

Article

A Land System Multifunctionality Perspective on Four Representative PLES Functional Conflicts: A Case Study of Shandong Province, China, 2010–2020

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Highlights

Please indicate how your work links to systems science via your contributions to systems practice, theory, and/or methodology.

- A land-system-oriented framework links multifunctionality, functional competition, and representative PLES functional conflicts.
- XGBoost–SHAP reveals nonlinear spatial associations and threshold-like responses in coupled land systems.

What are the main findings and/or the implications of the main findings?

- Land functions were substantially reconfigured, with grain-production-related conflicts generally showing higher functional competition intensity than ecological-function-related conflicts.
- Proxy-based competition patterns provide empirical references for functionally differentiated planning during 2010–2020.

Abstract

Land system multifunctionality is increasingly recognized as a key source of competition among production, living, and ecological functions. However, how these interactions are spatially manifested as functional competition within production–living–ecological space (PLES) through nonlinear relationships remains insufficiently understood. This study develops a land-system-oriented framework to assess four representative PLES functional conflicts within farmland production–ecological (PE) and natural ecological (E) spaces. Using Shandong Province, China, as a case study, we characterize PLES patterns in 2010, 2015, and 2020 and use a coupling-based index (D) as a proxy for functional competition intensity. XGBoost–SHAP is employed to examine the nonlinear spatial associations between selected environmental, socioeconomic, and spatial factors and proxy-based functional competition intensity during the 2010–2020 observation period. Results show that (1) the regional land system underwent marked functional reconfiguration, with urban–rural and fishing production–ecological spaces expanding while farmland production–ecological and natural ecological spaces contracted; (2) the four representative conflict scenarios exhibited pronounced spatial heterogeneity, with grain-production-related conflicts generally showing higher functional competition intensity than ecological-function-

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related conflicts; and (3) the dominant associated factors varied across conflict scenarios and exhibited distinct nonlinear response patterns. Overall, the findings reveal differentiated spatial associations between land-system multifunctionality and proxy-based functional competition intensity during 2010–2020. The identified response ranges provide empirical reference points for spatial monitoring and functionally differentiated territorial planning.

Keywords: land system multifunctionality; production-living-ecological space; functional competition intensity; XGBoost-SHAP model; Shandong Province

1. Introduction

Production–living–ecological spaces (PLES) constitute an integrated land system in which production, living, and ecological functions coexist and interact to sustain socioeconomic development and human well-being [1]. Rather than representing independent spatial categories, these functions continuously interact through the allocation and reconfiguration of land resources, making PLES a fundamental carrier of socioeconomic activities [2,3]. PLES conflict can be understood as an emergent property of land systems, arising when finite land resources fail to accommodate increasingly diversified and competing land-use demands [4,5]. With accelerating global urbanization, such conflicts have become increasingly prominent as interactions between human activities and land systems intensify [6,7]. Land system science provides an interdisciplinary perspective for understanding these changes by examining the coupled interactions among human activities, land-use decisions, and environmental processes across space and time. From this perspective, land-use conflicts are not isolated spatial problems but outcomes of competing societal demands and interactions among multiple land-system functions [8]. In China, the national territorial spatial planning strategy emphasizes efficient production space, livable living space, and healthy ecological space, making the coordination of PLES conflict a central objective of integrated spatial governance [9,10]. Existing research has primarily examined the origins [11], types [12], identification [13], evolution [14] and management of PLES conflicts [15]. However, because spatial conflicts often produce persistent and difficult-to-reverse consequences [16], characterizing the spatial intensity of functional competition is important for proactive monitoring and adaptive spatial governance [17].

The scientific delineation of PLES provides the foundation for identifying spatial conflicts and characterizing functional competition within land systems [18]. Owing to their operational simplicity and data availability, conventional classification approaches based on a single land-use function have been widely adopted in PLES studies [19]. However, individual land categories commonly perform multiple functions simultaneously across production, living, and ecological domains. Consequently, assigning land solely according to one dominant function tends to obscure the interactions, synergies, and trade-offs among functions, limiting the representation of the actual functional configuration of regional land systems [20,21]. Land System Functions (LSFs) describe the capacity of land systems to simultaneously provide production goods, living services, and ecological benefits to human society, thereby capturing both functional allocation and the relationships among multiple functions more effectively than single-function classifications [22]. This perspective suggests that PLES should be understood through land system multifunctionality, where multiple functions coexist, interact, and collectively shape the organization of territorial space. This understanding is consistent with international research on land-system multifunctionality, which emphasizes that land can simultaneously support multiple

economic, social, and ecological functions and that interactions among these functions may generate synergies, trade-offs, and competition [23,24]. In this sense, PLES can be viewed as a context-specific spatial operationalization of multifunctional land systems, in which production, living, and ecological functions provide a spatially explicit representation of multiple societal and environmental demands. Such a perspective connects the PLES framework with broader international discussions of land-use trade-offs and multifunctionality while retaining its relevance to China's territorial spatial planning context [25].

Context-specific prevention and management of PLES conflicts depend fundamentally on a reliable assessment of functional competition across land systems [26]. More broadly, international land-system research has increasingly emphasized that land-use conflicts arise from competing demands for limited land resources and from trade-offs among multiple land-system functions [24,25]. To this end, diverse assessment approaches have been proposed, including conflict index methods [27], multi-objective suitability evaluation [28] and land use scenario simulation [1]. These methods have substantially improved the identification of conflict patterns and their spatiotemporal evolution. Nevertheless, most assessments remain centered on land-use categories or landscape configurations, emphasizing the diagnosis of existing conflicts while providing limited insight into the dynamic interactions among multiple LSFs and their evolving trade-offs [29,30]. From a land system multifunctionality perspective, functional competition emerges from the interaction and reconfiguration of multiple functions rather than from land-use categories alone [31]. This understanding calls for a theoretical and methodological framework capable of tracing how interactions among LSFs generate conflict risk across space and time, thereby strengthening both the robustness and anticipatory capacity of conflict-risk assessment [17].

The emergence of PLES functional competition is driven by the coupled interaction between environmental conditions and socioeconomic processes within land systems [32,33]. Previous studies have explored these driving mechanisms using Geodetector, spatial econometric models, logistic regression, Random Forest, and Geographically Weighted Regression [34]. While these methods have strengthened understanding of factor importance and spatial heterogeneity, they predominantly emphasize independent effects or linear relationships, providing limited insight into the joint nonlinear responses, effect directions, and threshold behaviors arising from interactions among multiple drivers [35]. From a land system perspective, conflict evolution reflects the emergent outcomes of multiple interacting drivers rather than the influence of isolated factors. Machine-learning algorithms are well suited to capture such complex system dynamics by modeling nonlinear relationships between predictors and functional competition intensity and revealing critical threshold responses [36]. Accordingly, integrating machine-learning approaches into land system analysis enables the quantification of the direction and magnitude of multiple driving effects, the identification of nonlinear response patterns, and a more comprehensive understanding of conflict emergence and evolution. These insights provide stronger support for functional competition intensity assessment and adaptive territorial spatial governance [37,38].

Shandong Province represents a typical land system where agricultural production, rapid urbanization, and ecological conservation interact simultaneously. As one of China's major grain-producing regions and an economically developed coastal province, it also undertakes critical responsibilities for ecological protection and high-quality development within the Yellow River Basin. Under the combined pressures of cultivated-land conservation, urban expansion, and ecological protection, competition and coordination among production, living, and ecological functions have become increasingly prominent

[39]. These pressures are not unique to China, but are also characteristic of rapidly urbanizing and peri-urban regions where agricultural production, urban development, and ecological conservation compete for increasingly multifunctional land resources [40]. Shandong therefore provides a useful case for examining how multifunctional land systems respond to the simultaneous pressures of agricultural intensification, urban expansion, and ecological conservation, while also offering insights potentially relevant to other rapidly transforming regions. Against this background, this study develops a framework for assessing PLES functional competition intensity based on land system multifunctionality, using Shandong Province as the case study. Specifically, the study aims to: (1) to establish a raster-based PLES classification framework that captures the spatial organization and spatiotemporal evolution of different functional spaces within the regional land system; (2) to evaluate the spatial distribution and differentiation of functional competition intensity across four representative PLES conflict scenarios, focusing on four functional competitions within farmland PE and natural E spaces; (3) to identify the nonlinear relationships and threshold effects of environmental and socioeconomic factors associated with these representative functional competition patterns. By integrating land system multifunctionality with proxy-based functional competition assessment, this study provides theoretical support for territorial spatial governance, coordinated optimization of multiple functions, and adaptive spatial risk early warning.

