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Assessing Eco-Environmental Effects and Its Impacts Mechanisms in the Mountainous City: Insights from Ecological–Production–Living Spaces Using Machine Learning Models in Chongqing

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Abstract: In the face of accelerating land use changes, conflicts between land use patterns and the eco-environment are increasingly pronounced. By calculating the eco-environment quality index (EQI) adopting the ecological–production–living spaces (EPLS) framework, we evaluate the eco-environment quality of land use changes within Chongqing's central urban area from 2000 to 2020. The study employs a random forest model to elucidate the mechanisms influencing the eco-environment quality. The findings reveal the following: (1) Living spaces have expanded by 361.53 km^2, while production and the ecological spaces have been experiencing a significant reduction of 331.42 km^2 and 30.11 km^2 over two decades. (2) The eco-environment quality has steadily declined from 0.3665 in 2000 to 0.3501 in 2020, indicating a degradation in overall quality. There is notable spatial variation in eco-environment quality, typically displaying a "low center–high periphery" pattern. (3) Pesticide usage, grain production, and the added value of the primary industry are the primary factors affecting ecological quality. The findings of this study provide valuable insights for global urban planning and environmental management. Rapidly, land use change regions worldwide face similar conflicts between economic growth and ecological sustainability. This research underscores the need for integrated land use policies that balance development with environmental preservation. The methodologies and findings can inform international efforts to optimize land use patterns, improve ecological quality, and achieving sustainable development goals, offering adaptable strategies for policymakers and urban planners globally.

Keywords: ecological–production–living spaces; land use transformation; eco-environmental effects; random forest model

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1. Introduction

Rapid urbanization is a focal point of global attention today, especially in developing countries. While industrialization and urbanization drive socioeconomic development, they also lead to significant land use changes [1–3]. Land serves as the primary carrier for national spatial planning, and the land use structure is crucial for the macro-regulation of regional ecosystems. By altering the original land cover types and the socioeconomic activities they support, land use changes affect the quality of terrestrial ecosystems and ecosystem cycles [4–6]. Land use change is one of the important driving factors for global environmental changes [7,8], significantly impacting ecological elements such as hydrology [9,10], climate [11], soil quality [12], and biodiversity [13]. China has undergone significant land use functional transformations, especially in the functional transformation of the ecological–production–living spaces (EPLS). This transformation not only affects the regional land use efficiency but also has profound impacts on the eco-environment.

Meanwhile, the Chinese government has emphasized creating "efficient and intensive production space, livable and moderate living space, and beautiful ecological space" as the EPLS [14,15]. Therefore, it is essential to connect the evolution of the EPLS with land use transformation to the rational development and utilization of resources, achieving the optimization goals of national spatial functions.

In recent years, research on the impact of land use transformation on the eco-environment quality has received increasing attention. Most of the studies mainly focus on the effects on eco-environment quality in many aspects, including urban climate [16], ecosystem services [17–19], carbon metabolism [20,21], landscape patterns [22–24], etc. For example, Li et al. (2011) explored how landscape composition affects the urban heat island effect in Shanghai, China, showing the contributions of different land use types [16]. Martin et al. (2017) studied the impact of land use and climate change on water resources in the Yadkin–Pee Dee basin in North Carolina, finding significant effects from both factors, especially under drastic land use changes [19]; Gries et al. (2019) highlighted the role of land use changes in global climate change through surface albedo and carbon cycle alterations [21]; Deng et al. (2009) analyzed the impact of rapid urbanization on land use change and landscape patterns, noting a shift from agricultural land to urban land [22]; Khan et al. (2020) showed that in Islamabad, Pakistan, land use changes have a significant impact on the urban heat island effect, which also affects agricultural production [24]. These studies collectively demonstrate that land use transformation has significant impacts on various aspects of the eco-environment quality, and these impacts may vary under different geographical and socio-economic contexts. However, most of these studies focus on changes in a single land use type, lacking a systematic analysis of the comprehensive transformation of the EPLS and its eco-environmental effects.

