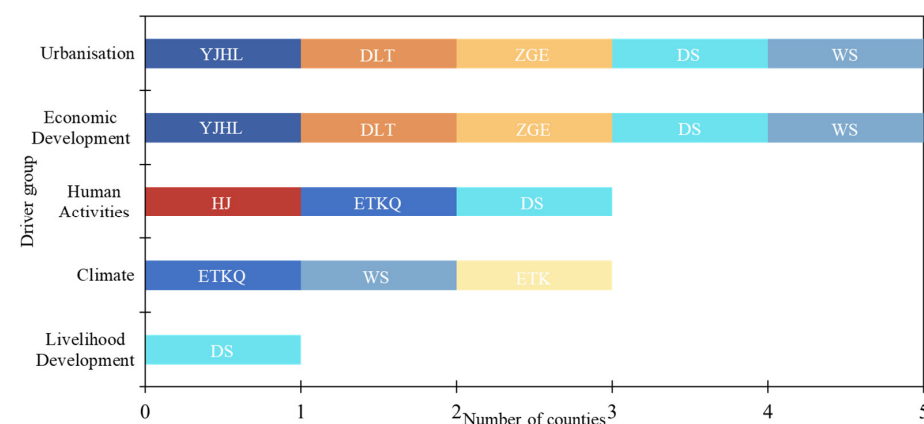


Figure 8. Driver importance ranking plot.

4. Discussion

4.1. Policy-Oriented Mechanism Analysis of GD

The present study found that *GR* was the dominant trend in Ordos between 2000 and 2020, although degradation remained significant. Notably, rapid urbanisation and economic development emerged as the potential drivers of *GD* in the study area. Previous research has demonstrated that both *GR* and urbanisation trends are closely linked to regional policy interventions [28,34,43]. To clarify the possible mechanism between policies, drivers, and the restoration process, we summarised the major ecological protection and urbanisation-related policies, along with their associated measures, based on an extensive review of the literature (Table 3). The overarching design concept of the policies listed in Table 3 is the Chinese government's vision of "Ecological Civilization" [44,45]. This vision has been implemented through a series of national ecological protection and restoration policies and was shown to indirectly influence *GD* and *GR* in this study. In this paper, we analyse the possible pathway between these key ecological protection policies and the processes of *GD* and *GR*.

A total of ten relevant policies were identified and categorised into two main groups. To comprehensively illustrate the positive impacts of these policies, we provide a concise synthesis of their significant ecological effects within Inner Mongolia, China, and at broader, region-independent scales (Table 3). The first group, Ecological Conservation and Restoration Policies, includes the Fencing Grassland and Moving Users (FGMUs), the Beijing–Tianjin Sand Source Control Engineering Project (BTSSCE), the Grain for Green Program (GGP), the Natural Forests Conservation Program (NFCP), the Ecosystem Services Compensation Project (ESCP), the Three-North Shelterbelt Development Program (TNSDP), and the Grassland Ecosystem Subsidy and Award Scheme (GESAS). The second group, Urbanisation and Energy Development Policies, comprises the Western Development Program (WDP), China's Energy and Chemical Golden Triangle (CEGT), and the Hohhot–Baotou–Ordos–Yulin Urban Agglomeration Development Plan (HBOYUA).

To understand the factors driving grassland restoration in Ordos, we examined the role of ecological protection policies based on previous studies. Evidence from the literature indicates that policy interventions have played a major role in promoting vegetation recovery in the region. Around the year 2000, a series of ecological protection policies were implemented by the central government to mitigate *GD*, particularly in Inner Mongolia. The core objective of these policies was to reduce anthropogenic disturbances through measures such as grazing bans, the relocation of herdsman, increased subsidy allocations, and the introduction of high-value livestock breeds. Consistently, Ma et al. (2019) demonstrated that the implementation of grazing prohibition policies had a significant positive impact, resulting in a pronounced greening trend in Ordos between 2000 and 2016 [46]. Furthermore, Wu et al. (2025) revealed that NPP in Ordos increased by 34.9 gC/m² from 2000 to 2021, driven by effective ecological protection strategies (BTSSCE, GGP, NFCP, ESCP, TNSDP, and GESAS) and favourable climatic conditions, including reduced evaporation and increased precipitation [47]. Therefore, the greater extent of *GR* than *GD* observed in this study can be largely attributed to the positive effects of ecological protection policies, which reduced human disturbance and promoted vegetation recovery.

Table 3. Qualitative and quantitative descriptions of key ecological and urban development policies.