2. Materials and Methods

2.1. Study Area

Shandong Province is situated in eastern China, extending from 34°22' to 38°24' N and from 114°47' to 122°42' E. The province comprises plains, hills, and mountainous areas, resulting in a heterogeneous land-use configuration (Figure 1). As a major agricultural and economically developed province, Shandong is important for grain supply and regional socioeconomic growth in China [41]. In 2020, the urbanization rate of Shandong Province was 63.05%, while its total population and gross domestic product (GDP) accounted for 7.1% and 7.2% of the corresponding national totals, respectively, reflecting the substantial concentration of population and economic activities in the province [42]. Recent regional strategies, including ecological conservation in the Yellow River Basin, the development of the Shandong Peninsula urban cluster, and the replacement of traditional growth engines, have intensified the trade-offs between land development and environmental protection. Urban expansion and industrial land demand have increasingly occupied cultivated and ecologically valuable land, thereby aggravating conflicts among production, living, and ecological functions. Accordingly, Shandong provides an appropriate case for examining the spatio-temporal evolution and determinants of PLES functional competition intensity. Such analysis can support more efficient spatial allocation and improve coordination among production, living, and ecological functions.

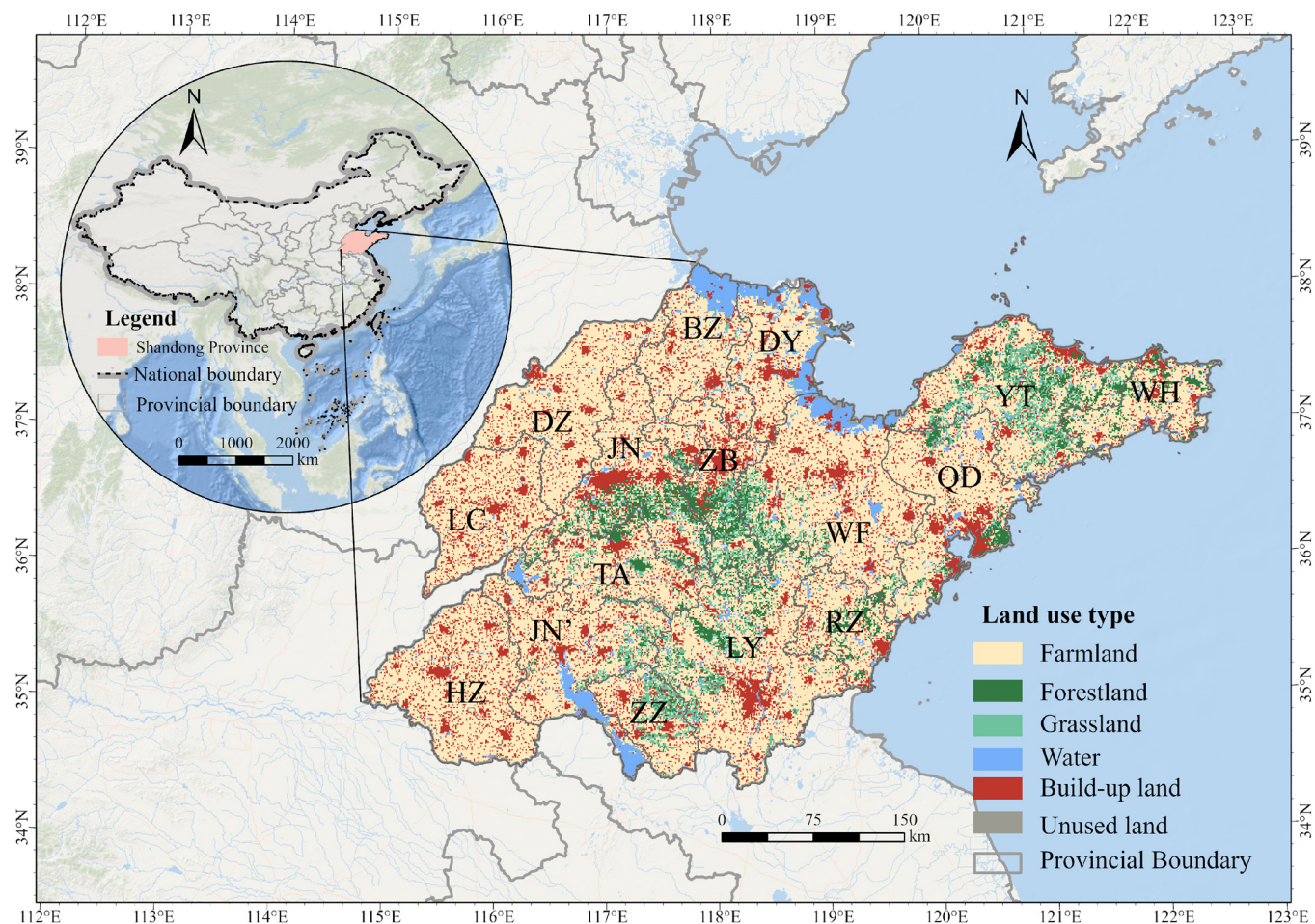


Figure 1. Overview of the study area. Notes: DZ: Dezhou, BZ: Binzhou, DY: Dongying, YT: Yantai, WH: Weihai, QD: Qingdao, WF: Weifang, ZB: Zibo, JN: Jinan, LC: Liaocheng, TA: Taian, RZ: Rizhao, LY: Linyi, ZZ: Zaozhuang, JN': Jining, HZ: Heze.

2.2. Research Framework

From a land system perspective, this study developed a land-system-oriented framework for assessing PLES functional competition intensity by integrating the multifunctionality of land systems (Figure 2). Given the diversity of functional interactions across PLES types, this study selects four representative conflict scenarios within farmland PE and natural E spaces for quantitative assessment of functional competition intensity. First, multi-source datasets were combined to evaluate both individual and integrated LSFs, and a raster-based classification framework was established to delineate PLES, enabling a quantitative characterization of the spatial organization and temporal evolution of PLES across Shandong Province in 2010, 2015, and 2020. Second, the Coupling Coordination Model (CCM) was employed to quantify functional competition intensity among urban–rural spaces, farmland spaces, and ecological spaces, classify functional competition intensity into different levels, and identify their spatiotemporal dynamics. Finally, by integrating multidimensional driving factors spanning natural conditions, socioeconomic development, and landscape patterns, the XGBoost–SHAP framework was applied to reveal nonlinear spatial associations and response patterns associated with functional competition intensity, nonlinear responses, and threshold effects, thereby providing both theoretical insights and empirical evidence for adaptive land system governance. The data sources are presented in Supplementary Material S1.

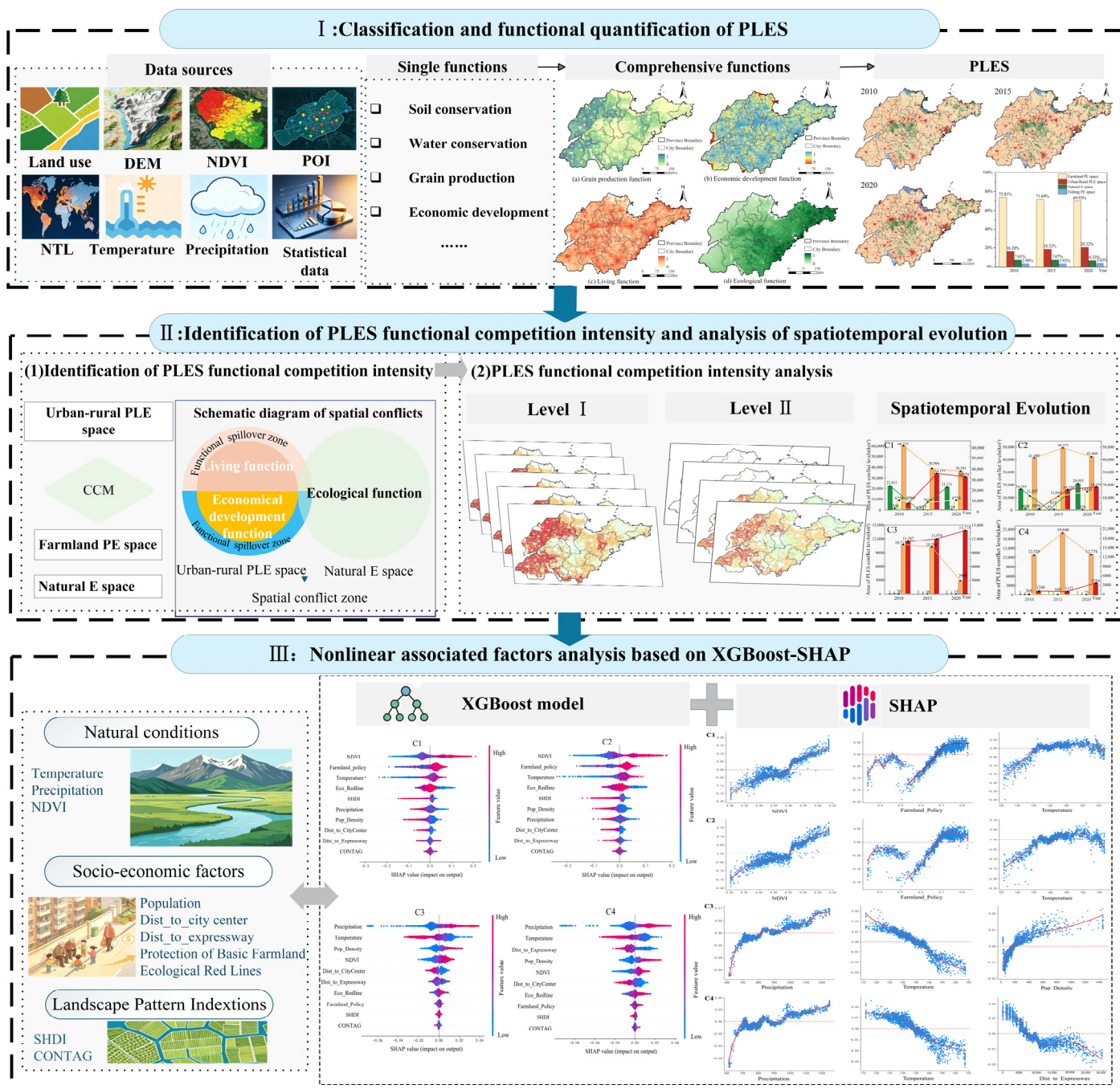


Figure 2. Research framework of this study.

