Environmental interpretation of spatial heterogeneity in the trade-offs and synergies of land use functions: A study based on the XGBoost-SHAP model Postprint

Authors: FENG Haoyuan, Xuebin Zhang, Peiji Shi, SHI Jing, WANG Ziyang, ZHANG Xuebin

Date: 2025-10-22T00:00:00+00:00

Abstract

Accurately revealing the spatial heterogeneity in the trade-offs and synergies of land use functions (LUFs) and their driving factors is imperative for advancing sustainable land utilization and optimizing land use planning. This is especially critical for ecologically vulnerable inland river basins in arid regions. However, existing methods struggle to effectively capture complex nonlinear interactions among environmental factors and their multifaceted relationships with trade-offs and synergies of LUFs, especially for the inland river basins in arid regions. Consequently, this study focused on the middle reaches of the Heihe River Basin (MHRB), an arid inland river basin in northwestern China. Using land use, socioeconomic, meteorological, and hydrological data from 2000 to 2020, we analyzed the spatiotemporal patterns of LUFs and their trade-off and synergy relationships from the perspective of production, living, ecological functions. Additionally, we employed an integrated Extreme Gradient Boosting (XGBoost)-SHapley Additive exPlanations (SHAP) framework to investigate the environmental factors influencing the spatial heterogeneity in the trade-offs and synergies of LUFs. Our findings reveal that from 2000 to 2020, the production, living, and ecological functions of land use within the MHRB exhibited an increasing trend, demonstrating a distinct spatial pattern of "high in the southwest and low in the northeast''. Significant spatial heterogeneity defined the trade-off and synergistic relationships, with trade-offs dominating human activity-intensive oasis areas, while synergies prevailed in other areas. During the study period, synergistic relationships between production and living functions and between production and ecological functions were relatively robust, whereas synergies in living-ecological functions remained weaker. Natural factors (digital elevation model (DEM), annual mean temperature, Normalized

Difference Vegetation Index (NDVI), and annual precipitation) emerged as the primary factors driving the trade-offs and synergies of LUFs, followed by socioeconomic factors (population density, Gross Domestic Product (GDP), and land use intensity), while distance factors (distance to water bodies, distance to residential areas, and distance to roads) exerted minimal influence. Notably, the interactions among NDVI, annual mean temperature, DEM, and land use intensity exerted the most substantial impacts on the relationships among LUFs. This study provides novel perspectives and methodologies for unraveling the mechanisms underlying the spatial heterogeneity in the trade-offs and synergies of LUFs, offering scientific insights to inform regional land use planning and sustainable natural resource management in inland river basins in arid regions.

Full Text

Preamble

J Arid Land (2025) 17(10): 1378–1401
doi: 10.1007/s40333-025-0058-y; CSTR: 32276.14.JAL.0250058y
Science Press Springer-Verlag

Environmental interpretation of spatial heterogeneity in the trade-offs and synergies of land use functions: A study based on the XGBoost-SHAP model

FENG Haoyuan[12], ZHANG Xuebin[1]*, SHI Peiji[1], SHI Jing[3], WANG Ziyang[1]

[1] College of Geography and Environmental Sciences, Northwest Normal University, Lanzhou 730070, China
[2] Engineering Research Center for Ecological and Environmental Damage Assessment of Gansu Province, Northwest Normal University, Lanzhou 730070, China
[3] College of Ecology, Lanzhou University, Lanzhou 730000, China

Abstract: Accurately revealing the spatial heterogeneity in the trade-offs and synergies of land use functions (LUFs) and their driving factors is imperative for advancing sustainable land utilization and optimizing land use planning, especially for ecologically vulnerable inland river basins in arid regions. However, existing methods struggle to effectively capture complex nonlinear interactions among environmental factors and their multifaceted relationships with trade-offs and synergies of LUFs, particularly for inland river basins in arid regions. Consequently, this study focused on the middle reaches of the Heihe River Basin (MHRB), an arid inland river basin in northwestern China. Using land use, socioeconomic, meteorological, and hydrological data from 2000 to 2020, we analyzed the spatiotemporal patterns of LUFs and their trade-off and synergy relationships from the perspective of production, living, and ecological functions. Additionally, we employed an integrated Extreme Gradient Boosting

(XGBoost)-SHapley Additive exPlanations (SHAP) framework to investigate the environmental factors influencing the spatial heterogeneity in the trade-offs and synergies of LUFs. Our findings reveal that from 2000 to 2020, the production, living, and ecological functions of land use within the MHRB exhibited an increasing trend, demonstrating a distinct spatial pattern of "high in the southwest and low in the northeast." Significant spatial heterogeneity defined the trade-off and synergistic relationships, with trade-offs dominating human activity-intensive oasis areas, while synergies prevailed in other areas. During the study period, synergistic relationships between production and living functions and between production and ecological functions were relatively robust, whereas synergies in living-ecological functions remained weaker. Natural factors (digital elevation model (DEM), annual mean temperature, Normalized Difference Vegetation Index (NDVI), and annual precipitation) emerged as the primary factors driving the trade-offs and synergies of LUFs, followed by socioeconomic factors (population density, Gross Domestic Product (GDP), and land use intensity), while distance factors (distance to water bodies, distance to residential areas, and distance to roads) exerted minimal influence. Notably, the interactions among NDVI, annual mean temperature, DEM, and land use intensity exerted the most substantial impacts on the relationships among LUFs. This study provides novel perspectives and methodologies for unraveling the mechanisms underlying the spatial heterogeneity in the trade-offs and synergies of LUFs, offering scientific insights to inform regional land use planning and sustainable natural resource management in inland river basins in arid regions.

Keywords: production function; living function; ecological function; trade-offs and synergies; Extreme Gradient Boosting (XGBoost); SHapley Additive exPlanations (SHAP); Heihe River Basin

*Corresponding author: ZHANG Xuebin (Email: zhangxb@nwnu.edu.cn)
Received 2025-04-25; revised 2025-09-03; accepted 2025-09-08

http://jal.xjegi.com; www.springer.com/40333

Citation: FENG Haoyuan, ZHANG Xuebin, SHI Peiji, SHI Jing, WANG Ziyang. 2024. Environmental interpretation of spatial heterogeneity in the trade-offs and synergies of land use functions: A study based on the XGBoost-SHAP model. Journal of Arid Land, 17(10): 1378–1401. https://doi.org/10.1007/s40333-025-0058-y; https://cstr.cn/32276.14.JAL.0250058y

1 Introduction

Land use functions (LUFs) denote the integrated capabilities of terrestrial resources to provide both tangible and intangible goods and services to human populations through direct and indirect pathways. These functions serve as fundamental pillars in maintaining planetary life-support systems, while also advancing societal welfare and fostering sustainable economic progress [?, ?].

Rapid socioeconomic development, accelerated urbanization, and intense human activities have led to challenges such as regional economic imbalance, uncoordinated resource allocation, inadequate institutional safeguards, and inefficient land use [?, ?, ?, ?]. These issues have significantly impacted the trade-offs and synergies of LUFs in China, particularly in arid inland river basins with relatively underdeveloped economies [?].

Confronting globally significant human-land conflicts and critical sustainability challenges in arid regions [?], these issues have generated increased societal demands for multifunctional land utilization and governance [?]. Complex trade-off and synergy relationships exist among distinct land use functional systems [?], and understanding their interactions and driving factors is essential for optimizing land use configurations, with profound implications for advancing spatial planning and promoting sustainable land management. However, accurately understanding the spatial complexity and heterogeneity underlying interactions between diverse LUFs in inland river basins remains a fundamental challenge. This study introduces a novel modeling approach to analyze the driving factors of spatial heterogeneity in the trade-offs and synergies of LUFs, aiming to identify key determinants and reveal their underlying operational mechanisms.