Policy Group	Year	Policy Name	Measures	Qualitative Examples of Policy Impacts
Ecological Conservation and Restoration Policies	2002–2008	Fencing Grassland and Moving Users (FGMUs) [6]	(1) Prohibit grazing and implement rotational grazing. (2) Relocate herdsman. (3) Promote development of high-yield farmland. (4) Breed livestock with high economic value.	(1) In Xilingol, grazing bans boosted grass height (+6.5–25 cm), coverage (+8.2–50%), and yield (+12.8–114.5 kg/mu). (2) By 2006, farmer income rose from 1823 to 3309 yuan. (3) In Hunshandake Desert, dunes shrank from 7120 to 4053 km ² , and sandstorm days dropped from 28 to 3 [48].
	2001–Now	Beijing–Tianjin Sand Source Control Engineering Project (BTSSCE) [49]	(1) Tree planting and afforestation. (2) Desertification control.	(1) Afforestation covered 6.496×10^8 acres. (2) Grassland improvement reached 1.2104×10^9 acres [50].
	1999–2010	Grain for Green Program (GGP) [51]	(1) Grazing and implement rotational grazing. (2) Scientific breeding (scientifically calculate the livestock carrying capacity to (3) promote grass–livestock balance). (4) Grass seed subsidies. (5) Ecological assessment rewards.	(1) About 10–20% of forest land increased. (2) About 10% of cropland decreased [52].
	2000–2020	Natural Forests Conservation Program (NFCP) [53]	(1) Establish strong organisational support systems. (2) Secure construction funding and policy support. (3) Deepen reforms and implement modern corporate systems. (4) Improve quality and efficiency through technological innovation. (5) Coordinate pension insurance for retired staff.	(1) Large-scale forest protection: The NFCP covered 1.5×10^6 km ² across 17 provinces, effectively curbing over-logging of natural forests. (2) Significant economic benefits: It generated a net benefit of about 2.9×10^{12} RMB/year against a cost of 0.9×10^{12} RMB/year, with a return on investment of over 3:1 [54].
	2001–2020	Ecosystem Services Compensation Project (ESCP) [55]	(1) Increase grazing ban subsidies. (2) Promote grass–livestock balance. (3) Facilitate ecological migration.	(1) Forest cover increased: By 2012, forest cover reached about one-fifth of the land area, and some decertified regions showed a trend of “people advancing, sand retreating.” (2) Water resources improved: Lake shrinkage slowed, some lake areas expanded, and marine resources were effectively protected [56].
	1978–2050	Three-North Shelterbelt Development Program (TNSDP) [57]	(1) Apply scientific and technological solutions under harsh conditions. (2) Achieve large-scale afforestation. (3) Improve agro-ecological environments.	(1) In the Three-North region, forest cover will rise from 5.05% in 1977 to 15.95% [58].
	2011–Now	Grassland Ecosystem Subsidy and Award Scheme (GESAS) [59]	(1) Implement grazing ban subsidies. (2) Encourage grassland–livestock balance. (3) Provide production subsidies to herders. (4) Apply performance-based reward systems.	(1) Grassland productivity in Xinjiang: By 2017, fresh grass yield in grazing-ban areas rose by 32.66% over 2010, and in-balance areas rose by 26.53%. (2) Vegetation recovery in Xinjiang: Compared with 2012–2016, overall vegetation cover increased by 1.71%, and height increased by 2.42 cm. (3) Reduced grazing pressure in Xinjiang: Grassland overload dropped from 33% in 2010 to 8.7%, greatly easing pressure on pastures [60].

Table 3. Cont.

Policy Group	Year	Policy Name	Measures	Qualitative Examples of Policy Impacts
Urbanisation and Energy Development Policies	2000–Now	Western Development Program (WDP) [61]	(1) Attract large-scale investments. (2) Introduce fiscal and institutional innovations to reduce regional income disparities.	(1) The GDP growth rate increased by 1.6% points [62].
	2010–Now	China’s Energy and Chemical Golden Triangle (CEGT) [63]	(1) Coordinated planning: Develop reform pilot zones in the “golden triangle”. (2) Scientific development: Strengthen coal production capacity. (3) Ordered conversion: Promote clean and efficient coal conversion. (4) Optimised transmission: Enhance energy transport infrastructure. (5) Multi-energy synergy: Promote circular energy utilisation. (6) Eco-low carbon: Construct environmentally friendly, water-saving parks.	(1) The fossil energy reserves amount to 201.02 billion tons of standard coal, accounting for 47.2% of the national total [64].
	2018–2035	Hohhot–Baotou–Ordos–Yulin Urban Agglomeration Development Plan (HBOYUA) [65]	(1) Foster coordinated industrial development. (2) Improve infrastructure interconnectivity. (3) Promote joint ecological and environmental governance. (4) Establish open, collaborative policy frameworks. (5) Innovate institutional coordination mechanisms.	(1) Hohhot–Baotou–Ordos–Yulin focuses on promoting ecological protection and green economic development [66].

4.2. Urbanisation and Economic Development Have Progressed Rapidly and Exerted Multifaceted Effects on GD in Ordos Since 2000

Urbanisation and economic development were identified as key potential drivers of GD in the eastern counties of DLT, ZGE, DS, WS, and YJHL. Figure 9 indicates that the urbanisation driver group exhibited substantial expansion between 2000 and 2020. The areas of urban land, mining land, rural settlements, and roads increased by 73 km², 893 km², 46 km², and 4961 km, respectively. Spatial analysis further reveals that most newly developed construction land was concentrated in the eastern part of the study area, designating this region as the primary zone of urban and mining expansion in Ordos.

The rapid urbanisation and economic development observed in Ordos can be primarily attributed to two factors: policy interventions and the region's abundant energy resources. For example, both the WDP and the HBOYUA have been instrumental. The WDP was launched to reduce the development gap between China's eastern and western regions and served as a key political driver of Ordos's rapid growth. Ordos capitalised on this policy opportunity—leveraging its rich coal and gas reserves—and transformed from a small settlement into a prosperous city beginning in 2000. In addition to national-level policies, regional government initiatives have also guided Ordos's development. The HBOYUA plan (Table 3), launched by the Inner Mongolia government in 2018, emphasised “accelerating the construction of the one-hour travel circle in Hohhot–Baotou–Ordos.” This improved regional connectivity, enhanced population mobility, and strengthened industrial linkages across urban centres, thereby promoting the urbanisation process of Ordos [67]. On the other hand, owing to its abundant, high-quality, and diverse coal reserves, Ordos contributed nearly one-fifth of China's coal supply in 2023, thereby playing a crucial and irreplaceable role in national energy security and supply stability [14].

Urbanisation in Ordos has primarily driven GD through both direct and indirect mechanisms. Directly, land-use conversion—particularly in eastern Ordos—has involved the transformation of approximately 114.4 km² of forest and 263.2 km² of cropland into urban and industrial land. This conversion has reduced vegetation cover [30]. Indirectly, excessive water consumption and rural-to-urban migration have also been critical drivers. The exponential growth of coal mining since 2000 has fuelled the expansion of coal-related industries such as coal washing and coal chemical production. These industries are characterised by high water usage, which has further accelerated groundwater depletion and led to a sharp decline in groundwater levels [68–72]. Rural-to-urban migration has had both positive and negative effects. On the positive side, the implementation of ecological protection policies since 2000 has encouraged the relocation of pastoralists from severely degraded lands to urban areas. Compensation measures have increased their incomes and reduced ecological pressure. These policies have also contributed to a decrease in livestock populations, promoted grassland recovery, and widened the socioeconomic gap between rural and urban populations [32]. However, the adverse effects of rural-to-urban migration should not be overlooked. The influx of people into urban areas—driven by the process of urbanisation—has accelerated economic growth but also contributed to ecological issues such as land desertification and further GD [73].