2.3. Classification of PLES

Within a land system, multiple functions coexist and interact across the same spatial unit, and the dominant combination of these functions determines the organization of production–living–ecological spaces [43]. Differences in regional spatial scales and land-use configurations generate distinct functional structures, which shape the capacity of land systems to provide productive outputs, living services, and ecological benefits [44]. Compared with conventional land-use classifications based on a single dominant function, a multifunctionality-oriented perspective better captures the coupled functional organization and interactions within land systems, thereby providing a more realistic representation of regional PLES [45]. PLES represents the spatial organization of production, living, and ecological functions within the land system. In this study, PLES were delineated according to secondary land-use types and their dominant functional combinations [46].

Four categories were identified: natural ecological (E) space, farmland production–ecological (PE) space, fishing production–ecological (PE) space, and urban and rural production–living–ecological (PLE) space (Supplementary Material S2). The classification provides the spatial basis for subsequent functional assessment. Land system multifunctionality was subsequently characterized through multiple spatialized indicators representing production, living, and ecological functions. Given the diversity of functional interactions across PLES types, the subsequent conflict-risk assessment focused on four representative functional competitions within farmland PE and natural E spaces, where the relevant competing functions could be consistently quantified using the established indicators.

2.4. Assessment of PLES Functional Competition Intensity

2.4.1. Methodology for Assessing Land System Multifunctionality

Based on the PLES classification, this study quantitatively evaluates PLE functions from a functional provision perspective. To reduce the effects of differences in indicator units and magnitudes, all variables are normalized using a min–max scaling method, resulting in values ranging from 0 to 1 [47]. After normalization, a weighted overlay approach is applied to integrate all indicators for functional assessment [48,49]. Subsequently, separate indices are derived for PLE functions.

Ecological functions encompass soil conservation, water conservation, and carbon sequestration and oxygen release; productive functions include grain production and economic development; and living functions cover public services, transportation accessibility, and residential safety. The three selected ecosystem services represent complementary regulating functions related to soil, water, and climate processes. Soil conservation reflects erosion regulation and soil retention, water conservation represents hydrological regulation, and carbon sequestration and oxygen release captures carbon regulation and atmospheric environmental maintenance [50]. At the grid scale, these functions are quantified using multiple models, including RUSLE [51,52], InVEST [53,54], CASA [49], along with kernel density estimation [55], and GIS-based contribution coefficient approaches [56]. The 15 min catchment method follows the GIS-based accessibility framework established in 15 min city research. For each POI category, the 15 min catchment area was delineated as the area reachable within a 15 min travel threshold [57], which provides a step-by-step GIS methodology for measuring, visualizing, and analyzing 15 min city accessibility. The use of a 1 km grid for accessibility computation is consistent with the approach adopted in the classification of the 15 min city across 339 Chinese cities [58], which computes reachable facilities within the 15 min walking threshold for each 1 km grid cell. In our implementation, a travel speed of 60 km/h was assumed, corresponding to a 15 km radius, following China's 15 min livable community planning framework [59]. All functional indices are mapped at grid resolution, producing spatiotemporal patterns of PLES functional intensity across Shandong Province. These results provide the functional basis for identifying representative conflict scenarios and constructing the subsequent functional competition intensity index described in Table 1. All weights are now listed in Supplementary Material S3.

Table 1. Indicator system and spatialization methods for the assessment of LSFs.

Functional Dimension	Specific Features	Quantitative Indicators	Formula for Spatialization Methods
Ecological functions	(a) Soil conservation function	The amount of soil conservation	This study utilized a modified RUSLE model to calculate soil retention, employed the InVEST model to assess water conservation in Shandong Province, and evaluated carbon sequestration and oxygen release capacity based on NPP estimates derived from the CASA model.
	(b) Water conservation function	The amount of water conservation	
	(c) Carbon sequestration and oxygen production function	The value of carbon sequestration and oxygen production	
Production functions	(d) Grain production function	Grain production value in farmland	Cereal production depends primarily on arable land. There is a linear relationship between NDVI and cereal production. In this study, the ratio of the total NDVI value for an administrative unit to the total NDVI value for its arable land is used as a coefficient to allocate cereal production to administrative units. The calculation formula is as follows: $FS = \left[\frac{NDVI(x)}{NDVI_{sum}} \right] \times G_{sum} \quad (1)$ In the equation, FS represents grain yield per unit area (t/hm²); $NDVI(x)$ denotes the vegetation cover index for administrative unit x; $NDVI_{sum}$ denotes the sum of the vegetation cover indices for arable land; and G_{sum} denotes the total grain yield (t).
	(e) Economic development function	Spatial spillover effects	Based on data from points of interest such as retail services, businesses and catering establishments, a vehicle speed of 60 km/h was selected and a “15 min catchment area” was defined as the radius of influence. Using Euclidean distance analysis and negative normalization, combined with weighted superposition, the radiation intensity of economic development functions was determined.
Living functions	(f) Public service function (g) Traffic service function	Spatial spillover effects	

(h) Residential security function

Using POI data covering government, cultural, educational and healthcare facilities, motorway exits, railways and roads of all grades, fire stations and police stations, and applying the same “15 min living circle” radius as for economic development, we calculate the coverage intensity of public services, transport services and residential safety. These are weighted with a ratio of 0.4:0.3:0.3 to derive the living functionality score.

2.4.2. Proxy-Based Assessment of PLES Functional Competition Intensity

The CCM is a simple yet effective method and has been extensively used to assess coordinated development among multiple systems, such as the ecological environment, urbanization, agriculture, industry, transportation, and population, across different spatial scales and regions [48,60]. Although CCM is conventionally described as a coupling coordination model, D is not interpreted here as a normative measure of harmonious coordination. In this study, U_1 and U_2 represent two competing land-system functions associated with a specific conflict scenario. When both functions exhibit high levels within the same spatial unit, the coupling-based index reflects stronger simultaneous functional demands and therefore greater intensity of potential competition between the two functions. Importantly, the conflict degree D derived from the CCM is used in this study as a proxy-based measure of functional competition intensity rather than a direct observation or externally validated measure of realized PLES conflict. Accordingly, references to “conflict risk” in relation to the D index refer specifically to proxy-based functional competition intensity represented by D . Higher D values indicate stronger functional competition within the assessment framework, but should not be interpreted as independently observed conflict events or as an externally validated measure of realized conflict. In this study, the coupling coordination index framework is applied at the grid scale to derive D , which represents the interaction intensity between two competing land functions [61]. Four representative functional conflict scenarios are identified according to the functional characteristics of different PLES types. C1 represents the conflict between economic development and grain production within farmland production–ecological space; C2 represents the conflict between living and grain production within farmland production–ecological space; C3 represents the conflict between economic development and ecological functions within natural ecological space; and C4 represents the conflict between living and ecological functions within natural ecological space. Thus, the production, living, and ecological functional dimensions are represented across the four scenarios through their corresponding functional indices. For each conflict scenario, the two competing functional indices are denoted as U_1 and U_2 , respectively. The coupling degree (C) and comprehensive coordination index (T) are first calculated based on the two functional indices, and the functional competition intensity (D) is subsequently derived as follows:

$$D = \sqrt{C \times T} \quad (2)$$

$$C = 2 \times \sqrt{\frac{U_1 \times U_2}{(U_1 + U_2)^2}} \quad (3)$$

$$T = \alpha U_1 + \beta U_2 \quad (4)$$

where D denotes functional competition intensity used as a proxy indicator; C denotes the coupling degree; T is the comprehensive coordination index; U_1 and U_2 are the standardized values of the two PLES function types; and α and β are weighting coefficients. In this study, equal weights are assigned ($\alpha = \beta = 0.5$) to calculate the proxy-based functional competition intensity represented by D .