Amid a heightened national emphasis on ecological issues and a growing awareness of ecological security [?, ?, ?], the trade-offs and synergies of LUFs have become a central topic of research in related fields. The diversity of LUFs, spatial heterogeneity, and human demand preferences result in dynamic interactions among these functions, predominantly characterized by trade-offs and synergies [?, ?, ?, ?]. Trade-offs are typically expressed through resource competition and spatial conflicts between functions, while synergies reflect mutual enhancement and coordinated development [?]. Current research on these relationships has been conducted across multiple spatial scales, including watersheds, urban agglomerations, cities, and provinces [?, ?, ?]. These studies focus on conceptual frameworks, theoretical foundations, spatiotemporal patterns, influencing factors, multiscale effects, and relationship dynamics [?, ?, ?, ?]. Overall, while current quantification methods for the trade-offs and synergies of LUFs are largely grounded in analytical frameworks derived from ecosystem service research, existing assessments predominantly emphasize static, macro-scale analyses. Investigations systematically exploring the spatiotemporal dynamics of these nonlinear relationships through a spatial heterogeneity lens remain limited. Consequently, inadequate understanding of spatial distribution patterns and driving factors hinders evidence-based decision support for effective land management policies.

In the context of spatial heterogeneity research, the Geographically Weighted Regression (GWR) model is widely acknowledged as an effective method [?], which has been extensively applied in fields such as geography, economics, natural resource management, and urban planning studies [?]. However, the GWR model is constrained by localized hypothesis constraints, computational complexity, and limited capacity for processing high-dimensional data and model interpretability [?]. For instance, the GWR model assumes linear relationships, including that all explanatory variables operate at the same spatial scale and determines a single bandwidth across all regression coefficients. This approach may obscure scale variations in the operating scales of these variables and undermine the accuracy of the corresponding coefficient estimates [?]. These challenges necessitate the development of innovative methodological approaches to enhance spatial analysis frameworks.

Recent advancements in machine and deep learning algorithms have facilitated the extraction of features and patterns from large datasets, offering more accurate and efficient solutions to complex problems [?, ?]. Methods such as Gradient Boosting Decision Tree (GBDT), Extreme Gradient Boosting (XGBoost), and Random Forest (RF) have been applied to quantify spatial heterogeneity. The XGBoost model, an enhanced version of GBDT incorporating regularization to mitigate overfitting, demonstrates superior performance in both predictive accuracy and computational efficiency, and has been widely adopted in ecology, Geographic Information System (GIS), and computer science [?, ?]. Compared with traditional approaches like GWR, XGBoost is particularly effective in capturing spatial heterogeneity without relying on data generation assumptions, effectively addressing nonlinear and complex interactions [?]. However, XGBoost is limited by opaque computational processes, with restricted interpretability of the relationship between input data and output results, and is typically regarded as a black-box model. In contrast, SHapley Additive exPlanations (SHAP) is an interpretability framework based on the Shapley value concept from cooperative game theory; it can effectively identify key features and explore complex interactions among feature variables [?]. Therefore, investigating spatial heterogeneity in the trade-offs and synergies of LUFs using the integrated XGBoost-SHAP framework can provide more precise guidance for sustainable land resource management.

The Heihe River Basin (HRB), a quintessential inland river system in northwestern China, functions as a critical ecological zone in maintaining regional balance and combating desertification [?, ?, ?]. Its midstream region, characterized by oasis ecosystems, supports high population density and intensive socioeconomic activities, functioning as both a vital ecological barrier and grain production base [?, ?]. However, threats from desertification, urban expansion, and water scarcity have become major ecological challenges in this area [?], posing severe challenges to sustainable development. This study focuses on the middle reaches of the Heihe River Basin (MHRB), analyzing the spatiotemporal evolution patterns of LUFs as well as the spatial distribution features of trade-offs and synergies among these functions from the production-living-ecological perspective. Furthermore, based on the integrated XGBoost-SHAP model, this study interprets the characteristics of environmental factors influencing the spatial heterogeneity in the trade-offs and synergies of LUFs, with the aim of providing scientific support for watershed spatial planning and sustainable natural resource management in the inland river basins in arid regions.

2 Materials and Methods

2.1 Study area

The MHRB (38°08 -40°55 N, 97°51 -101°36 E), which is situated in the central Hexi Corridor and constitutes a critical component of the HRB, encompasses cities, counties, and districts including Jinta, Jiayuguan, Suzhou, Sunan, Gaotai, Linze, Ganzhou, Minle, and Shandan (Fig. 1 [Figure 1: see original paper]).

The annual temperature ranges from -11.3°C to 9.5°C (from south to north) and the annual precipitation varies between 79 and 701 mm, characterizing a typical temperate continental arid climate. The MHRB constitutes a typical desert-oasis composite ecosystem composed of two primary geomorphic units: the oasis plain region and the desert region. The oasis plain region features flat terrain and is densely populated (over 65% of the basin' s total population), with the population density exceeding the regional level of the Hexi Corridor. This fertile alluvial zone serves as the MHRB' s primary agricultural base, contributing over 70% of both cultivated land and grain output. However, intensive agricultural activities have rendered this area the most water-consumptive region, with a relatively high degree of aridity [?]. The desert region is characterized by a transitional landscape of Gobi desert interspersed with fragmented oases, with extreme water scarcity (scarce precipitation and intense evaporation), fragile ecosystems, severe aeolian sand encroachment, and land degradation, thereby constituting a key area for ecological conservation and management in the MHRB [?]. In recent years, rapid population growth and socioeconomic development have intensified human-land conflicts within the basin, leading to severe ecological and social challenges [?]. These dynamics have significantly influenced the evolution of LUFs, posing significant challenges to sustainable development in the basin.

Fig. 1 Overview of the study area (middle reaches of the Heihe River Basin) based on digital elevation model (DEM; a) and spatial distribution of land use types in the study area (b)

2.2 Data sources

The data used in this study primarily consist of land use, socioeconomic, meteorological, and hydrological data, with specific sources detailed in Table 1 . Among these, land use data were interpreted using human-computer interactive visual interpretation, with an overall accuracy exceeding 88.95%. This dataset comprises 6 first-level classifications and 25 second-level classifications. Wind speed and precipitation data were sourced from the China Meteorological Data Service Center. By applying spatial interpolation to station observations, we obtained monthly number of precipitation days, monthly average wind speeds, and monthly counts of days with mean wind speeds exceeding 5 m/s at a height of 2 m above ground for the years 2000 and 2020. Slope and slope direction data were calculated from digital elevation model (DEM). Socio-economic data including residential areas, water bodies, and road networks were extracted from the land use data, and distance metrics were derived using proximity analysis. All spatial datasets were uniformly projected into the uniform coordinate system (WGS_{{{1984}}_{{Albers}}}) and resampled to a consistent resolution of 500 m$×$500 m grid cells using the Cubic Convolution interpolation method. This technique can estimate pixel values by fitting a smooth curve based on 16 neighboring pixels, making it particularly suitable for continuous data use.

2.3 LUF indicator system

This study classified LUFs into production, living, and ecological categories through systematic integration of the natural and anthropogenic characteristics within the MHRB, guided by principles of practicality and operationalizability [**?**, **?**]. The production function is represented exclusively by food supply, primarily because the MHRB in Zhangye City serves as a major commercial grain base in the Hexi Corridor, where agricultural production dominates the regional economic structure [**?**, **?**]. Accordingly, our calculation integrated outputs of grain, meat, dairy, and aquatic products, which are spatially allocated using Normalized Difference Vegetation Index (NDVI) to quantify the capacity for effective agricultural provisioning and fulfillment of fundamental production objectives [**?**]. Living function was measured through residential carrying capacity (reflecting the capacity of land resources to accommodate human settlements) and economic carrying capacity (representing the capacity of economic systems to sustain living standards). For ecological function, we selected the following four services: wind erosion control, water yield, carbon storage, and habitat quality. Given the vast desert region that constrains human settlements to oases, wind erosion control proves critical for maintaining oasis ecological security. Water yield is essential for maintaining a stable water supply for production and domestic use, while carbon storage and habitat quality reflect climate regulation capacity and the status of biodiversity conservation, respectively. Computational formulas for each sub-function are detailed in Table 2 .