Economic development was identified as a key potential driver of GD in the eastern counties of DLT, ZGE, DS, WS, and YJHL. Ordos's GDP increased dramatically over a short period: in 2011, it even surpassed Hong Kong. By 2015, the city's total GDP reached 422.6 billion yuan, ranking first nationwide in per capita GDP [73]. However, this rapid growth has relied on coal and related industries. Coal mining and coal-chemical industries have not only occupied large areas of grassland as mining sites and supporting infrastructure but also consumed enormous volumes of water, further accelerating groundwater

depletion [69]. In summary, *GD* in Ordos has been shaped predominantly by the dual forces of urbanisation and economic growth.

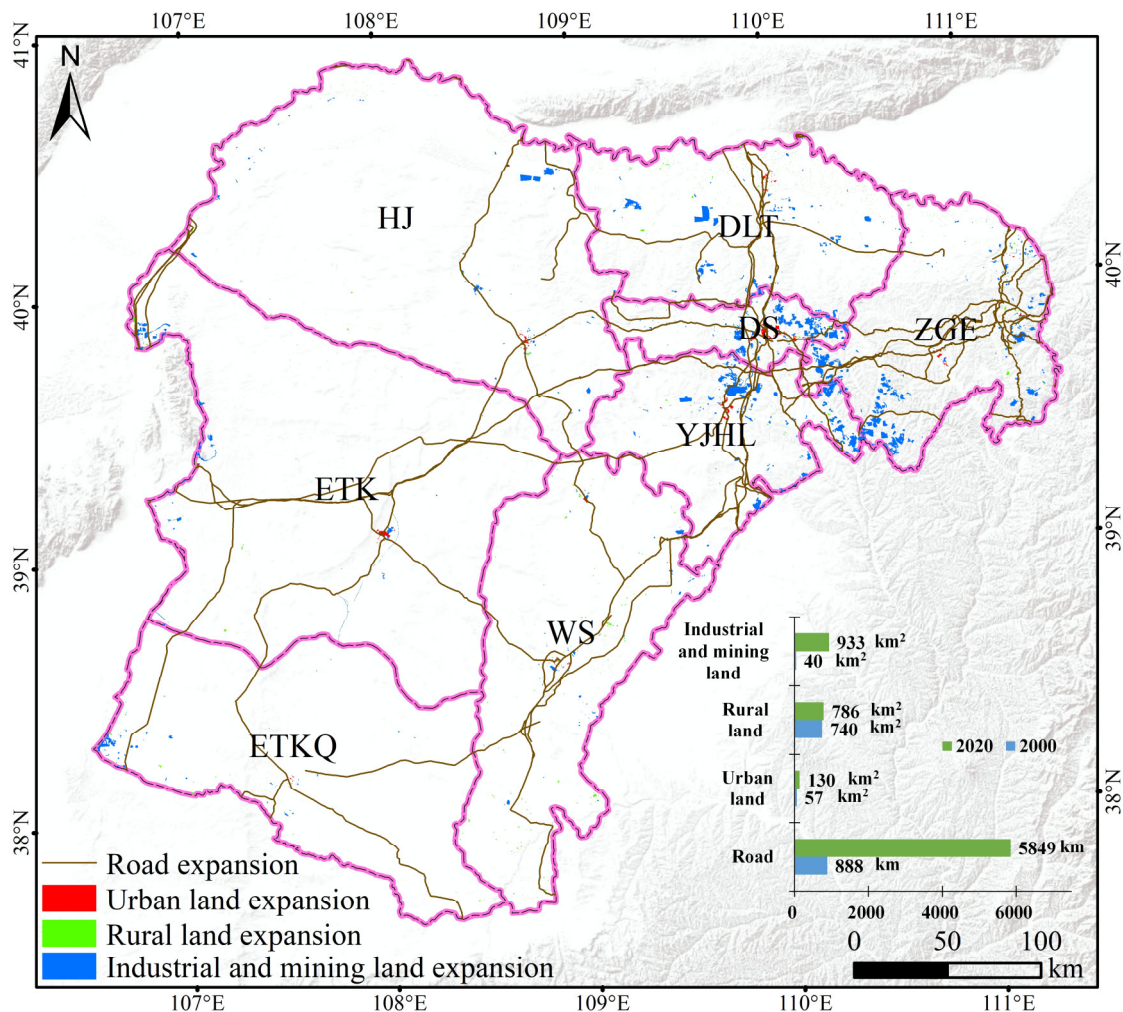


Figure 9. Changes in drivers of urbanisation (2000–2020).

4.3. Policy Suggestions

Based on the partial-order ranking results of *GD* drivers in Ordos, differentiated grassland management should be implemented at the county level. In the western counties, *GD* is jointly driven by climatic constraints and human activities. Low precipitation, high aridity, and fragile grassland ecosystems increase the sensitivity of these areas to climate variability. In addition, grazing pressure and land-use activities in the western region further intensify grassland degradation. By contrast, land-use changes in the eastern counties are mainly driven by urbanisation and economic development, which are closely associated with higher population density, rapid urban expansion, coal-based industrial development, mining activities, and infrastructure construction.

Accordingly, based on the identified potential driver groups, a five-part policy recommendation is proposed for the following different county types: (1) urbanisation- and economic-development-dominated counties; (2) human-activity-dominated counties; (3) climate-dominated counties; (4) livelihood-development-dominated counties; and (5) multi-driver counties.

First, urbanisation and economic development were identified as the dominant driver groups in the four eastern counties and in WS. In these areas, local governments should prioritise delineating urban growth boundaries and accelerating the low-carbon transfor-

mation of coal-based industries. For instance, they should promote the development of water-saving technologies in coal mining and processing [74]. From an ecological protection perspective, greater investment is required to mitigate the ecological impacts of urbanisation. This includes enhancing comprehensive governance and ecological restoration of mining operations [73].