The index D ranges from 0 to 1, where higher values correspond to higher levels of functional competition intensity. Based on this proxy indicator, the spatial heterogeneity and spatiotemporal dynamics of functional competition are examined by classifying D into different competition-intensity levels; the classification criteria are provided in Supplementary Material S4.

2.5. XGBoost-SHAP

As a gradient-boosting tree ensemble algorithm, XGBoost iteratively constructs multiple weak regression trees based on classification and regression trees (CART) and combines them through weighted aggregation to capture complex nonlinear relationships. Its regularization scheme constrains model complexity and helps improve generalization performance [62,63]. SHAP interprets model predictions by decomposing them into the marginal contributions of individual features based on Shapley value theory, providing both local and global model interpretability [63]. In this study, SHAP values are used to characterize the relative contribution of each explanatory variable to the modelled functional competition intensity patterns. Combined with SHAP dependence analysis, this approach identifies nonlinear spatial associations and response patterns between land-system conditions and functional competition intensity [64].

An XGBoost-SHAP framework is employed, with the grid-scale functional competition intensity index (D) as the dependent variable. Ten explanatory variables, including temperature, precipitation, NDVI, population density, SHDI, CONTAG, distance to city center, distance to motorway, protected basic farmland, and ecological redline areas, are used as predictors [65]. Some explanatory variables, particularly NDVI and accessibility-related variables, are also involved in the construction of certain functional indicators. Therefore, the XGBoost-SHAP analysis is not intended to establish independent causal effects or to identify causal driving mechanisms. Instead, it is used to characterize nonlinear spatial associations between observed land-system conditions and the resulting functional competition intensity patterns. The potential overlap between explanatory variables and functional indicators is explicitly considered when interpreting variable importance, SHAP values, and response patterns. In this study, the XGBoost-SHAP analysis was conducted as a single-year cross-sectional analysis for 2020. To reduce the potential inflation of predictive performance caused by spatial autocorrelation, the sampled pixels were grouped into approximately 10×10 -pixel spatial blocks, corresponding to approximately $10 \text{ km} \times 10 \text{ km}$ at the 1 km raster resolution. Approximately 80% of the spatial blocks were assigned to model training and the remaining 20% were retained as an independent spatial hold-out test set. The block-level partitioning means that the proportions of individual observations in the training and test sets were not exactly 80% and 20%, respectively. Within the training set, model robustness was further evaluated using 10-fold spatial block cross-validation, with each fold holding out a distinct set of spatial blocks. Model performance was assessed using the coefficient of determination (R^2) and root mean square error (RMSE). The independent spatial test set was not used during cross-validation or model fitting and was used only for final performance evaluation. SHAP values were subsequently calculated for the fitted models to quantify the relative contribution and direction of each predictor and to characterize nonlinear associations between predictors and functional competition intensity.

3. Results

3.1. PLES Patterns and Spatiotemporal Evolution

According to the Shandong Province land-use survey and the PLES classification framework (Supplementary Material S2), the spatial organization of PLES within the regional land system shows pronounced heterogeneity, with substantial changes in the distribution of different functional spaces during 2010–2020 (Supplementary Material S5). Farmland PE space is predominantly concentrated in the plains of northwestern and southwestern Shandong, forming a relatively stable and contiguous spatial pattern. In contrast, natural E space is mainly distributed across mountainous, hilly, and coastal areas. Urban and rural PLE space exhibits a network-like configuration structured around

major cities and transportation corridors, whereas fishing PE space is primarily located along the Shandong Peninsula coastline and around large lakes and reservoirs. Between 2010 and 2020, the functional configuration of the land system shifted toward increasing urban and fishing functions, while farmland and natural ecological functions generally contracted. Specifically, the proportion of farmland PE space declined from 73.81% to 69.93%, and the areas of greatest reduction largely coincided with zones of urban expansion, indicating substantial conversion of farmland to construction land. During the same period, urban and rural PLE space increased from 16.20% to 20.32%, with expansion concentrated in Jinan, Qingdao, and the Yellow River Delta. Natural E space displayed a fluctuating trajectory, initially increasing before declining overall, whereas fishing PE space expanded continuously, with growth primarily occurring along the Bohai Bay coastline and the Yellow River Delta.

3.2. Identification and Analysis of PLES Functional Competition Intensity

3.2.1. Functional Zoning for Land System Multifunctionality

At the grid scale, this study quantified the spatial distribution of four LSFs in Shandong Province, including grain production, economic development, living, and ecological functions (Figure 3). Among these, areas with high grain production values are concentrated in traditional grain-producing regions such as western Shandong, the Yellow River floodplain in northern Shandong, and the Jiaolai River Plain, exhibiting a pattern of “higher in the west and lower in the east, and higher on the plains and lower in the hills” (Figure 3a). Economic development functions exhibit prominent point-axis agglomeration and core areas, which diminish with increasing distance (Figure 3b). Areas with high residential function values are concentrated in the central urban districts of various cities and areas with dense public services, expanding into built-up areas as the “15 min community living circle” initiative progresses (Figure 3c). Areas with high ecological function values are distributed across the mountainous and hilly regions of central and southern Shandong, the hilly areas of the Jiaodong Peninsula, and coastal wetlands such as the Yellow River Delta (Figure 3d). Collectively, these four LSFs exhibit both spatial overlap and competitive distributions, reflecting the multifunctional organization of the regional land system. By quantifying their spatial supply capacity and distributional relationships, this assessment provides the functional basis for subsequent assessment and interpretation of PLES functional competition intensity.

3.2.2. Spatial Patterns of PLES Functional Competition Intensity

The assessment of PLES functional competition intensity revealed pronounced spatial heterogeneity in Shandong’s land system during 2010–2020, with grain-production-related conflicts consistently exceeding those linked to ecological functions (Figure 4). Specifically, within farmland PE space, both C1 and C2 exhibited five risk levels, from low to highest, with moderate and high-risk areas dominating across the province. Spatially, these areas were concentrated mainly in the Central Shandong Plain and parts of Northwest Shandong, forming patchy or strip-like patterns with risk decreasing from the core to the periphery. Temporally, high-risk C1 contracted substantially, from 69,255 km² in 2010 to 36,541 km² in 2020, indicating progressive shrinkage of high-risk areas. By contrast, C2 fluctuated: its high-risk area increased from 41,400 km² in 2010 to 49,373 km² in 2015, before declining to 42,469 km² in 2020. In natural E space, C3 and C4 were characterized by high and highest risk levels and were more spatially concentrated than conflicts in farmland PE space. Medium-to-high-risk patches were distributed mainly in the hilly regions of south-central Shandong and selected coastal ecological zones. Notably, the highest-risk area of C3 expanded from 11,387 km² in 2010 to 13,775 km² in 2020, while that of C4 increased from 1240 km² to 3758 km² over the same period. These trends indicate a

progressive expansion of the areas with the highest ecological-function-related competition intensity, especially C4.