2.4 Carbon density and its adjustment

Accurately calibrating carbon density parameters constitutes a critical prerequisite for regional carbon storage quantification. This study estimated carbon density based on four components for different land use types in the MHRB: aboveground vegetation carbon density, belowground vegetation carbon density, soil carbon density, and carbon density of dead organic matter [**?**]. In the process of carbon density coefficient adjustment, regional climate characteristics and soil properties should be considered [**?**, **?**]. Therefore, we modified the carbon density coefficients according to regional climate information and carbon density data specific to the MHRB.

The adjustment process considered precipitation and temperature effects on both biomass and soil carbon density. For biomass carbon density, adjustment coefficients were calculated based on annual precipitation and temperature differences between the MHRB and national reference values. For soil carbon density, adjustments were made based on precipitation patterns. The integrated adjustment coefficient for biomass carbon density combines both precipitation and temperature effects, enabling more accurate representation of regional carbon storage capacity.

2.5 Determination of LUFs

In this study, we quantified three LUFs at a spatial resolution of 500 m$\times$500 m using a grid-based method and multidimensional indicators with diverse attributes. Given that higher values for each sub-function denote greater functional intensity, with larger magnitudes corresponding to stronger performance, all indicators exert unidirectional positive effects on integrated assessment of land use functionality without hierarchical differentiation. Consequently, this study employed an equal weighting method combined with spatial overlay techniques to comprehensively evaluate LUFs.

Since the production functionality is represented exclusively by grain output in this framework, it is operationally equivalent to grain production metrics [**?**]. Additionally, due to differences in the measurement units of the indicators, normalization was performed prior to integration. The normalization process and the calculation formulas for each function are as follows:

where Yi denotes the normalized value of the grid cell i; and Xi, Xmin, and Xmax represent the value of the grid cell i, the minimum value, and the maximum value within the raster dataset, respectively.

where LF denotes the living function; and VPi and NFPi represent the normalized residential carrying capacity and economic carrying capacity, respectively.

where EF denotes the ecological function; and CTi, SLi, Wi, and Qi represent the normalized carbon storage, wind erosion control, water yield, and habitat quality, respectively.

To clarify the spatiotemporal patterns of LUFs in the MHRB, this study employed the natural breaks method to classify the intensities of production, living, and ecological functions into five levels: high, higher, medium, lower, and low. The assessment data for each LUF from 2000 to 2020 were spatially overlaid and visualized.

2.6 Temporal scale trade-off and synergy assessment

Pearson correlation analysis has been widely used and empirically validated in numerous studies to quantify the trade-offs and synergies of LUFs [**?**, **?**]. Therefore, this study employed ArcGIS 10.7 and SPSS 25.0 software to first extract LUF data and subsequently apply Pearson correlation coefficients to quantify functional trade-offs and synergies. The Pearson correlation coefficient was calculated as follows:

where rxy denotes the correlation coefficient; m denotes the sample size; xi and yi represent the values of two distinct LUFs for grid cell i; and $\bar{x}$ and $\bar{y}$ are the average values of two LUFs. A synergistic relationship (positive correlation) exists when rxy>0.00, whereas rxy<0.00 suggests a trade-off relationship (negative correlation). If rxy=0.00, there is no correlation between LUFs.

2.7 Spatial scale trade-off and synergy assessment

Root Mean Square Error (RMSE) has been extensively applied in the spatial analyses of trade-offs and synergies of LUFs [?, ?, ?]. Consequently, this study employed RMSE to quantify the spatial trade-offs and synergies of LUFs in the MHRB. RMSE extends traditional trade-off analysis to account for spatial heterogeneity in rates of variation, thereby addressing the absence of explicit spatial information [?].

In this study, the difference in LUFs between 2020 and 2000 was used as the fundamental variable to capture historical spatial changes. The RMSE formula is as follows:

where LUFst denotes the standardized difference between two periods of LUFs; and LUFst denotes the expected value of the LUFst. RMSE measures the vertical distance from discrete points to the 1:1 line. An RMSE value closer to 1.00 indicates stronger trade-offs, whereas a value closer to zero reflects stronger synergies [?, ?]. Following previous research [?], this study classified the RMSE values into five distinct levels—strong synergy, weak synergy, not relevant, weak trade-off, and strong trade-off—in ascending order using the natural breaks method.

2.8 Machine learning models

Machine learning models can quantify the mechanisms of interaction between environmental factors and trade-offs/synergies of LUFs, and are particularly effective for analyzing nonlinear relationships with large datasets. In this study, we adopted four machine learning models: Support Vector Regression (SVR), RF, Linear Regression (LR), and XGBoost. The dataset was divided into 70% for training and 30% for testing. We adjusted the hyperparameters of each model using the randomized grid search method, and selected the optimal model based on goodness-of-fit (R^2), RMSE (where lower values indicate smaller deviations between predicted and observed values), and prediction–observation distance metrics.

Although the feature importance values from the XGBoost model can identify which environmental variables are significant, this approach is limited in directly quantifying the interactive effects of environmental factors on the dependent variable. To address this limitation, we introduced the SHAP method as a complementary analytical tool to enhance the interpretability and depth of model results. The SHAP framework provides two complementary perspectives: global interpretability and local interpretability [?, ?]. Global interpretability illustrates the overall contribution of each feature across the entire dataset using SHAP summary plots, while local interpretability employs SHAP force plots to decompose individual predictions and their feature-specific contributions, which is particularly effective in revealing interactions among features [?]. Furthermore, the application of SHAP significantly improves model transparency in explaining complex nonlinear relationships, thereby mitigating the limitations of interpretability inherent in traditional LR model.

where i denotes the contribution of feature i; S denotes the subset that does not include the feature i; L denotes the set of l features; and f(S {i}) and f(S) denote the model outcomes with and without feature i, respectively.

LUF dynamics are shaped by the integrated effects of regional natural environments and socioeconomic development, thereby influencing trade-off and synergy relationships among LUFs. Aligned with the study area' s context and guided by principles of factor representativeness and data availability, we selected 12 representative driving factors across three dimensions—socioeconomic attributes, geographic location, and natural conditions—to analyze variations in the trade-offs and synergies of LUFs. Socioeconomic factors encompass population density, Gross Domestic Product (GDP), and land use intensity. Distance factors (geographic location) comprise distance to residential areas, distance to water bodies, and distance to roads. Natural factors include NDVI, annual precipitation, annual mean temperature, slope direction, slope, and DEM. The spatial distribution of each influencing factor is shown in Figure 2 [Figure 2: see original paper].

Fig. 2 Spatial distribution of 12 influencing factors on the trade-offs and synergies of land use functions (LUFs). (a), X_1 (population density); (b), X_2 (Gross Domestic Product, GDP); (c), X_3 (land use intensity); (d), X_4 (distance to residential areas); (e), X_5 (distance to water bodies); (f), X_6 (distance to roads); (g), X_7 (Normalized Difference Vegetation Index, NDVI); (h), X_8 (annual precipitation); (i), X_9 (annual mean temperature); (j), X_{10} (slope direction); (k), X_{11} (slope); (l), X_{12} (DEM).

3 Results

3.1 Spatiotemporal evolution characteristics of LUFs

Statistical analysis revealed that spatial declines in all three functions were negligible, whereas increases were more evident. Consequently, spatial changes were categorized into three levels: unchanged, low-level increase, and high-level increase (Fig. 3 [Figure 3: see original paper]). Consistent spatiotemporal change patterns were observed across all three LUFs during both 2000–2010 and 2010–2020 periods, manifesting progressive growth trends. This continuity stemmed from the desert-oasis ecosystem matrix that characterized the study area, wherein natural constraints mediated socioeconomic development-driven land use changes into persistent yet gradual pathways. Consequently, our analysis prioritized holistic change dynamics of land use over the full 2000–2020 timeframe.