Second, human-activity-dominated counties, including HJ, ETKQ, and DS, should prioritise regulating grazing intensity, optimising livestock structure, improving grazing rotation systems, and promoting sustainable agricultural and pastoral practices. These measures can help reduce direct human disturbance and alleviate pressure on grassland ecosystems [75].

Third, the climate driver group was the dominant factor influencing *GD* in the less-developed western counties of WS, ETK, and ETKQ, where average annual precipitation is only 200–300 mm compared with 300–400 mm in the east [14]. This lower rainfall makes the climate the key driver of *GD* in these counties. Unlike the urbanised eastern counties, socioeconomic disturbances in ETK and ETKQ are relatively limited, further amplifying the role of climate drivers in *GD*. In such areas, ecological construction policies should prioritise grassroots and locally led actions to mitigate climate variability. For example, implementation of dynamic grazing bans, county drought preparedness (using fodder banks), and the promotion of high-value alternative livelihoods—such as ecotourism—can enhance local climate adaptation capacity.

Fourth, the livelihood-development-dominated county, DS, should prioritise improving livelihood sustainability through alternative income sources, such as ecotourism and ecological compensation.

Fifth, in multi-driver counties, such as ETKQ, WS, DLT, ZGE, YJHL, and DS, single-factor governance is insufficient as *GD* is affected by several interacting drivers. For these counties, intervention priorities should be determined according to the dominant driver identified by the POT–HDT results. The highest-ranked driver group should be treated as the primary governance target, while secondary driver groups should be addressed through supporting measures.

4.4. Advantages and Disadvantages of POT

The potential driver groups for *GD* in Ordos were identified using POT in combination with HDT. Building on previous applications in chemical hazard assessment [25], ecosystem services [26], and water quality evaluation [27], this study extends POT to grassland degradation by identifying potential driver groups at the county level to support targeted policy recommendations.

POT has several advantages over other commonly used methods. Unlike Principal Component Analysis (PCA), it does not reduce multiple indicators to linear combinations or a single composite score, allowing the original multidimensional information to be retained. Unlike Geographically Weighted Regression (GWR), POT does not require the specification of spatial weights or assume linear relationships between drivers and *GD*. It also differs from causal inference models because it does not estimate the independent causal effect of each driver. Instead, POT compares driver groups through multidimensional dominance relationships, while HDT clearly visualises their hierarchical levels, dominance relationships, and incomparability. These characteristics make POT–HDT suitable for identifying the relative influence of different driver groups and policies to prioritise across counties.

Despite its advantages, POT–HDT has several limitations. First, the analysis is conducted at the county level, which may mask intra-county heterogeneity. Therefore, dominant drivers should be interpreted as overall county-level patterns rather than uniform drivers across counties. Future studies could apply POT–HDT to finer spatial units, such as townships or

grids. Second, this study does not explicitly account for lagged effects between driving factors and changes in *GD*. The results reflect relative dominance patterns during the study period rather than delayed causal responses. Future research could use earlier driver data to predict subsequent changes in *GD* and explore potential delayed effects. Third, some indicators are strongly correlated, as shown by the Pearson correlation analysis (Figure S6). While POT-HDT does not require statistical independence, high correlations may increase shared influence within a driver group. POT-HDT does not remove this redundancy or estimate independent causal effects. Therefore, results should be interpreted as relative dominance patterns and associations with *GD*, rather than independent causal effects.

5. Conclusions

This study provides a comprehensive analysis of *GD* and *GR* in Ordos from 2000 to 2020, with a particular focus on the spatiotemporal patterns and primary driving forces behind these changes. The results demonstrate that, although significant progress has been made in restoring grasslands, degradation remains a persistent issue, driven predominantly by urbanisation and economic development. Between 2000 and 2020, 6.9% of the grassland area in Ordos underwent restoration, while 5.0% degraded. These findings indicate that restoration efforts have been relatively successful; however, the ongoing threat of degradation requires continued attention. Urbanisation and economic development were identified as the dominant factors driving *GD* in five of the region's eight counties.

The findings suggest that addressing *GD* in Ordos necessitates a region-specific policy approach. The eastern counties and WS, where urbanisation and economic development are dominant, should prioritise urban growth control, low-carbon transformation of coal-based industries, and ecological restoration of mining areas. Human-activity-dominated counties, including HJ, ETKQ, and DS, should focus on regulating grazing intensity and improving livestock management. By contrast, climate-dominated western counties, such as WS, ETK, and ETKQ, should strengthen drought adaptation and climate-resilient grassland management. For livelihood-development-dominated and multi-driver counties, alternative livelihoods, ecological compensation, and priority-based integrated governance should be promoted according to the dominant driver identified by POT-HDT.

This study underscores the importance of targeted, multidimensional strategies for managing fragile grassland ecosystems. The application of POT and the HDT has provided a robust framework for identifying the potential drivers of *GD*, yielding valuable insights for future conservation planning. By integrating these methods, this study not only quantifies the relative influence of various drivers but also visualises their hierarchical relationships, facilitating more informed, evidence-based decision-making for land management and policy development. Moreover, the framework and insights developed here can be applied to other regions with similar ecological challenges, extending the relevance of this study beyond Ordos.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/earth7040118/s1>, Figure S1: Comparison of candidate drivers between GD and non-degraded grassland (non-GD) areas in 2000 and 2020; Table S1: Comparison of potential driver values between degraded and non-degraded grasslands; Figure S2: Map of the net change in land use and land cover, 2000–2020; Figure S3: Net Change in Land Use/Cover in Ordos, 2000–2020; Figure S4: GD and GR in banner of Ordos between 2000–2020; Figure S5: All driver changes between 2000 and 2020; Table S2: Hasse diagrams for 2000 to 2020; Figure S6: Pearson Correlation Heatmap of Grassland Degradation Drivers (2000–2020).