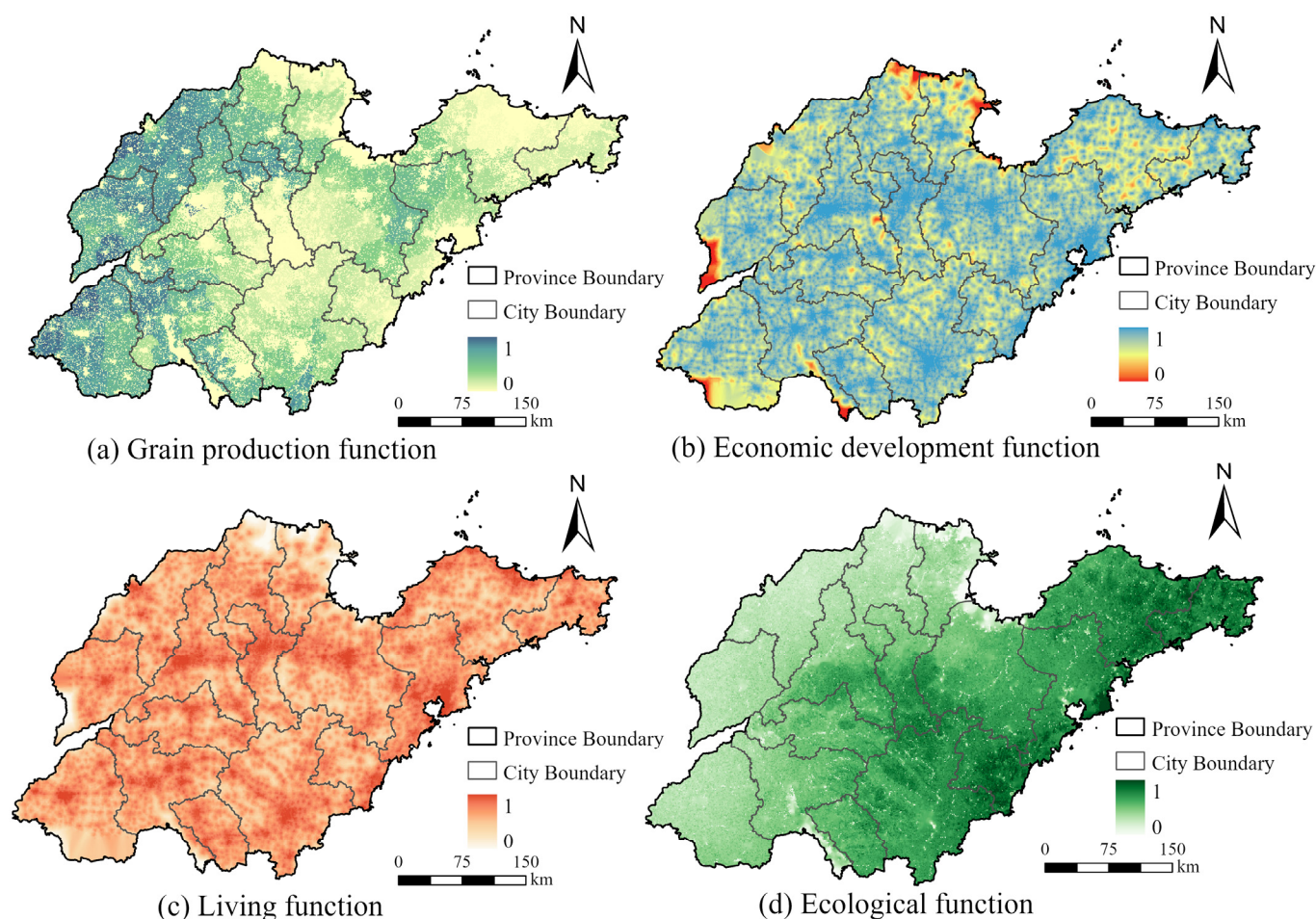


Figure 3. Comprehensive LSFs in Shandong Province.

As shown in the PLES functional competition intensity Level II classification map, conflict intensity is closely related to shifts in functional dominance across different development contexts (Figure 5). In farmland PE space, areas dominated by economic development are concentrated in central and northwestern Shandong Province, where the expansion of construction land has significantly encroached on farmland; in contrast, areas dominated by grain production are primarily located in the eastern coastal regions and areas with a strong agricultural foundation, where the land-use structure remains relatively stable. Conflicts between residential functions and grain production exhibit distinct urban-rural gradients. Areas dominated by residential functions are primarily distributed around towns and cities and in regions with good transportation access; those dominated by grain production, on the other hand, are mostly distributed in agriculture-dominated areas far from urban centers, forming patchy distributions. In natural E space, areas dominated by economic development functions are concentrated in regions with frequent resource exploitation and dense infrastructure, forming strip-like distributions along transportation corridors and in the direction of urban expansion; In contrast, areas dominated by ecological functions are scattered across regions with good ecological baseline conditions and low development intensity. Conflicts between residential and ecological functions: those dominated by residential functions mostly occur at the urban periphery, appearing as isolated points or patches; those dominated by ecological functions are

commonly found around nature reserves and key ecological patches, forming relatively continuous spatial patterns.

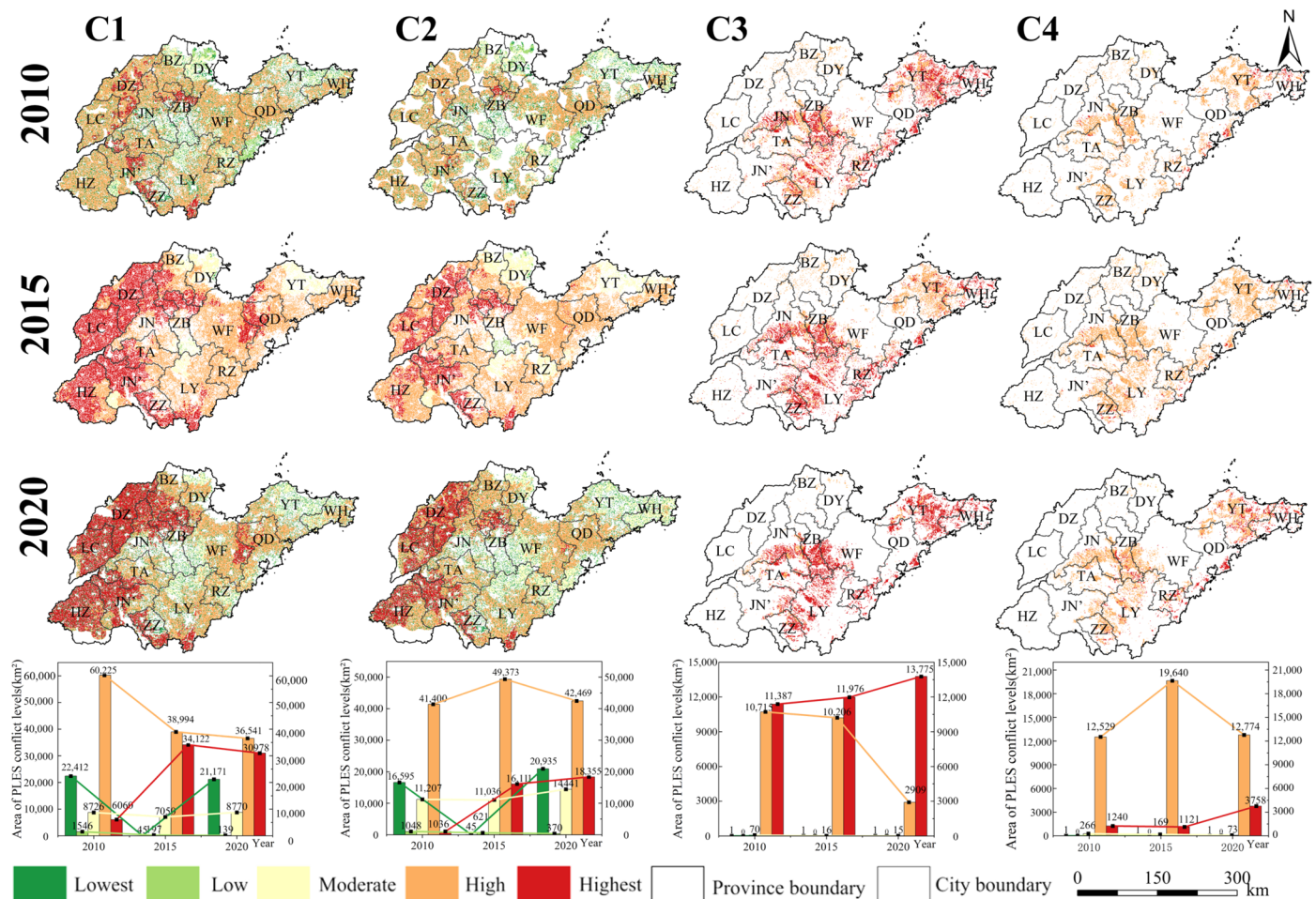


Figure 4. Level I classification and proportion of PLES functional competition intensity at different stages in Shandong Province in 2010, 2015, and 2020. Notes: C1 and C3 represent economic function conflicts with production and ecological functions, while C2 and C4 represent living function conflicts with the same, within farmland PE and natural E spaces, respectively.

3.3. Nonlinear Spatial Associations with PLES Functional Competition Intensity

3.3.1. Relative Contributions of Associated Factors

Based on the XGBoost-SHAP model, the relative contributions of the explanatory variables to the modelled functional competition intensity patterns were evaluated (Figure 6). The results reveal both commonalities and differences across conflict types. In farmland PE space, conflicts between economic development and grain production, as well as between living functions and grain production, show relatively strong associations with NDVI, protected basic farmland, and temperature. Among these variables, NDVI exhibits the largest mean absolute SHAP contribution in the corresponding models. However, because NDVI is also involved in the estimation of the grain production function, this contribution should be interpreted as an association with the resulting functional competition intensity pattern rather than as an independent causal effect. In natural E space, precipitation and temperature show relatively large contributions to the modelled functional competition intensity patterns, while population density and transportation accessibility also exhibit notable associations. These results indicate that the spatial distribution of ecological functional competition intensity is associated with a combination of climatic conditions and human-accessibility characteristics. Importantly, the SHAP results

describe model-based spatial associations and relative contributions; they do not establish that individual environmental, socioeconomic, accessibility, or policy-related variables independently cause changes in PLES functional competition intensity.