During 2000–2020, the production function of the MHRB showed a significant increasing trend, with food yield increasing from 35.9 to 91.6 t/km^2. Spatially, the oasis plain region exhibited higher production capacity due to sufficient water resources and favorable climatic conditions supporting food production. Conversely, the desert region under the influence of the Badain Jaran Desert featured an arid climate with predominantly gravelly and sandy soils that hindered vegetation growth, resulting in diminished food supply capacity. Over the last two decades, areas with high-level production function increased by 20.92%, areas with medium-level production function by 5.29%, and areas with lower-level production function by 20.93%, while areas with low-level production function decreased by 46.53%. Areas with higher-level production function remained relatively stable with only a 0.21% increase. This transformation primarily stemmed from recent consolidation of fragmented cultivated lands into centralized, large-scale high-yield fields, coupled with modernized infrastructure including high-efficiency irrigation and advanced management systems, which dramatically enhanced productivity and expanded high-efficiency oasis zones. Concurrently, population growth and economic drivers further propelled cultivated land expansion.

The living function demonstrated an increasing trend during the study period, with the mean value rising from 0.007 in 2000 to 0.036 in 2020. Elevated living function levels were particularly evident in Jiayuguan, Suzhou, Ganzhou, and Minle, primarily due to their concentrated populations, higher levels of economic development, and larger residential carrying capacity, while other areas exhibited comparatively lower living function levels. In 2000, areas with high- and higher-level living function were primarily distributed in localized regions of Jiayuguan, Suzhou, and Ganzhou, constituting 0.30% and 0.33% of the total area, respectively. Areas with medium-level living function were mainly concentrated in Suzhou and Ganzhou, comprising 5.58% of the total area. Areas with lower-level living function predominated in the oasis zones of Jinta, Sunan, Gaotai, Ganzhou, Minle, and Shandan, covering 29.36% of the study area. The remaining 64.43% was classified as low-level living function areas. By 2020, the proportional coverages of areas with medium-, higher-, and high-level living function had increased significantly to 8.33%, 8.37%, and 15.82% of the total study area, respectively, while the coverages of areas with lower- and low-level living function exhibited declining trends. Overall, the spatial configuration of living function underwent substantial transformations over the last two decades. The most pronounced increases occurred in Jiayuguan, Suzhou, and Ganzhou, driven by rapid population growth and economic development during this period, thereby substantially enhancing living security levels.

From 2000 to 2020, ecological function exhibited limited temporal and spatial variations, with the mean value increasing marginally from 0.96 to 0.97. Areas with high- and higher-level ecological function were observed in Sunan and the southern parts of Shandan, primarily due to their proximity to the Qilian Mountains, which ensures a stable water supply from abundant precipitation and glacial meltwater, along with favorable ecological conditions. Oasis zones nourished by the HRB formed expansive contiguous oases with high vegetation coverages, which were categorized mainly as areas with medium-level ecological function, while the remaining areas were dominated by lower- and low-level ecological function. Notably, oasis areas showed functional enhancement due to recent ecological restoration initiatives (e.g., integrated watershed industrial management of mountains-rivers-forests-farmlands-lakes-grasslands-deserts) and eco-transformation. Conversely, the arid and environmentally harsh Badain Jaran Desert in the desert region remains ecologically fragile, as implementing effective conservation measures proves impractical under such extreme climatic constraints, resulting in persistently weak ecological performance.

Fig. 3 Spatial distribution of areas with different levels of production, living, and ecological functions in 2000 (a–c), 2010 (d–f), and 2020 (g–i), as well as area changes in production, living, and ecological functions from 2000 to 2020 (j-l)

3.2 Spatial distribution characteristics of trade-offs and synergies of LUFs

This study quantified the overall and spatial trade-offs and synergies of LUFs in the MHRB from 2000 to 2020. Compared with the full-period (2000–2020) pattern, both sub-periods (2000–2010 and 2010–2020) exhibited weaker trade-off and synergy intensities (Fig. 4 [Figure 4: see original paper]). With the exception of a slightly negative association between production and living functions during 2010–2020, all other inter-functional relationships maintained consistent trade-off and synergy directions with the full-period analysis. Spatially, sub-period configurations demonstrated strong similarity to long-term distributions (Fig. 5 [Figure 5: see original paper]). These findings indicate that short-term fluctuations in human activities or natural conditions trigger localized and limited trade-off and synergy responses. Conversely, long-term cumulative effects progressively amplify these interactions, leading to broadly intensified trade-offs and synergies.

From a functional perspective, the full period 2000–2020 demonstrated strong synergistic relationships between production and living functions and between production and ecological functions, with correlation coefficient (r) values of 0.38 and 0.33, respectively (Fig. 4). The living-ecological function pair exhibited a weaker synergy, with a relatively low coefficient value (r=0.06). Spatially, strong trade-offs in production-living functions were observed in localized areas within Jinta, Suzhou, Sunan, Gaotai, and Ganzhou during 2000–2020 (Fig. 5g-i), accounting for 1.84% of the total study area. Areas exhibiting weak trade-offs and no significant correlations between production and living functions were concentrated in oasis zones, covering 7.22% and 9.54% of the total study area, respectively. Areas with weak and strong synergies in production-living functions were mainly located in non-oasis zones, with proportions of 66.24% and 15.31%, respectively. The spatial distribution of trade-offs and synergies in production-ecological functions was similar to that in production-living functions, with the area proportions of strong trade-offs, weak trade-offs, no significant correlation, weak synergies, and strong synergies being 2.11%, 7.23%, 10.40%, 64.91%, and 15.42%, respectively. For the relationship of living and ecological functions, strong synergies dominated spatially (84.33% of the total study area), followed by weak synergies (10.70%) concentrated in Suzhou and Ganzhou. Overall, production-living and production-ecological function pairs exhibited stronger synergies, while living-ecological function pair showed weaker synergies. All these three relationships displayed significant spatial heterogeneity, with trade-offs prominent in human activity-intensive oasis areas and synergies prevailing elsewhere.

Fig. 4 Correlation relationships of different LUFs (production, living, and ecological functions) during 2000–2010 (a1–a3), 2010–2020 (b1–b3), and 2000–2020 (c1–c3). r, correlation coefficient; ***, significance at $P<0.001$ level. The red line is the linear fitting line for the correlation between the two LUFs.

Fig. 5 Spatial distribution of trade-offs and synergies between different LUFs (production, living, and ecological functions) during 2000–2010 (a–c), 2010–2020 (d–f), and 2000–2020 (g–i)

3.3 Environmental factors influencing trade-offs and synergies

3.3.1 Model training and comparison This study compared the R^2, RMSE, and prediction–observation distance metrics of SVR, RF, LR, and XGBoost models (Table 3). The XGBoost model exhibited unparalleled performance in fitting trade-offs and synergies across all three LUF pairs. Specifically, this model achieved the highest R^2 values (0.61, 0.55, and 0.53) and the lowest RMSE values (0.048, 0.052, and 0.037) for trade-offs and synergies of production-living, production-ecology, and living-ecology function pairs, respectively, except for a slightly higher RMSE in production-living function pair compared with RF. For example, while LR model showed a relatively high R^2 value (0.45) in fitting trade-offs and synergies in production-living functions, its predictions deviated significantly at extreme values (Fig. 6 [Figure 6: see original paper]). SVR model performed slightly better than LR model but still exhibited poor performance at higher values. Both RF and XGBoost models maintained minimal deviations across all value ranges. Thus, XGBoost model was selected for subsequent interpretation of environmental factors influencing the trade-offs and synergies of LUFs.

Table 3 Statistic metrics of RF, SVR, LR, and XGBoost models in fitting trade-offs and synergies between different LUFs (production, living, and ecological functions)

Model	Production-living functions	Production-ecological functions	Living-ecological functions
XGBoost	$R^2 = 0.61$, RMSE = 0.048	$R^2 = 0.55$, RMSE = 0.052	$R^2 = 0.53$, RMSE = 0.037

Note: RF, Random Forest; SVR, Support Vector Regression; LR, Linear Regression; XGBoost, Extreme Gradient Boosting; LUFs, land use functions; R^2, Goodness-of-fit; RMSE, Root Mean Square Error.

Fig. 6 Comparison between actual and predicted values in fitting trade-offs and synergies in production-living functions using different machine learning models. (a), RF (Random Forest); (b), SVR (Support Vector Regression); (c), LR (Linear Regression); (d), XGBoost (Extreme Gradient Boosting).