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Abbreviations

The following abbreviations are used in this manuscript:

GD	Grassland Degradation
GR	Grassland Restoration
POT	Partial Order Theory
HDT	Hasse Diagram Technique
ETK	Etuoque
ETKQ	Etuoqueqian
DLT	Dalate
ZGE	Zhungeer
DS	Dongsheng
YJHL	Yijinhuoluo
HJ	Hangjin
WS	Wushen
GLC_FCS30	Global Land-Cover product with a Fine Classification System at 30 m resolution
IDW	Inverse Distance Weighting
FGMU	Fencing Grassland and Moving Users
BTSSCE	Beijing–Tianjin Sand Source Control Engineering Project
GGP	Grain for Green Program
NFCP	Natural Forests Conservation Program
ESCP	Ecosystem Services Compensation Project
GESAS	Grassland Ecological Subsidy and Award System
BTSSCE	Beijing–Tianjin–Sand Source Control Project
TNSDP	Three-North Shelterbelt Development Program
NPP	Net Primary Productivity
NDVI	Normalized Difference Vegetation Index
HBOYUA	Hohhot–Baotou–Ordos–Yulin Urban Agglomeration Development Plan

References

1. Yang, F.; Wang, Z.; Zhai, Y.; Yang, X.; Bao, T.; Wang, Y. Monitoring Vegetation Dynamics in Desertification Restoration Areas of Wuzhumuqin Grassland Ecosystem. *Appl. Sci.* **2025**, *15*, 6855. [\[CrossRef\]](#)
2. Liu, J.; Zhang, Z.; Xu, X.; Kuang, W.; Zhou, W.; Zhang, S.; Li, R.; Yan, C.; Yu, D.; Wu, S.; et al. Spatial Patterns and Driving Forces of Land Use Change in China during the Early 21st Century. *J. Geogr. Sci.* **2010**, *20*, 483–494. [\[CrossRef\]](#)
3. He, Y.; Liang, Y.; Liu, L.; Yin, Z.; Huang, J. Loss of Green Landscapes Due to Urban Expansion in China. *Resour. Conserv. Recycl.* **2023**, *199*, 107228. [\[CrossRef\]](#)
4. Bardgett, R.D.; Bullock, J.M.; Lavorel, S.; Manning, P.; Schaffner, U.; Ostle, N.; Chomel, M.; Durigan, G.; Fry, E.L.; Johnson, D.; et al. Combatting Global Grassland Degradation. *Nat. Rev. Earth Environ.* **2021**, *2*, 720–735. [\[CrossRef\]](#)
5. Hao, L.; Sun, G.; Liu, Y.; Gao, Z.; He, J.; Shi, T.; Wu, B. Effects of Precipitation on Grassland Ecosystem Restoration under Grazing Exclusion in Inner Mongolia, China. *Landsc. Ecol.* **2014**, *29*, 1657–1673. [\[CrossRef\]](#)
6. Mei, Y.; Batunacun; An, C.; Wu, Y.; Bao, Y.; Liu, K.; Feng, Y.; Hu, Y.; Hai, C.; Nendel, C. Identifying the Dominant Drivers of Grassland Degradation in Inner Mongolia, China. *Ecol. Indic.* **2025**, *179*, 114161. [\[CrossRef\]](#)
7. Zhao, Y.; Chang, C.; Zhou, X.; Zhang, G.; Wang, J. Land Use Significantly Improved Grassland Degradation and Desertification States in China over the Last Two Decades. *J. Environ. Manag.* **2024**, *349*, 119419. [\[CrossRef\]](#) [\[PubMed\]](#)
8. Arabameri, A.; Chandra Pal, S.; Costache, R.; Saha, A.; Rezaie, F.; Seyed Danesh, A.; Pradhan, B.; Lee, S.; Hoang, N.-D. Prediction of Gully Erosion Susceptibility Mapping Using Novel Ensemble Machine Learning Algorithms. *Geomat. Nat. Hazards Risk* **2021**, *12*, 469–498. [\[CrossRef\]](#)
9. Wang, S.; Dai, E.; Jia, L.; Wang, Y.; Huang, A.; Liao, L.; Cai, L.; Fan, D. Assessment of Multiple Factors and Interactions Affecting Grassland Degradation on the Tibetan Plateau. *Ecol. Indic.* **2023**, *154*, 110509. [\[CrossRef\]](#)
10. Chen, J.; Zhao, X.; Zhang, H.; Qin, Y.; Yi, S. Evaluation of the Accuracy of the Field Quadrat Survey of Alpine Grassland Fractional Vegetation Cover Based on the Satellite Remote Sensing Pixel Scale. *ISPRS Int. J. Geo-Inf.* **2019**, *8*, 497. [\[CrossRef\]](#)