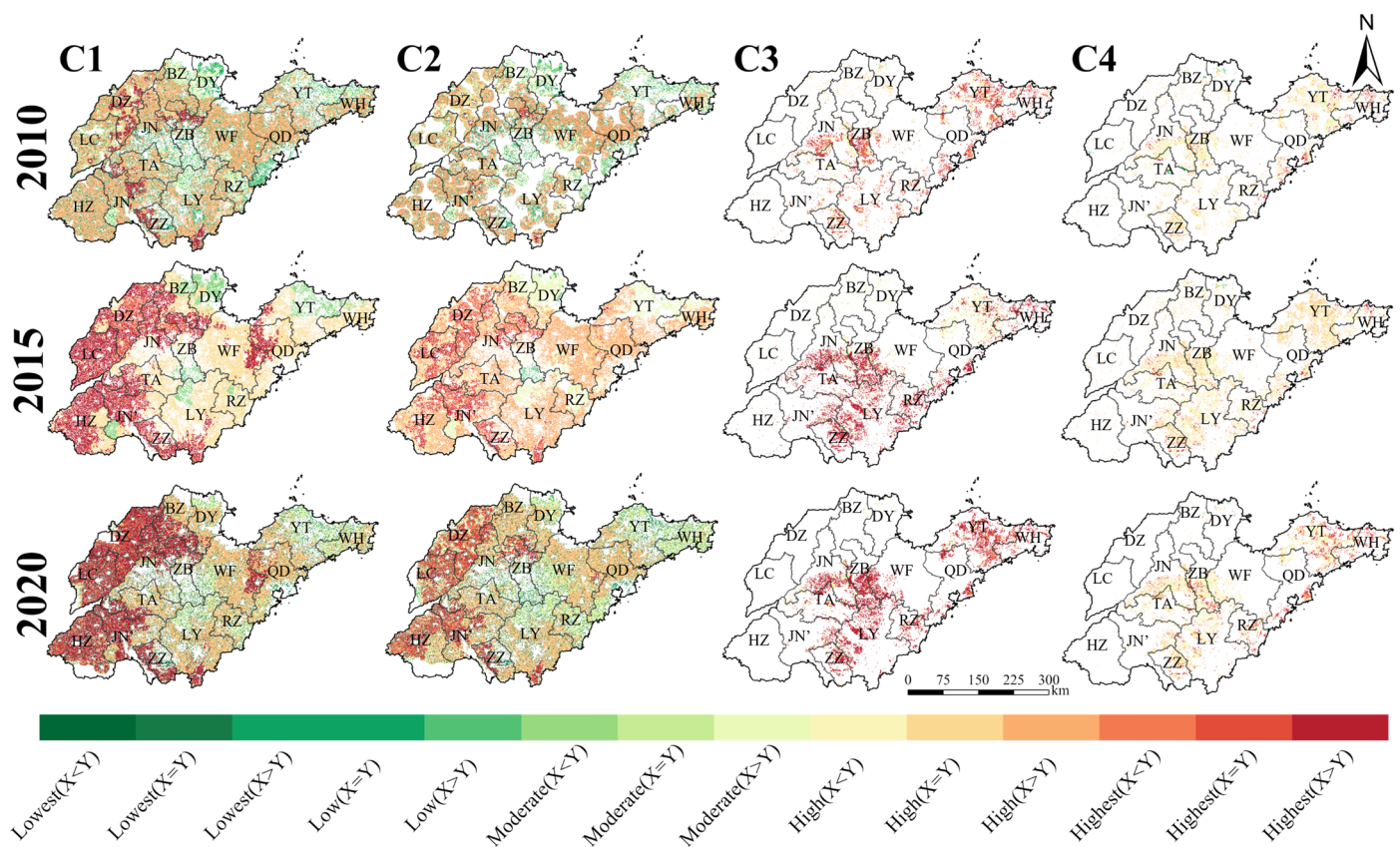


Figure 5. Level II classification of PLES functional competition intensity at different stages in Shandong Province in 2010, 2015, and 2020.

The spatial validation results indicated clear differences in predictive performance among the four conflict scenarios (Supplementary Material S6). Based on the independent spatial test set, the XGBoost models achieved R^2 values of 0.7818, 0.7598, 0.3566, and 0.3479 for C1, C2, C3, and C4, respectively, with corresponding RMSE values of 0.0528, 0.0529, 0.0268, and 0.0269. The 10-fold spatial block cross-validation produced mean R^2 values of 0.7671 ± 0.0174 for C1, 0.7631 ± 0.0321 for C2, 0.3974 ± 0.0974 for C3, and 0.4346 ± 0.1326 for C4. The corresponding mean RMSE values were 0.0542 ± 0.0026 , 0.0512 ± 0.0038 , 0.0275 ± 0.0020 , and 0.0293 ± 0.0016 , respectively. C1 and C2 showed relatively strong and stable spatial predictive performance, with close agreement between the independent spatial test and cross-validation results. In contrast, C3 and C4 exhibited lower R^2 values and greater fold-to-fold variability, indicating weaker and more spatially heterogeneous predictive performance. Nevertheless, the cross-validation R^2 values remained positive across all folds, suggesting that the predictor set retained explanatory information for these two conflict scenarios despite their greater spatial heterogeneity. These results provide a spatially more conservative basis for the subsequent SHAP interpretation of non-linear associations.

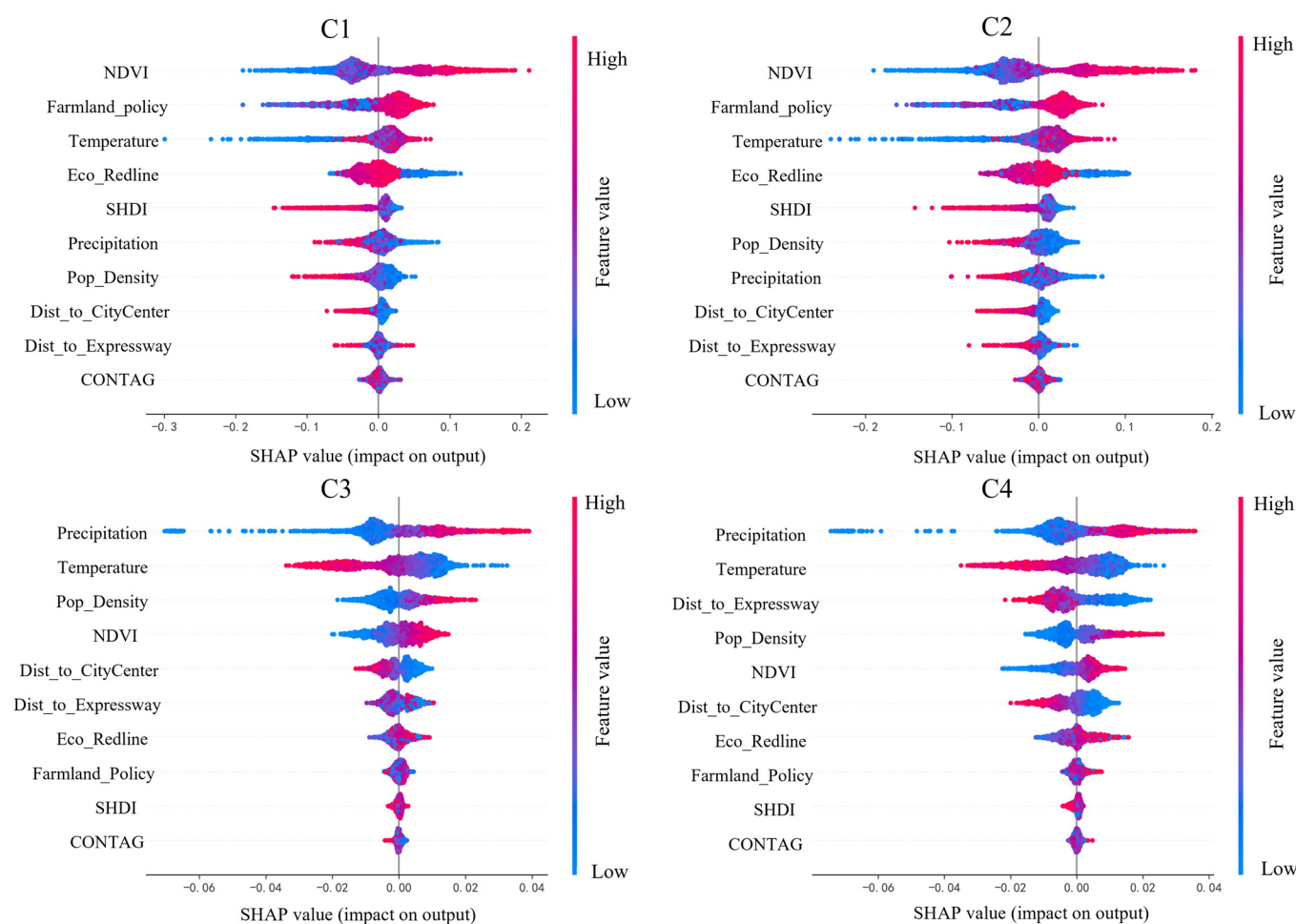


Figure 6. Ranking of the importance of factors associated with PLES functional competition intensity.