3.3.2 Contributions of environmental factors to trade-offs and synergies of LUFs Based on the analysis of trade-offs and synergies of LUFs, this study analyzed the SHAP values of environmental factors influencing the spatial heterogeneity in the trade-offs and synergies of LUFs (Fig. 7a [Figure 7: see original paper]1–a2) and plotted single-factor SHAP dependence diagrams (Fig. 7b1–b12).

Fig. 7 SHapley Additive exPlanations (SHAP) characteristics of environmental factors influencing trade-offs and synergies in production-living functions. (a1), importance of global feature; (a2), importance of local feature; (b1), X_1 (population density); (b2), X_2 (GDP); (b3), X_3 (land use intensity); (b4), X_4 (distance to residential areas); (b5), X_5 (distance to water bodies); (b6), X_6 (distance to roads); (b7), X_7 (NDVI); (b8), X_8 (annual precipitation); (b9), X_9 (annual mean temperature); (b10), X_{10} (slope direction); (b11), X_{11} (slope); (b12), X_{12} (DEM).

Global feature importance analysis revealed that the spatial heterogeneity of trade-offs and synergies in production-living functions was primarily influenced by natural factors, followed by socioeconomic factors, whereas distance factors had minimal impact. Among natural factors, NDVI had the strongest influence, followed by land use intensity, annual mean temperature, and DEM. Among distance factors, distance to water bodies had the strongest effect. Locally, NDVI and land use intensity exhibited positive impacts (indicating that higher values enhanced trade-offs), whereas annual mean temperature and DEM showed negative impacts (higher values favored synergies). Although distance to water bodies had a notable effect, it lacked a clear positive or negative trend. Further analysis using SHAP dependence diagrams identified several thresholds: NDVI>0.38 and land use intensity>4000 positively influenced trade-offs; annual mean temperatures between -2.5°C and 7.5°C favored synergies, while values outside this range enhanced trade-offs; DEM<1700 m increased trade-offs, whereas higher elevations reduced trade-offs.

The spatial heterogeneity of trade-offs and synergies in production-ecological functions was also dominated by natural factors (Fig. 8 [Figure 8: see original paper]), with socioeconomic and distance factors playing minor roles. NDVI remained the most influential factor, followed by land use intensity, DEM, annual mean temperature, and distance to water bodies. Specifically, NDVI and land use intensity showed positive impacts, annual mean temperature had a negative impact, and DEM and distance to water bodies displayed no clear directional effects. Analysis based on single-factor SHAP dependence plots revealed that when NDVI>0.38 and land use intensity>4000, both exerted positive effects on trade-offs in production-ecological functions. This trend was consistent with their impacts on trade-offs in production-living functions. Additionally, DEM ranging from 1500 to 3500 m exerted negative effects on trade-offs, while values outside this range had positive effects. Temperature thresholds were consistent with above-mentioned findings: synergies prevailed when annual mean temperature was between -2.5°C and 7.5°C, with trade-offs dominating beyond this range.

For trade-offs and synergies in living-ecological functions (Fig. 9 [Figure 9: see original paper]), spatial heterogeneity was primarily driven by socioeconomic and natural factors, with distance factors having minimal impact. Land use intensity was the strongest driver, followed by GDP and NDVI. Land use intensity, GDP, and NDVI all exhibited clear positive effects on trade-offs. Specifically, land use intensity>3000 began to enhance trade-offs, with effects becoming more pronounced above 6000. GDP and population density also increasingly promoted trade-offs as their values increased.

3.3.3 Interaction characteristics of environmental factors This study further analyzed the interaction dependence plots of the top three environmental factors influencing the trade-offs and synergies of LUFs (Fig. 10 [Figure 10: see original paper]). The results showed that interactions among NDVI, land use intensity, and annual mean temperature had significant effects on trade-offs and synergies in production-living functions. When NDVI exceeded 0.40, high land use intensity interacted with NDVI to exert negative effects on trade-offs in production-living functions, while its interaction with annual mean temperature generated positive effects. Conversely, when NDVI fell below 0.20, interactions involving low land use intensity slightly enhanced trade-offs. Notably, although NDVI and land use intensity individually exhibited positive impacts on trade-offs between production and living functions in single-factor analyses, their high-value interactions paradoxically suppressed trade-offs. Regions with high land use intensity, primarily dense construction land areas, demonstrated synergistic development patterns when combined with high NDVI. At land use intensity levels around 3700, interactions with higher annual mean temperatures had negative effects on trade-offs in production-living functions. For trade-offs in production-ecological functions, higher land use intensity exerted stronger negative effects when NDVI exceeded 0.20, while interactions involving low land use intensity when NDVI<0.20 slightly increased trade-offs. DEM interactions with

NDVI>0.20 showed divergent effects based on elevation: lower DEM (<1500 m) had positive effects on trade-offs, whereas higher DEM (>1500 m) reduced them. For the trade-offs and synergies of living-ecological functions, only the interaction between land use intensity and NDVI was relatively significant. When both were high, they exerted a negative impact on the trade-offs of living-ecological functions.

Fig. 8 SHAP characteristics of environmental factors influencing trade-offs and synergies in production-ecological functions. (a1), importance of global feature; (a2), importance of local feature; (b1), X_1 (population density); (b2), X_2 (GDP); (b3), X_3 (land use intensity); (b4), X_4 (distance to residential areas); (b5), X_5 (distance to water bodies); (b6), X_6 (distance to roads); (b7), X_7 (NDVI); (b8), X_8 (annual precipitation); (b9), X_9 (annual mean temperature); (b10), X_{10} (slope direction); (b11), X_{11} (slope); (b12), X_{12} (DEM).

Fig. 9 SHAP characteristics of environmental factors influencing trade-offs and synergies in living-ecological functions. (a1), importance of global feature; (a2), importance of local feature; (b1), X_1 (population density); (b2), X_2 (GDP); (b3), X_3 (land use intensity); (b4), X_4 (distance to residential areas); (b5), X_5 (distance to water bodies); (b6), X_6 (distance to roads); (b7), X_7 (NDVI); (b8), X_8 (annual precipitation); (b9), X_9 (annual mean temperature); (b10), X_{10} (slope direction); (b11), X_{11} (slope); (b12), X_{12} (DEM).

Fig. 10 Cross-dependence of SHAP values for key environmental factors influencing trade-offs and synergies between different LUFs. (a1–a3), production-living functions; (b1–b3), production-ecological functions; (c1–c3), living-ecological functions.

4 Discussion

4.1 Anthropogenic impacts on spatiotemporal dynamics of LUFs

The MHRB is one of the most human activity-intensive regions in inland river basins, where spatiotemporal changes in LUFs are influenced not only by natural conditions but also by human activities. In early stages of development, extensive agricultural practices prevailed, involving continuous reclamation of grasslands to meet food demands. This led to slow expansion of oases and continued reliance on traditional irrigation methods, resulting in sustained degradation of ecosystem zones such as natural grasslands and wetlands, particularly in oasis areas where land use changes were most pronounced [?]. Since the implementation of ecological civilization measures, LUFs in the HRB have transitioned from resource exploitation to eco-economic development models. Under rigid water resource constraints, industrial and agricultural productions have been compelled to shift toward green and water-saving practices, enhancing guarantees of ecological water use and leading to partial vegetation recovery in downstream desert region [?]. Rapid urbanization has accelerated rural-to-urban labor migration, promoting land transfer and driving urban development alongside the intensification and expansion of agricultural land use [?]. Consequently, production and living functions in oasis areas have increased markedly. With strengthened land use planning controls, key ecological zones such as the Qilian Mountains and Heihe Wetland have been integrated into national ecological security barrier plans [?]. Enhanced enforcement of ecological protection red lines and increased ecological compensation mechanisms have significantly improved the MHRB' s overall ecological functions.