11. Li, J.; Okin, G.S.; Alvarez, L.; Epstein, H. Quantitative Effects of Vegetation Cover on Wind Erosion and Soil Nutrient Loss in a Desert Grassland of Southern New Mexico, USA. *Biogeochemistry* **2007**, *85*, 317–332. [\[CrossRef\]](#)
12. Wang, J.; Brown, D.G.; Chen, J. Drivers of the Dynamics in Net Primary Productivity across Ecological Zones on the Mongolian Plateau. *Landsc. Ecol.* **2013**, *28*, 725–739. [\[CrossRef\]](#)
13. Hu, Y.; Nacun, B. An Analysis of Land-Use Change and Grassland Degradation from a Policy Perspective in Inner Mongolia, China, 1990–2015. *Sustainability* **2018**, *10*, 4048. [\[CrossRef\]](#)
14. Batunacun. Scenario Analysis of Ecosystem Service Changes—A Case Study of Ordos. Ph.D. Thesis, Institute of Geographical Science and Natural Resources Research, Chinese Academy of Sciences, Beijing, China, 2020.
15. Zhang, N.; Li, Z.; Feng, Y.; Li, X.; Tang, J. Development and Application of a Vegetation Degradation Classification Approach for the Temperate Grasslands of Northern China. *Ecol. Indic.* **2023**, *154*, 110857. [\[CrossRef\]](#)
16. Yan, H.; Ran, Q.; Hu, R.; Xue, K.; Zhang, B.; Zhou, S.; Zhang, Z.; Tang, L.; Che, R.; Pang, Z.; et al. Machine Learning-Based Prediction for Grassland Degradation Using Geographic, Meteorological, Plant and Microbial Data. *Ecol. Indic.* **2022**, *137*, 108738. [\[CrossRef\]](#)
17. Verburg, P.H.; Chen, Y.; Veldkamp, T.A. Spatial Explorations of Land Use Change and Grain Production in China. *Agric. Ecosyst. Environ.* **2000**, *82*, 333–354. [\[CrossRef\]](#)
18. Pochiraju, B.; Kollipara, H.S.S. Statistical Methods: Regression Analysis. In *Essentials of Business Analytics*; Pochiraju, B., Seshadri, S., Eds.; International Series in Operations Research & Management Science; Springer International Publishing: Cham, Switzerland, 2019; Volume 264, pp. 179–245.
19. Mohammed, S.; Budach, L.; Feuerpfeil, M.; Ihde, N.; Nathansen, A.; Noack, N.; Patzlaff, H.; Naumann, F.; Harmouch, H. The Effects of Data Quality on Machine Learning Performance on Tabular Data. *Inf. Syst.* **2025**, *132*, 102549. [\[CrossRef\]](#)
20. Fang, Y.; Zhao, X.; Liu, N.; Zhang, W.; Shi, W. Analyzing Spatiotemporal Variations and Driving Factors of Grassland in the Arid Region of Northwest China Surrounding the Tianshan Mountains. *Remote Sens.* **2024**, *16*, 1952. [\[CrossRef\]](#)
21. Xie, Y.; Sha, Z. Quantitative Analysis of Driving Factors of Grassland Degradation: A Case Study in Xilin River Basin, Inner Mongolia. *Sci. World J.* **2012**, *2012*, 169724. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Brüggemann, R.; Carlsen, L. Introduction to Partial Order Theory Exemplified by the Evaluation of Sampling Sites. In *Partial Order in Environmental Sciences and Chemistry*; Brüggemann, R., Carlsen, L., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 61–110.
23. Yue, L. Multi Criteria Decision Making Method of Poset with Weight. *Oper. Res. Manag. Sci.* **2018**, *27*, 26–31.
24. Brüggemann, R.; Patil, G.P. *Ranking and Prioritization for Multi-Indicator Systems: Introduction to Partial Order Applications*; Springer: New York, NY, USA, 2011.
25. Brüggemann, R.; Voigt, K. Antichains in Partial Order, Example: Pollution in a German Region by Lead, Cadmium, Zinc and Sulfur in the Herb Layer. *MATCH-Commun. Math. Comput. Chem.* **2011**, *67*, 731–744.