3.3.2. Nonlinear Responses of Functional Competition Intensity to Land-System Variables

SHAP dependence analysis indicates that the associations between selected land-system variables and PLES conflict-risk patterns are nonlinear and vary across different ranges of the explanatory variables (Figure 7). In the conflict between economic development and grain production, NDVI shows a predominantly positive SHAP association, with the response changing from negative to positive around an NDVI value of approximately 0.1. This value is treated as an empirical response point within the fitted model rather than a causal or universal threshold. Temperature shows a positive association with the modelled conflict-risk pattern at lower values, with the response becoming less pronounced around 13 °C.

For the conflict between living and grain production, the response patterns are broadly similar to those observed for economic development versus grain production. For the conflict between economic development and ecological functions, precipitation and population density show relatively weak positive associations, whereas the SHAP response to temperature becomes increasingly negative above approximately 13 °C. A similar negative temperature response is observed for the conflict between living and ecological functions, while precipitation shows a weaker response and shorter distance to highways is associated with higher modelled conflict-risk values. Across the four conflict scenarios, farmland-related conflicts generally exhibit more consistently positive response patterns for several key variables, whereas ecological conflicts show more differentiated

nonlinear associations, particularly for temperature. These results indicate that the relationship between land-system conditions and conflict-risk patterns varies across environmental and socioeconomic contexts. The identified response points are therefore interpreted as empirical response ranges or threshold-like patterns within the study period and study area, rather than as universal critical thresholds or causal effects.

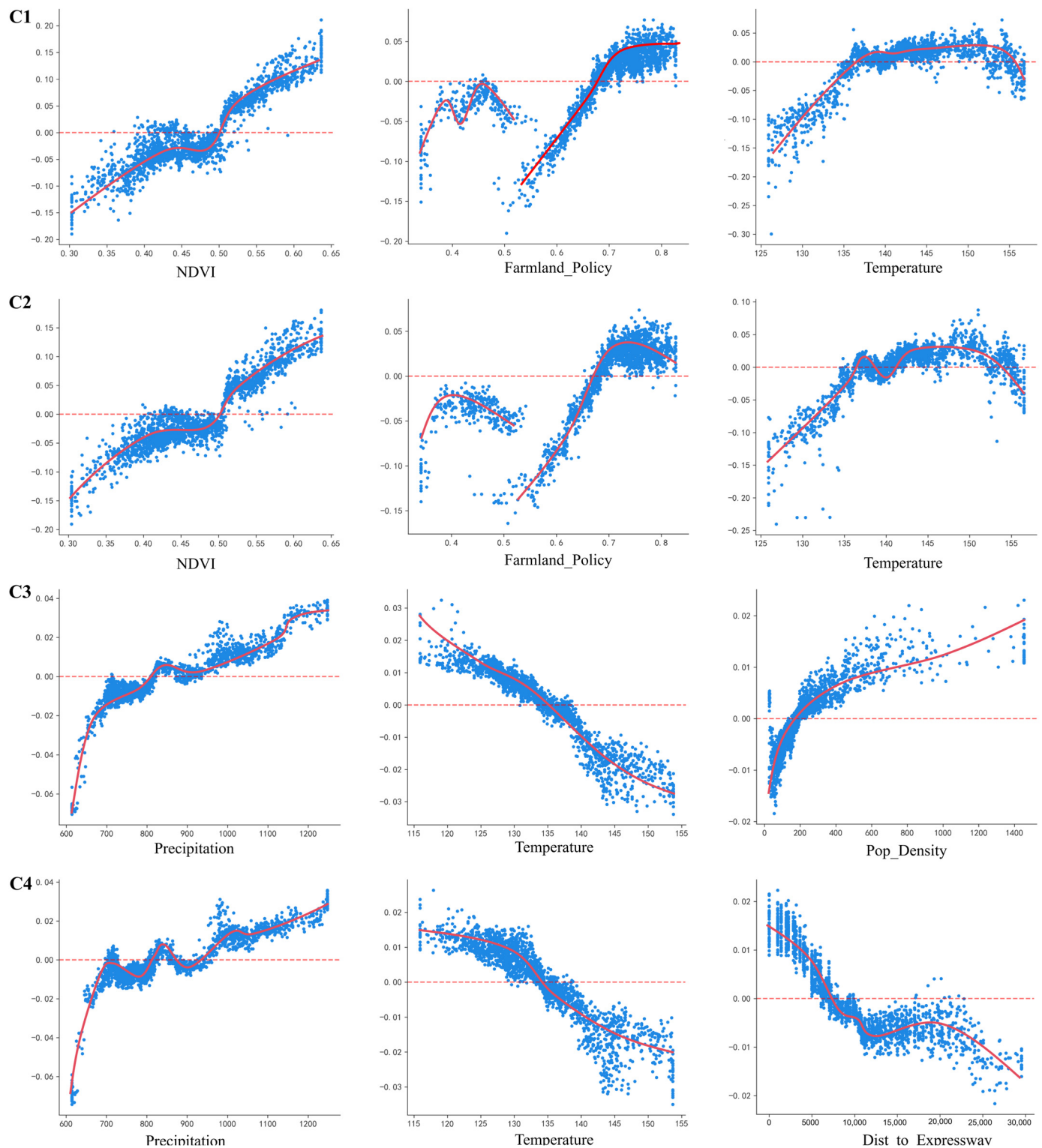


Figure 7. Nonlinear responses of PLES functional competition intensity to associated land-system factors.

4. Discussion

4.1. Land System Multifunctionality and PLES Functional Competition Intensity

The results provide empirical support for the proposition that land system multifunctionality constitutes the functional context in which PLES functional competition is spatially manifested. Multifunctionality does not inherently generate conflict; rather, functional competition intensity becomes more pronounced when production, living, and ecological functions coexist with intensified competition or spatial overlap. In Shandong, the pronounced spatial heterogeneity of functional competition intensity and its changes over time corresponded to the differentiated reorganization of PLES and land functions. This indicates that functional competition intensity is associated not simply with land-use conversion, but with the spatial reconfiguration and relative balance of multiple land functions. This finding extends the land-use conflict perspective by shifting attention from competition between individual land-use types toward interactions among multiple functions embedded within the land system. Previous research has increasingly demonstrated that urban development, food production, and ecosystem services may involve simultaneous trade-offs rather than independent optimization [66]. For example, quantitatively compared urban services, food production, and ecosystem services and showed that alternative land-sharing and land-sparing strategies generated different trade-offs among these functions. Similarly, a recent PLES assessment in Mainland Southeast Asia identified substantial spatial competition between urban, cropland, and biodiversity-related functions, with more than 50% of croplands overlapping biodiversity hotspots in several countries [67]. These findings support the broader proposition that spatial competition is closely related to the coexistence and configuration of multiple land functions, although its spatial expression varies across contexts.

The grid-scale results further demonstrate that such functional competition is spatially heterogeneous, with localized conflict patches and transition zones that may be obscured by administrative-unit assessments (Supplementary Material S7). The theoretical implication is therefore that land system multifunctionality provides the functional context for conflict, whereas the spatial configuration and relative balance of functions are associated with the intensity and distribution of functional competition intensity. In this sense, the present study does not treat multifunctionality itself as a source of conflict, but clarifies the conditions under which multifunctional land systems exhibit spatially differentiated functional competition intensity.

4.2. Nonlinear Responses

The XGBoost-SHAP results further demonstrate that the relationship between land-system conditions and PLES functional competition intensity is predominantly nonlinear. Population density, temperature, NDVI, and distance to the city center showed pronounced response patterns, indicating that the association between functional competition intensity and environmental, socioeconomic, and spatial conditions changes across different ranges rather than following a simple monotonic relationship. This finding is consistent with international research showing that changes in one land function can produce heterogeneous effects on other functions depending on the intensity and spatial context of land-use change. For example, modelling of peri-urban agriculture in Barcelona showed that a 31% and 115% expansion of peri-urban agricultural land could increase local food production by 24% and 86%, respectively, while simultaneously increasing irrigation-water requirements by 10.0% and 43.5% [68]. The result illustrates how strengthening one function can simultaneously intensify pressures on other functions, providing a useful international reference for interpreting the nonlinear relationships identified in this study.

The SHAP dependence analysis identified an apparent response transition around 13 °C, above which temperature was associated with a change toward lower predicted ecological functional competition intensity. This pattern may reflect the combined influence of thermal conditions on vegetation growth and ecosystem functioning. One possible interpretation is that temperature captures part of the climatic conditions associated with vegetation activity and ecosystem functioning. However, this interpretation remains a testable hypothesis rather than a mechanism demonstrated by the present analysis. The observed relationship may also reflect covariation between temperature and other spatial characteristics, including latitude, topography, and regional hydroclimatic conditions. Although precipitation and NDVI were included as predictors, the model did not explicitly control for all potential geographical confounders, and their joint effects cannot be ruled out. Moreover, the approximately 13 °C threshold was identified visually from the SHAP dependence plot rather than estimated through a formal change-point test. It should therefore be interpreted as an exploratory, data-driven transition in the model-derived association, not as a statistically confirmed or universally applicable ecological threshold. These considerations highlight the need for further methodological assessment of the robustness and transferability of the observed response pattern.