4.2 Underlying mechanisms of trade-offs and synergies in LUFs

The results of this study indicate predominantly synergistic relationships among LUFs in the MHRB, with synergies concentrated in the desert region due to minimal human activities across underutilized lands (Gobi, bare ground, and deserts), combined with agriculture' s dual role in providing food or raw materials while directly enhancing farmers' livelihoods and employment, thereby positively reinforcing synergies in production-living functions [?]. Sustainable farming practices further maintain ecological equilibrium and biodiversity, thereby facilitating synergies in production-ecological functions [?]. Conversely, human-intensive oasis zones exhibit dominant trade-offs as agricultural and socioeconomic cores; escalating land-use pressures from population and economic growth intensify functional conflicts. For example, cultivated land expansion and urbanization-driven construction sprawl encroach on ecological lands, while environmental protections constrain agricultural intensity to preserve ecological balance [?].

4.3 Environmental factors analysis and policy implications

Analysis of environmental factor contributions to trade-offs and synergies of LUFs reveals that, in the MHRB, these relationships are predominantly influenced by natural factors (NDVI, annual mean temperature, DEM, and annual precipitation), followed by socioeconomic factors, with distance factors having the least impact. This indicates that in arid inland river basins of northwestern China, natural geographic characteristics fundamentally determine the basic patterns of trade-offs and synergies of LUFs. These driving factors differ significantly from those in other regions, e.g., humid and semi-humid regions. For instance, in Kunming City of China (a humid region), distance factors exert stronger influence than natural or socioeconomic drivers on trade-offs and synergies both in production-ecological functions and production-living functions [?]. This stems from Kunming City' s abundant precipitation (1000 mm annual average), robust ecological baseline, and significant spatial separation between high-function zones. Urban expansion (distance to city center) and road construction have intensified landscape fragmentation, critically shaping local land use interactions. Conversely, the MHRB—constrained by natural conditions—concentrates high production-living-ecological functions within oasis zones, where distance factors minimally impact functional trade-offs and synergies. Therefore, for the MHRB, priority should be given to ecological conservation and functional enhancement in the desert region to amplify basin-wide synergies, while drawing on lessons from Kunming City to prevent unplanned boundary expansion from degrading ecosystems during urban development.

Simultaneously, socioeconomic factors require attention, particularly in the oasis plain region characterized by intensive human activities where trade-offs of LUFs are dominant. Among socioeconomic factors, land use intensity exhibits a significant positive influence on trade-off relationships of LUFs within the region. Therefore, future efforts should optimize the spatial distribution of land use patterns to integrate production, living, and ecological lands, leverage urban agglomeration effects, and concentrate regional population, industries, education, healthcare, and cultural resources in central towns. This approach would reduce the encroachment of construction land on ecologically critical areas [?], thereby alleviating pressure from human production and living activities on the ecological environment. In areas with relatively high habitat quality, unnecessary development should be minimized to prioritize ecological functions [?]. Oasis peripheries, characterized by low habitat quality and dominated by unused lands such as Gobi, bare ground, and deserts, should actively implement ecological shelterbelt projects. Guided by the principle of ecological priority, water-saving and low-carbon green industries should be appropriately introduced in these zones to enhance both their production and ecological functions [?]. Additionally, land use management must account for interactions among environmental factors. For example, in high-intensity land-use areas (i.e., densely built-up zones), increasing green spaces to elevate regional NDVI would promote synergistic development of living-ecological functions. Although natural factors such as DEM, slope, slope direction, annual mean temperature, and annual precipitation are immutable, land use intensity can be optimized within feasible limits by leveraging their interactive effects with other factors to mitigate the escalation of the trade-offs in LUFs.

4.4 Strengths, limitations and future directions

Machine learning and deep learning algorithms provide innovative methodologies for ecological research, with their complex architectures significantly outperforming traditional statistical methods in both performance and accuracy. This study employed an integrated XGBoost-SHAP framework, demonstrating its scalability and efficiency for large-scale spatial data analysis. This approach can effectively capture key drivers, facilitate deeper exploration of factors influencing spatial heterogeneity in the trade-offs and synergies of LUFs, offer novel perspectives for related research, and deliver profounder insights into the formation mechanisms of complex interaction patterns among LUFs.

Analyzing the factors influencing the spatial heterogeneity in the trade-offs and synergies of LUFs is fundamental for deciphering multifunctional mechanisms, optimizing functional zoning, and informing land-use decisions [?, ?]. However, the environmental mechanisms governing this heterogeneity remain intricate; although we selected 12 representative factors spanning natural conditions, geographic location, and socioeconomic dimensions, data limitations resulted in the exclusion of certain variables, thereby potentially constraining comprehensiveness of environmental interpretation. Future research must refine factor selection criteria. Simultaneously, the XGBoost-SHAP framework exhibits inherent limitations in processing complex geospatial relationships—particularly for predictions at data-sparse margins or distribution boundaries where SHAP values may demonstrate suboptimal performance and instability, thereby affecting interpretative reliability. Future studies should conduct multi-dimensional and multi-grid-scale comparative analyses to enhance the explanatory accuracy of spatial heterogeneity drivers. Furthermore, this study found that significant changes occur in the trade-offs and synergies of LUFs when the land use intensity reaches around 4000. Future research could employ scenario simulations to investigate trends of these trade-offs under different land use intensity levels (or other environmental factors), thereby offering more precise guidance for regional policy implementation.

5 Conclusions

This study analyzed the spatiotemporal evolution characteristics and trade-offs/synergies of LUFs in the MHRB from a production-living-ecological perspective, employing the integrated XGBoost-SHAP model to explore environmental factors driving spatial heterogeneity. Between 2000 and 2020, LUFs in the MHRB exhibited a consistent upward trend across all periods. Production and living functions increased significantly in oasis areas, though accompanied by declines in local ecological functions. Consequently, compared to the desert region, the oasis plain region exhibited relatively significant trade-offs among production, living, and ecological functions. Trade-offs and synergies of LUFs in the study area were predominantly influenced by natural factors (NDVI, annual mean temperature, DEM, and annual precipitation), followed by socioeconomic factors, with distance factors exerting minimal impact. Specifically, when NDVI, DEM, and land use intensity reached approximately 0.38, 1700 m, and 4000, respectively, distinct critical thresholds were identified in the trade-offs and synergies of LUFs. In addition, interactions among three natural factors—NDVI, annual mean temperature, and DEM—and land use intensity significantly impacted trade-offs and synergies of LUFs. Therefore, land management measures should integrate interactions between land use intensity and natural drivers to promote synergistic development of LUFs.

Overall, this study identified and interpreted spatial heterogeneity in the trade-offs and synergies of LUFs using the XGBoost-SHAP framework, and effectively captured key influencing factors and interactions among different environmental variables, offering novel perspectives and methodologies for understanding the formation mechanisms of spatial heterogeneity in the trade-offs and synergies of LUFs. Future research should incorporate additional environmental factors to comprehensively reflect complex feedback mechanisms of human-ecological system interactions.

Conflict of interest: The authors declare that they have no known competing

financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements: This research was funded by the University Teachers Innovation Fund Project of Gansu Province (2025A-001) and the Northwest Normal University Young Teachers' Scientific Research Ability Improvement Plan (NWNU-LKQN2024-20).

Author contributions: Conceptualization: FENG Haoyuan, ZHANG Xuebin; Data curation: ZHANG Xuebin; Formal analysis: FENG Haoyuan; Funding acquisition: FENG Haoyuan; Investigation: FENG Haoyuan, SHI Jing; Methodology: FENG Haoyuan, SHI Jing; Project administration: ZHANG Xuebin, SHI Peiji; Resources: FENG Haoyuan, ZHANG Xuebin, SHI Peiji; Software: FENG Haoyuan, SHI Jing, WANG Ziyang; Supervision: ZHANG Xuebin, SHI Peiji; Validation: WANG Ziyang; Visualization: FENG Haoyuan, SHI Jing; Writing - original draft: FENG Haoyuan; Writing - review and editing: ZHANG Xuebin, SHI Peiji. All authors approved the manuscript.

References

Alam S A, Starr M, Clark B J F. 2013. Tree biomass and soil organic carbon densities across the Sudanese woodland savannah: A regional carbon sequestration study. *Journal of Arid Environments*, 89: 67–76.