26. Tsonkova, P.; Böhm, C.; Quinkenstein, A.; Freese, D. Application of Partial Order Ranking to Identify Enhancement Potentials for the Provision of Selected Ecosystem Services by Different Land Use Strategies. *Agric. Syst.* **2015**, *135*, 112–121. [\[CrossRef\]](#)
27. Simon, U.; Brüggemann, R.; Pudenz, S.; Behrendt, H. Aspects of Decision Support in Water Management: Data Based Evaluation Compared with Expectations. In *Partial Order in Environmental Sciences and Chemistry*; Brüggemann, R., Carlsen, L., Eds.; Springer: Berlin/Heidelberg, Germany, 2006; pp. 221–236.
28. Wu, W.; De Pauw, E.; Zucca, C. Using Remote Sensing to Assess Impacts of Land Management Policies in the Ordos Rangelands in China. *Int. J. Digit. Earth* **2013**, *6*, 81–102. [\[CrossRef\]](#)
29. Zhu, L.; Sun, W.; Wu, J.; Fan, D. Spatiotemporal Distribution of Carbon Sink Indicators—NPP and Its Driving Analysis in Ordos City, China. *Appl. Sci.* **2023**, *13*, 6457. [\[CrossRef\]](#)
30. Fang, Z.; Ding, T.; Chen, J.; Xue, S.; Zhou, Q.; Wang, Y.; Wang, Y.; Huang, Z.; Yang, S. Impacts of Land Use/Land Cover Changes on Ecosystem Services in Ecologically Fragile Regions. *Sci. Total Environ.* **2022**, *831*, 154967. [\[CrossRef\]](#) [\[PubMed\]](#)
31. Jia, A.; Chen, F.; Feng, N.; Meng, D.; Zheng, S. Model Construction and Implementation of Ordos Energy Super Basin, NW China. *Pet. Explor. Dev.* **2024**, *51*, 1628–1640. [\[CrossRef\]](#)
32. Woodworth, M.D. Ordos Municipality: A Market-Era Resource Boomtown. *Cities* **2015**, *43*, 115–132. [\[CrossRef\]](#)
33. Woodworth, M.D. Frontier Boomtown Urbanism: City Building in Ordos Municipality, Inner Mongolia Autonomous Region, 2001–2011. Available online: <https://escholarship.org/uc/item/9cr46717> (accessed on 7 July 2026).
34. Batunacun; Wieland, R.; Lakes, T.; Yunfeng, H.; Nendel, C. Identifying Drivers of Land Degradation in Xilingol, China, between 1975 and 2015. *Land Use Policy* **2019**, *83*, 543–559. [\[CrossRef\]](#)
35. Liu, L.; Zhang, X.; Gao, Y.; Chen, X.; Shuai, X.; Mi, J. Finer-Resolution Mapping of Global Land Cover: Recent Developments, Consistency Analysis, and Prospects. *J. Remote Sens.* **2021**, *2021*, 5289697. [\[CrossRef\]](#)
36. Wang, Y.; Sun, Y.; Cao, X.; Wang, Y.; Zhang, W.; Cheng, X. A Review of Regional and Global Scale Land Use/Land Cover (LULC) Mapping Products Generated from Satellite Remote Sensing. *ISPRS J. Photogramm. Remote Sens.* **2023**, *206*, 311–334. [\[CrossRef\]](#)
37. Li, X.; An, C.; Batunacun; Feng, Y.; Liu, K.; Mei, Y. Partial Order Ranking of the Key Drivers of Grassland Conversion in the Urban–Grassland Interface: A Case Study of the Hohhot–Baotou–Ordos Region. *Appl. Sci.* **2025**, *15*, 5906. [\[CrossRef\]](#)
38. Nabil, M.; Zhang, M.; Wu, B.; Bofana, J.; Elnashar, A. Constructing a 30m African Cropland Layer for 2016 by Integrating Multiple Remote Sensing, Crowdsourced, and Auxiliary Datasets. *Big Earth Data* **2022**, *6*, 54–76. [\[CrossRef\]](#)
39. Cao, J.; Yeh, E.T.; Holden, N.M.; Qin, Y.; Ren, Z. The Roles of Overgrazing, Climate Change and Policy as Drivers of Degradation of China’s Grasslands. *Nomadic Peoples* **2013**, *17*, 82–101. [\[CrossRef\]](#)
40. Shao, L.; Chen, H.; Zhang, C.; Huo, X. Effects of Major Grassland Conservation Programs Implemented in Inner Mongolia since 2000 on Vegetation Restoration and Natural and Anthropogenic Disturbances to Their Success. *Sustainability* **2017**, *9*, 466. [\[CrossRef\]](#)
41. Hu, Y.; Batunacun. An Analysis of Land-Use and Land-Cover Change in the Zhujiang–Xijiang Economic Belt, China, from 1990 to 2017. *Appl. Sci.* **2018**, *8*, 1524. [\[CrossRef\]](#)
42. Hilckmann, A.; Bach, V.; Brüggemann, R.; Ackermann, R.; Finkbeiner, M. Partial Order Analysis of the Government Dependence of the Sustainable Development Performance in Germany’s Federal States. In *Partial Order Concepts in Applied Sciences*; Fattore, M., Brüggemann, R., Eds.; Springer International Publishing: Cham, Switzerland, 2017; pp. 219–228.
43. Batunacun; Nendel, C.; Hu, Y.; Lakes, T. Land-use Change and Land Degradation on the Mongolian Plateau from 1975 to 2015—A Case Study from Xilingol, China. *Land Degrad. Dev.* **2018**, *29*, 1595–1606. [\[CrossRef\]](#)
44. Esarey, A.; Haddad, M.A.; Lewis, J.I.; Harrell, S. (Eds.) *Greening East Asia: The Rise of the Eco-Developmental State*; University of Washington Press: Seattle, WA, USA, 2020.
45. Zhu, J.; Shang, Z.; Jiang, S.; Shi, Y.; Feng, Q.; Zhao, X.; Qi, X.; Yan, Y.; Su, Y.; He, J. Key scientific issues in grassland ecosystem conservation, restoration, and functional enhancement. *Natl. Nat. Sci. Found. China* **2024**, *38*, 658–667.
46. Ma, Q.; Long, Y.; Jia, X.; Wang, H.; Li, Y. Vegetation Response to Climatic Variation and Human Activities on the Ordos Plateau from 2000 to 2016. *Environ. Earth Sci.* **2019**, *78*, 709. [\[CrossRef\]](#)
47. Wu, X.; Hao, W.; Qu, G.; Yang, L. Spatial-Temporal Pattern of Vegetation Net Primary Productivity and Its Natural Driving Factors in Ordos Section of the Yellow River Basin. *Atmosphere* **2025**, *16*, 89. [\[CrossRef\]](#)
48. Mengke. Study on the Effects of Enclosing and Transferring on Grassland Productivity in Xilinguole. Master’s Thesis, Chinese Academy of Agricultural Sciences, Beijing, China, 2007.
49. Zeng, X.; Zhang, W.; Liu, X.; Cao, J.; Shen, H.; Zhao, X.; Zhang, N.; Bai, Y.; Yi, M. Change of Soil Organic Carbon after Cropland Afforestation in ‘Beijing-Tianjin Sandstorm Source Control’ Program Area in China. *Chin. Geogr. Sci.* **2014**, *24*, 461–470. [\[CrossRef\]](#)
50. Chen, Y.; Wu, Q.; Chen, N.X. Ecological Benefit Evaluation of the Beijing-Tianjin Sandstorm Source Control Project in Beijing. *Adv. Mater. Res.* **2011**, *356–360*, 2479–2483. [\[CrossRef\]](#)
51. Song, X.; Peng, C.; Zhou, G.; Jiang, H.; Wang, W. Chinese Grain for Green Program Led to Highly Increased Soil Organic Carbon Levels: A Meta-Analysis. *Sci. Rep.* **2014**, *4*, 4460. [\[CrossRef\]](#) [\[PubMed\]](#)