The spatial validation results also suggest that the strength of the observed associations varied among conflict scenarios. The relatively stable performance for C1 and C2 supports the robustness of the identified nonlinear associations, whereas the lower and more variable predictive performance for C3 and C4 indicates greater spatial heterogeneity in the relationships between the selected factors and ecological-function-related functional competition intensity. Accordingly, the SHAP results should be interpreted as evidence of nonlinear spatial associations and relative contributions to proxy-based functional competition intensity rather than as causal effects or universally transferable predictive relationships.

4.3. Policy Implications

The combined findings suggest that the D-based assessment should be understood as a proxy-based representation of functional competition intensity associated with the interaction and rebalancing of multiple land functions, rather than as a direct observation of realized PLES conflict. This perspective provides a conceptual link between land system multifunctionality and proxy-based functional competition assessment: multifunctionality determines the coexistence of different functional demands, while their spatial configuration and nonlinear responses to environmental and socioeconomic conditions shape where functional competition intensity becomes more pronounced.

This interpretation has two theoretical implications. First, it complements conventional land-use conflict studies by emphasizing functional competition rather than land-use conversion alone. A landscape may contain several compatible functions without exhibiting substantial conflict, whereas functional competition intensity may increase when the spatial arrangement or relative intensity of these functions creates stronger competition. Second, it introduces nonlinearity as an important property of the multifunctionality–conflict relationship. The observed threshold-like responses indicate that the association between functional competition intensity and land-system conditions can change substantially across different environmental and socioeconomic ranges. Thus, the relationship between multifunctionality and functional competition intensity should not be conceptualized as a uniform linear response.

From a governance perspective, the findings provide empirical references for functionally differentiated spatial planning, while their application should remain bounded by the 2010–2020 observation period. The spatial patterns identified in this study can help inform the selection of areas and indicators for subsequent monitoring, particularly in

functional transition zones where production, living, and ecological demands overlap. The nonlinear response ranges may also support early risk identification by highlighting ranges of environmental, socioeconomic, and spatial conditions associated with higher proxy-based functional competition intensity during the observation period. These ranges should be treated as empirical reference points rather than operational warning thresholds or evidence of current risk conditions. Their application to contemporary territorial planning requires updated, temporally consistent observations and further assessment. The governance implication is not to eliminate multifunctionality, but to manage the spatial relationships among competing functions. In agricultural–ecological transition areas, this may involve coordinating production intensity with ecological conservation; in rapidly urbanizing areas, it may involve regulating development intensity and protecting essential ecological and agricultural functions. Such differentiated management is consistent with the principle that the objective of territorial planning is not to maximize a single land function, but to maintain a more balanced configuration of multiple functions. Overall, the theoretical contribution of this study lies in connecting multifunctionality, spatial configuration, and nonlinear response within a unified interpretation of PLES functional competition intensity. This provides a basis for understanding functional competition intensity as a spatially differentiated outcome of functional competition and for translating nonlinear empirical evidence into functionally differentiated territorial planning and monitoring.

4.4. Limitations and Prospects

Although this study provides an empirical application of a proxy-based framework for assessing representative PLES functional competition intensity at the regional scale and reveals the nonlinear responses and threshold behaviors, several limitations warrant further investigation.

(1) In this study, *D* is used as a proxy-based measure of functional competition intensity between competing functions, rather than as a direct or externally validated measure of realized conflict. Future research should compare or validate this proxy indicator against independent evidence of functional conflict, land-use transition, or other observed manifestations of functional competition. This study did not conduct a systematic sensitivity analysis of indicator weights or catchment radii. Although the weights and the 15 min catchment radius were based on established planning standards and previous studies, parameter uncertainty may affect the magnitude of the functional competition intensity index. Future research should test alternative weighting schemes and catchment radii, and validate the results with independent land-use transition data. (2) The performance of the XGBoost–SHAP framework remains sensitive to sample composition and parameter settings, and its robustness should be further evaluated through comparative analyses. Its analysis provides useful insights into nonlinear spatial associations, but the estimated variable contributions and response ranges should be interpreted within the study context and not as independent causal effects or universal thresholds. The temperature-related threshold identified from the SHAP dependence plot is exploratory and has not been independently validated using formal change-point analysis. In addition, potential confounding by topography, latitude, and other spatially structured environmental factors cannot be excluded; therefore, the identified threshold should not be interpreted as a causal or universally transferable critical value. (3) The quantitative functional competition intensity assessment represents four selected functional competitions rather than all possible interactions across the four PLES categories. Although urban and rural PLE space and fishing PE space were included in the PLES classification and spatiotemporal analysis, their internal functional conflicts were not quantified. This design was adopted to

maintain consistent functional definitions and comparable indicators across the four assessed conflict scenarios. Future studies could extend the framework to additional functional competitions within urban and rural PLE and fishing PE spaces, thereby providing a more comprehensive characterization of PLES functional interactions. (4) Temporal validity is an important consideration of this study. The empirical analysis is limited to the 2010–2020 observation period. We acknowledge that more recent products are available for individual data components, including annual land-cover and nighttime-light datasets. However, the four representative conflict scenarios are assessed through a linked analytical sequence involving land-use classification, PLES delineation, land-system multifunctionality assessment, conflict index calculation, and driver analysis. Updating only selected input layers would not, by itself, establish a temporally comparable assessment of the complete framework for 2023 or 2024, and could introduce inconsistencies among indicators and analytical stages. We therefore retain 2010, 2015, and 2020 as the benchmark years for the present analysis and interpret the results strictly as empirical patterns and associations observed during 2010–2020, rather than as a representation of current conditions. Future work should extend the complete analytical sequence using temporally harmonized recent datasets and independently assess the proxy indicator against external evidence of functional conflict or land-use change.

Future research could further examine the transferability of the framework by incorporating region-specific parameters, multi-source governance indicators, and multi-model comparative validation. Such efforts would improve the ability of the framework to explain how land system multifunctionality generates functional competition intensity under different territorial contexts while providing more robust evidence for adaptive spatial governance.

5. Conclusions

This study developed a land-system-oriented framework to examine four representative PLES functional conflicts within farmland PE and natural E spaces. Using the coupling-based index (D) as a proxy for functional competition intensity, we analyzed the spatial patterns of these conflicts and their nonlinear associations with selected environmental, socioeconomic, and spatial factors across Shandong Province in 2010, 2015, and 2020. The main findings are as follows.

First, the regional land system underwent substantial functional reconfiguration during 2010–2020: farmland production–ecological (PE) space remained dominant but decreased from 73.81% to 69.93%, whereas urban and rural production–living–ecological (PLE) space increased from 16.20% to 20.32%; fishing PE space expanded continuously, while natural ecological (E) space declined overall. These changes indicate a shift in the regional spatial configuration toward greater urban and human-use influence during 2010–2020, with potential implications for the allocation of agricultural and ecological functions. Second, D-based functional competition intensity exhibited pronounced functional and spatial differentiation. Grain-production-related conflicts were generally more intensive than ecological conflicts, with medium and high-risk areas concentrated mainly in farmland PE space, whereas ecological conflicts were less intensive but remained concentrated in localized environmentally sensitive areas. This suggests that spatial variations in D-based functional competition intensity are associated with the functional interactions and trade-offs represented in different land-system contexts, rather than being captured by land-use change alone. Third, functional competition intensity showed predominantly nonlinear associations with environmental, socioeconomic, and spatial variables. NDVI, protected basic farmland, and temperature were strongly associated with functional competition intensity in farmland PE space, whereas precipitation and temper-

ature showed stronger associations in natural E space, with population density and transportation accessibility also related to spatial variations in functional competition intensity. The nonlinear response patterns indicate that the associations between these factors and proxy-based functional competition intensity varied across different ranges of observed conditions. The response ranges identified by SHAP should be interpreted as data-driven empirical patterns specific to the study area and the 2010–2020 observation period, rather than as universal thresholds, causal transition points, or direct predictors of current conflict risk.

Together, these results provide an empirical application of a land-system-oriented framework for examining representative PLES functional conflicts and their proxy-based functional competition intensity during 2010–2020, offering empirical references for integrated land-use planning and functionally differentiated governance.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/systems14101320/s1>, Table S1: Data source; Table S2: Type of PLES; Table S3: Indicator weights; Table S4: Criteria for classifying functional competition intensity levels; Table S5: Performance evaluation metrics of the XGBoost model; Figure S1: PLES distribution maps for Shandong Province in 2010, 2015, and 2020; Figure S2: Distribution of high-conflict areas (C1–C4) from 2010 to 2020 and a statistical map of PLES conflicts across the 16 cities of Shandong Province. References citation [69–72].

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