Bahr S. 2024. The relationship between urban greenery, mixed land use and life satisfaction: An examination using remote sensing data and deep learning. *Landscape and Urban Planning*, 251: 105174, doi: 10.1016/j.landurbplan.2024.105174.

Bai M, Li Z L, Huo P Y, et al. 2023. Propagation characteristics from meteorological drought to agricultural drought over the Heihe River Basin, Northwest China. *Journal of Arid Land*, 15(5): 523–544.

Boulot E. 2025. The environmental statehood of ecological restoration: An institutional analysis of three regulatory case studies. *Global Environmental Change*, 91: 102982, doi: 10.1016/j.gloenvcha.2025.102982.

Bureau of Statistics of Gansu Province. 2001–2021a. *Gansu Rural Yearbook*. Beijing: China Statistics Press. (in Chinese)

Bureau of Statistics of Gansu Province. 2001–2021b. *Gansu Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Bureau of Statistics of Zhangye City. 2001–2021. *Zhangye Statistical Bulletin of National Economic and Social Development*. [2025-02-09]. https://www.zhangye.gov.cn/sjfb/tjgb/ghb.html. (in Chinese)

Chen F, Leung Y, Wang Q, et al. 2024. Spatial non-stationarity test of regression relationships in the multiscale geographically weighted regression model. *Spatial Statistics*, 62: 100846, doi: 10.1016/j.spasta.2024.100846.

Chen F X, Li Y R, Liu Y S. 2025. Spatial-temporal evolution and coupling coordination of land use functions across China by fusing multiple-source heterogeneous data. *Land Use Policy*, 155: 107590, doi: 10.1016/j.landusepol.2025.107590.

Department of Water Resources of Gansu Province. 2001–2021. *Gansu Provincial Water Resources Bulletin*. [2025-02-09]. https://slt.gansu.gov.cn/slt/c106726/c106732/c106773/zcfg.shtml. (in Chinese)

Geng Y W, Li X S, Chen J Q. 2025. Integration of land use resilience and efficiency in China: Analysis of spatial patterns, impacts on SDGs, and adaptive management strategies. *Applied Geography*, 175: 103490, doi: 10.1016/j.apgeog.2024.103490.

Hanacek K, Rodriguez-Labajos B. 2018. Impacts of land-use and management changes on cultural agroecosystem services and environmental conflicts-A global review. *Global Environmental Change*, 50: 41–59.

He H X, Yan J N, Liang D, et al. 2024. Time-series land cover change detection using deep learning-based temporal semantic segmentation. *Remote Sensing of Environment*, 305: 114101, doi: 10.1016/j.rse.2024.114101.

Huang F J, Tang J Q, Lin H L, et al. 2023a. Built environment effects on the spatio-temporal distribution of shared bikes based on multi-scale geographic weighted regression. *Geographical Research*, 42(9): 2405–2418. (in Chinese)

Huang F X, Zuo L Y, Gao J B, et al. 2023b. Exploring the driving factors of trade-offs and synergies among ecosystem service functional zones. *Ecological Indicators*, 109827, doi: 10.1016/j.ecolind.2022.109827.

Jafary P, Shojaei D, Rajabifard A, et al. 2024. Automated land valuation models: A comparative study of four machine learning and deep learning methods based on a comprehensive range of influential factors. *Cities*, 151: 105115, doi: 10.1016/j.cities.2024.105115.

Jiang S, Meng J J, Zhu L K. 2020. Spatial and temporal analyses of potential land use conflict under the constraints of water resources in the middle reaches of the Heihe River. *Land Use Policy*, 97: 104773, doi: 10.1016/j.landusepol.2020.104773.

Kassun B W, Kallio M, Trømborg E, et al. 2025. Land use and land cover change, trade-offs, and synergies between ecosystem services in a dry Afromontane Forest. *Journal for Nature Conservation*, 85: 126874, doi: 10.1016/j.jnc.2025.126874.

Ke L, Lei N, Zhang S L, et al. 2025. Estimation of blue carbon stock in the Liaohe Estuary wetland based on soil thickness and multi-scenario modeling. *Ecological Indicators*, 171: 113201, doi: 10.1016/j.ecolind.2025.113201.

Khan F, Abbass K, Qun W, et al. 2025. Moderating role of digital media on environmental awareness and environmental beliefs to shape farmers' behavioral intentions towards sustainable agricultural land conservation practices. *Journal of Environmental Management*, 373: 123845, doi: 10.1016/j.jenvman.2024.123745.

Li K, Zhao J S, Li Y P, et al. 2025. Identifying trade-offs and synergies among land use functions using an XGBoost-SHAP model: A case study of Kunming, China. *Ecological Indicators*, 172: 113330, doi: 10.1016/j.ecolind.2025.113330.

Li Q R, Jia Y L, Wang H J, et al. 2023a. Analysis of trade-off and synergy effects of ecosystem services in Hebei Province from the perspective of ecological function area. *Acta Geographica Sinica*, 78(11): 2833–2849. (in Chinese)

Li S N, An W Z, Zhang J, et al. 2023b. Optimizing limit lines in urban-rural transitional areas: Unveiling the spatial dynamics among trade-offs and synergies of land use functions. *Habitat International*, 102907, doi: 10.1016/j.habitatint.2023.102907.

Li X, Lu L, Cheng G, et al. 2001. Quantifying landscape structure of the Heihe River Basin, North-west China using FRAGSTATS. *Journal of Arid Environments*, 48(4): 521–535.

Liu J M, Pei X T, Zhu W Y, et al. 2024. Water-related ecosystem services interactions and their natural-human activity drivers: Implications for ecological protection and restoration. *Journal of Environmental Management*, 352: 120101, doi: 10.1016/j.jenvman.2024.120101.

National Bureau of Statistics. 2001–2021. *China Statistical Yearbook*. Beijing: China Statistics Press. (in Chinese)

Nie H R, Zhao Y, Zhu J, et al. 2024. Ecological security pattern construction in typical oasis area based on ant colony optimization: A study in Yili River Valley, China. *Ecological Indicators*, 169: 112770, doi: 10.1016/j.ecolind.2024.112770.

Peng Y Z, Yu G I. 2024. Model multifactor analysis of soil heavy metal pollution on plant germination in Southeast Chengdu, China: Based on redundancy analysis, factor detector, and XGBoost-SHAP. *Science of the Total Environment*, 954: 176605, doi: 10.1016/j.scitotenv.2024.176605.

Qiao W F, Li C, Dai L L, et al. 2024. Progress and prospects in the study of coupling rural multifunctional evolution and land use transitions. *Geographical Research*, 43(6): 1556–1571. (in Chinese)

Qu Y B, Zhan L Y, Wei C C, et al. 2024. Interactive transition of cultivated land and construction land during China' s urbanization: A coordinated analytical framework of explicit and implicit forms. *Land Use Policy*, 138: 107049, doi: 10.1016/j.landusepol.2024.107049.

Rallings A M, Smukler S M, Gergel S E, et al. 2019. Towards multifunctional land use in an agricultural landscape: A trade-off and synergy analysis in the Lower Fraser Valley, Canada. *Landscape and Urban Planning*, 184: 88–100.

Reith E, Gosling E, Knoke T, et al. 2022. Exploring trade-offs in agro-ecological landscapes: Using a multi-objective land-use allocation model to support agroforestry research. *Basic and Applied Ecology*, 64: 103–119.

Ren J, Ma R R, Huang Y H, et al. 2024. Identifying the trade-offs and synergies of land use functions and their influencing factors of Lanzhou-Xining urban agglomeration in the upper reaches of Yellow River Basin, China. *Ecological Indicators*, 158: 111279, doi: 10.1016/j.ecolind.2023.111279.

Shim S H, Choi J H. 2024. Building an XGBoost model based on landscape metrics and meteorological data for nonpoint source pollution management in the Nakdong River watershed. *Ecological Indicators*, 165: 112156, doi: 10.1016/j.ecolind.2024.112156.