52. Bennett, M.T. China's Sloping Land Conversion Program: Institutional Innovation or Business as Usual? *Ecol. Econ.* **2008**, *65*, 699–711. [[CrossRef](#)]
53. El-Rawy, M.; Sayed, S.Y.; AbdelRahman, M.A.E.; Makhloof, A.; Al-Arifi, N.; Abd-Ellah, M.K. Assessing and Segmenting Salt-Affected Soils Using in-Situ EC Measurements, Remote Sensing, and a Modified Deep Learning MU-NET Convolutional Neural Network. *Ecol. Inform.* **2024**, *81*, 102652. [[CrossRef](#)]
54. Xia, C.; Cao, S. Determining the Success of China's Forest Conservation Policy: A Cost–Benefit Analysis of China's Natural Forest Conservation Program. *Earth Syst. Environ.* **2024**, *8*, 1795–1808. [[CrossRef](#)]
55. Démurger, S.; Pelletier, A. Volunteer and Satisfied? Rural Households' Participation in a Payments for Environmental Services Programme in Inner Mongolia. *Ecol. Econ.* **2015**, *116*, 25–33. [[CrossRef](#)]
56. Liu, M.; Liu, H. Analysis on the practice effects and problems of ecological compensation mechanism. *Chin. Fish. Econ.* **2015**, *33*, 33–38.
57. Mu, H.; Li, X.; Ma, H.; Du, X.; Huang, J.; Su, W.; Yu, Z.; Xu, C.; Liu, H.; Yin, D.; et al. Evaluation of the Policy-Driven Ecological Network in the Three-North Shelterbelt Region of China. *Landsc. Urban Plan.* **2022**, *218*, 104305. [[CrossRef](#)]
58. Zhai, J.; Wang, L.; Liu, Y.; Wang, C.; Mao, X. Assessing the Effects of China's Three-North Shelter Forest Program over 40 Years. *Sci. Total Environ.* **2023**, *857*, 159354. [[CrossRef](#)] [[PubMed](#)]
59. Sageri, Ma, J.; Siriguleng; Gao, X.; Su, Q. Benefit Analysis of the Grassland Ecological Protection reward-compensation mechanism policy in Ordos. *Grassl. Prataculture* **2016**, *28*, 3–5.
60. Li, H.; Zou, S.; Li, X. Analysis and evaluation of subsidy and incentive mechanism for grassland ecological protection in Xinjiang. *Herbiv. Livest.* **2019**, 51–55. [[CrossRef](#)]
61. Long, H.; Wu, X.; Wang, W.; Dong, G. Analysis of Urban-Rural Land-Use Change during 1995–2006 and Its Policy Dimensional Driving Forces in Chongqing, China. *Sensors* **2008**, *8*, 681–699. [[CrossRef](#)] [[PubMed](#)]
62. Jia, J.; Ma, G.; Qin, C.; Wang, L. Place-Based Policies, State-Led Industrialisation, and Regional Development: Evidence from China's Great Western Development Programme. *Eur. Econ. Rev.* **2020**, *123*, 103398. [[CrossRef](#)]
63. Zhao, Y.; Yin, Z.; Zhang, X.; Kuang, Y.; Zhao, Y.; Liu, J.; Zhang, Q.; Li, Y. Collaborative Control Path of Pollution and Carbon Reduction in Industrial Field in Hohhot–Baotou–Ordos Region of Inner Mongolia. *Heliyon* **2024**, *10*, e40695. [[CrossRef](#)] [[PubMed](#)]
64. Xu, X.; Xu, X. Can Resource Policy Adjustments Effectively Curb Regional “Resource Curse”? New Evidences from the “Energy Golden Triangle Area” of China. *Resour. Policy* **2021**, *73*, 102146. [[CrossRef](#)]
65. Liu, Y. Research on Ecological Risk Assessment and Prediction Simulation of Hohhot-Baotou -Ordos-Yulin Urban Agglomeration Areas. Master's Thesis, Inner Mongolia University of Finance and Economics, Hohhot, China, 2024.
66. Chen, Y.; Cao, W.; Ding, K.; Wang, S.; Du, P. Comprehensive Assessment of Ecological Vulnerability in Arid-Semiarid Regions Based on the ACEVI Model and ANP-EWM Method: A Case Study of the HBOYUA (China). *Ecol. Inform.* **2025**, *90*, 103344. [[CrossRef](#)]
67. Miao, H.; Zhou, H. Evaluation of County-Level Economic Efficiency and Its Spatiotemporal Differentiation in Hohhot-Baotou-Ordos-Yulin Urban Agglomeration in China. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 99. [[CrossRef](#)]
68. Tao, S.; Fang, J.; Zhao, X.; Zhao, S.; Shen, H.; Hu, H.; Tang, Z.; Wang, Z.; Guo, Q. Rapid Loss of Lakes on the Mongolian Plateau. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 2281–2286. [[CrossRef](#)] [[PubMed](#)]
69. Zeng, X.; Liu, Z.; He, C.; Ma, Q.; Wu, J. Quantifying Surface Coal-Mining Patterns to Promote Regional Sustainability in Ordos, Inner Mongolia. *Sustainability* **2018**, *10*, 1135. [[CrossRef](#)]
70. Qian, T.N.; Bagan, H.; Kinoshita, T.; Yamagata, Y. Spatial-Temporal Analyses of Surface Coal Mining Dominated Land Degradation in Hologol, Inner Mongolia. *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.* **2014**, *7*, 1675–1687. [[CrossRef](#)]
71. Xu, X.; Cai, H.; Sun, D.; Hu, L.; Banson, K. Impacts of Mining and Urbanization on the Qin-Ba Mountainous Environment, China. *Sustainability* **2016**, *8*, 488. [[CrossRef](#)]
72. Yang, X.; Scuderi, L.A.; Wang, X.; Scuderi, L.J.; Zhang, D.; Li, H.; Forman, S.; Xu, Q.; Wang, R.; Huang, W.; et al. Groundwater Sapping as the Cause of Irreversible Desertification of Hunshandake Sandy Lands, Inner Mongolia, Northern China. *Proc. Natl. Acad. Sci. USA* **2015**, *112*, 702–706. [[CrossRef](#)] [[PubMed](#)]
73. Wang, L. Main Eco-Environmental Problems of Urbanization in Ordos Area. Master's Thesis, Inner Mongolia University, Hohhot, China, 2017.
74. Dong, S.; Xu, B.; Yin, S.; Han, Y.; Zhang, X.; Dai, Z. Water Resources Utilization and Protection in the Coal Mining Area of Northern China. *Sci. Rep.* **2019**, *9*, 1214. [[CrossRef](#)] [[PubMed](#)]
75. Zhang, J.; Ren, X.; Liu, X.; Biswas, A.; Fan, Y.; Wang, X. Synergistic Climate-Human Interactions Promote Grassland Restoration over Degradation: Evidence from China's Major Grassland Ecosystems. *J. Environ. Manag.* **2026**, *400*, 128782. [[CrossRef](#)] [[PubMed](#)]

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