Su Y Q, Feng Q, Liu W, et al. 2023. Improved understanding of trade-offs and synergies in ecosystem services via fine land-use classification and multi-scale analysis in the arid region of Northwest China. *Remote Sensing*, 15(20): 4976, doi: 10.3390/rs15204976.

Ustaoglu E, Aydınoglu A C. 2019. Regional variations of land-use development and land-use/cover change dynamics: A case study of Turkey. *Remote Sensing*, 11(7): 885, doi: 10.3390/rs11070885.

Viruel E, Fontana C A, Puglisi E, et al. 2022. Land-use change affects the diversity and functionality of soil bacterial communities in semi-arid Chaco region, Argentina. *Applied Soil Ecology*, 172: 104362, doi: 10.1016/j.apsoil.2021.104362.

Wang S L, Jin X B, Han B, et al. 2025. Understanding the process and mechanism of agricultural land transition in China: Based on the interactive conversion of cropland and natural ecological land. *Journal of Environmental Management*, 376: 124585, doi: 10.1016/j.jenvman.2025.124585.

Wang Y F, Cheng L L, Zheng Y, et al. 2024a. Evolution of land use functions and their trade-offs/synergies relationship in resource-based cities. *Ecological Indicators*, 165: 112175, doi: 10.1016/j.ecolind.2024.112175.

Wang Y X, Ao Y H, Li Z G. 2022. Evapotranspiration characteristics of different oases and effects of human activities on evapotranspiration in Heihe River Basin.

Remote Sensing, 14(24): 6283, doi: 10.3390/rs14246283.

Wang Z Y, Shi P J, Li X H, et al. 2024b. Response mechanism and promotion path of habitat quality to land use change in Hexi Corridor area. *Environmental Science*, 45(12): 6910–6921. (in Chinese)

Wei C, Wu Z, Xing J, et al. 2024. Trade-off or synergy? Dynamic analysis and policy insights on land use functions in China. *Environmental Impact Assessment Review*, 105: 107399, doi: 10.1016/j.eiar.2023.107399.

Wu D, Zheng L, Wang Y, et al. 2024. Dynamics in construction land patterns and its impact on water-related ecosystem services in Chengdu-Chongqing urban agglomeration, China: A multi-scale study. *Journal of Cleaner Production*, 469: 143022, doi: 10.1016/j.jclepro.2024.143022.

Wu F, Zhan J Y, Güneralp İ. 2015. Present and future of urban water balance in the rapidly urbanizing Heihe River Basin, Northwest China. *Ecological Modelling*, 318: 254–264.

Wu Q Q, Meng J J. 2023. Analysis of the evolution and driving factors of production-living-ecological space pattern in the Heihe River Basin from 1980 to 2020, China. *Acta Scientiarum Naturalium Universitatis Pekinensis*, 59(6): 970–980. (in Chinese)

Xiao X Y, Hu M Y, Li X B, et al. 2018. Analysis on changes of agricultural structure and its driving factors in the middle reaches of Heihe River at plot scale—A case study of Zhangye City. *Journal of Natural Resources*, 33(3): 386–397. (in Chinese)

Xu A K, Hu M J, Shi J, et al. 2024. Construction and optimization of ecological network in inland river basin based on circuit theory, complex network and ecological sensitivity: A case study of Gansu section of Heihe River Basin. *Ecological Modelling*, 488: 110578, doi: 10.1016/j.ecolmodel.2023.110578.

Yan Y, Guan Q Y, Shao W Y, et al. 2023. Spatiotemporal dynamics and driving mechanism of arable ecosystem stability in arid and semi-arid areas based on Pressure-Buffer-Response process. *Journal of Cleaner Production*, 421: 138553, doi: 10.1016/j.jclepro.2023.138553.

Yang D F, Wang X M, Han R N. 2023a. Nonlinear and synergistic effects of the built environment on street vitality: The case of Shenyang. *Urban Planning Forum*, 5: 93–102. (in Chinese)

Yang H J, Liu Z X, Yin J, et al. 2025. Coordination and driving analysis of 'Production-Living-Ecological' functions of cultivated land use change in Yunnan Province based on multi-source time series data. *Geojournal*, 90: 108, doi: 10.1007/s10708-025-11354-0.

Yang Y Y, Ren X Z, Yan J M. 2023b. Trade-offs or synergies? Identifying dynamic land use functions and their interrelations at the grid scale in urban agglomeration. *Cities*, 140: 104384, doi: 10.1016/j.cities.2023.104384.

Yu S H, Hu X Y, Sheng Y H, et al. 2025. Similarity and geographically weighted regression considering spatial scales of features space. *Spatial Statistics*, 97: 100897, doi: 10.1016/j.spasta.2025.100897.

Yuan Y Y, Guo W, Tang S Q, et al. 2024. Effects of patterns of urban green-blue landscape on carbon sequestration using XGBoost-SHAP model. *Journal of Cleaner Production*, 476: 143640, doi: 10.1016/j.jclepro.2024.143640.

Zhang H Z, Tang Q, He X B, et al. 2024. Land use function changes and trade-offs/synergies across topographic gradients in the Three Gorges Reservoir Area, China. *Journal of Cleaner Production*, 469: 143233, doi: 10.1016/j.jclepro.2024.143233.

Zhang J, Li S N, Lin N F, et al. 2022. Spatial identification and trade-off analysis of land use functions improve spatial zoning management in rapid urbanized areas, China. *Land Use Policy*, 116: 106058, doi: 10.1016/j.landusepol.2022.106058.

Zhang Z P, Guan Q Y, Zhao B, et al. 2025. Multi-objective optimal allocation of agricultural water and land resources in the Heihe River Basin: Coupling of climate and land use change. *Journal of Hydrology*, 653: 132783, doi: 10.1016/j.jhydrol.2025.132783.

Zhao D S, Zhu Y, Wu S H, et al. 2022. Simulated response of soil organic carbon density to climate change in the northern Tibet permafrost region. *Geoderma*, 405: 115455, doi: 10.1016/j.geoderma.2021.115455.

Zheng J T, Wang P, Shi H Y, et al. 2023. Quantitative analysis of the influence factors and extent of soil heavy metals based on CatBoost model and SHAP interpretation method. *Acta Scientiae Circumstantiae*, 43(4): 448–456. (in Chinese)

Zhong L N, Wang J, Zhang X, et al. 2020. Effects of agricultural land consolidation on ecosystem services: Trade-offs and synergies. *Journal of Cleaner Production*, 264: 121412, doi: 10.1016/j.jclepro.2020.121412.

Zhou Q, Zhang Y L, Wu F. 2021. Evaluation of the most proper management scale on water use efficiency and water productivity: A case study of the Heihe River Basin, China. *Agricultural Water Management*, 246: 106671, doi: 10.1016/j.agwat.2020.106671.

Zhu C M, Dong B Y, Li S N, et al. 2021. Identifying the trade-offs and synergies among land use functions and their influencing factors from a geospatial perspective: A case study in Hangzhou, China. *Journal of Cleaner Production*, 314: 128026, doi: 10.1016/j.jclepro.2021.128026.

Zhu G F, Wang L, Liu Y W, et al. 2022. Snow-melt water: An important water source for *Picea crassifolia* in Qilian Mountains. *Journal of Hydrology*, 613: 128441, doi: 10.1016/j.jhydrol.2022.128441.

Zou L L, Liu Y S, Wang J Y, et al. 2021. An analysis of land use conflict potentials based on ecological-production-living function in the southeast coastal area of China. *Ecological Indicators*, 122: 107297, doi: 10.1016/j.ecolind.2020.107297.

Zou M Z, Deng Y Y, Du T S, et al. 2023. Agricultural transformation towards delivering deep carbon cuts in China' s arid inland areas. *Environment International*, 180: 108245, doi: 10.1016/j.envint.2023.108245.

Zubaida M. 2024. Trade-offs and synergies between ecosystem services in Yutian County along the Keriya River Basin, Northwest China. *Journal of Arid Land*, 16(7): 943–962.

Note: Figure translations are in progress. See original paper for figures.