Research on the impact of land use change on eco-environment quality has predominantly concentrated on flat, coastal, and metropolitan cities at different scales [25,26]. For metropolitan cities, studies included biodiversity loss and climate change due to urbanization in New York and Los Angeles [27,28]. In terms of research scale, previous studies have mostly focused on national [6,29,30], provincial [31–33], urban agglomerations [34–36], or individual county-level cities [17,37,38]. For example, Zhou et al. (2020) and Chen et al. (2023) have discussed global and regional impacts on climate and landscape patterns, respectively [39,40]. Xiong et al. (2022) analyzed the land use changes in Qishan County over the past 20 years, focusing on the transition from farmland and forestland to urban land [37]; Olorunfemi et al. (2020) used GIS and remote sensing technology to analyze the impact of land use changes on eco-environment quality at the county level in Ekiti State, Nigeria [38]. The research covered many conditions, including flat, coastal, and metropolitan environments. For instance, Chen et al. (2022) studied the water quality, sea level rise, and vegetation productivity impacted by rapid urban expansion in coastal cities [26]. Mountain cities face unique challenges due to their complex topography, which influences land use patterns, hydrology, and biodiversity differently than flat or coastal cities. The steep slopes and varied elevations in mountain cities lead to distinct ecological processes and environmental impacts, requiring tailored approaches to land management and ecological protection. However, there are still relatively few cases analyzing land use transformation and its eco-environmental effects in mountain cities. Research on the mechanisms affecting changes in eco-environmental effects is also limited.

The eco-environment quality index, which quantifies eco-environmental quality changes due to land use transformation, is essential for coordinating land development and ecological protection. Environmental assessment is essential for monitoring ecosystem health and ensuring sustainable management practices. Ecological quality (EQ) evaluates the general well-being of natural systems and the services they provide. The ecological quality index, as a more specific and detailed indicator, assesses the ecological quality of the ecosystem by considering various biotic and abiotic factors, including species diversity, water quality, soil health, and air purity. Eco-environmental effects refer to the impacts of land use changes on the eco-environment. By linking changes in land use types to local ecological environmental changes, the eco-environment quality index (EQI) provides a deeper and more focused understanding of how land development and transformation impact the eco-environment. Currently, research on the EQI mainly focuses on habitat quality [41–44], and ecosystem structure and functional value [45–47]. In terms of research indicators, it primarily utilizes single indicators such as NPP and NDVI [48–50], or adopts methods such as ecological security pattern recognition [51–53], ecosystem service value models [54], and landscape pattern evaluations [55,56]. Regarding the influencing mechanisms, most studies mainly use methods such as multiple linear regression models [57,58], GWR models [59,60], and GTWR models [61,62] to explore linear relationships. However, these traditional linear regression models cannot effectively reflect the impact of these characteristics on eco-environmental effects. The random forest model offers several advantages in this context: it can handle high-dimensional data efficiently, capture complex nonlinear relationships, identify and rank the importance of different variables, is robust to overfitting due to its ensemble nature, and is flexible and scalable to various data types and scales. These characteristics make the random forest model particularly suitable for analyzing land use changes and their eco-environmental effects [63,64]. Despite these advantages, the random forest model still needs to be further applied and validated within the framework of the EQI.

Chongqing, a mountainous economic center and transportation hub in western China, has experienced substantial transformations in ecological–production–living spaces (EPLS), impacting both land use efficiency and the eco-environment. The central urban area of Chongqing is located in the upstream region of the Yangtze River, at the tail end of the Three Gorges Reservoir Area, and it serves as an important functional area for the construction of ecological civilization in western China. In recent years, the rapid land use changes in the central urban area have led to increasingly prominent conflicts between land use and ecological protection. The space for ecological security assurance is being squeezed, and the ecological risk level is relatively high [65]. In light of this, this study focuses on the central urban area as the research area, aiming to explore the following three questions: (1) What are the characteristics of the land use functional transformation of the EPLS in the central urban area from 2000 to 2020? (2) What are the spatial and temporal changes in the ecological environment effects caused by this transformation? (3) What mechanisms affect the ecological environment effects?

Additionally, the importance of this study is manifested in several aspects: Firstly, the research will provide empirical evidence for understanding the laws of land use functional transformation in the EPLS of mountainous cities, which will contribute to regional land use planning and eco-environmental protection. Secondly, by combining long time-series data analysis and spatial statistical methods, this study will reveal the dynamic evolution characteristics of the transformation of the EPLS. Finally, by using the random forest model to explore the key factors influencing land use change effects, this study will provide more accurate and detailed case analyses. This study has significant implications beyond China, offering valuable global insights for urban planners and policymakers. The methodological approach of integrating remote sensing data with socio-economic statistics and employing advanced machine learning models can be applied to various urban contexts worldwide. For example, rapidly urbanizing regions in India, Brazil, and Africa can adopt similar frameworks to manage land use changes and mitigate eco-environmental impacts. Furthermore, understanding the mechanisms behind eco-environmental degradation can aid international efforts in achieving the United Nations Sustainable Development Goals (SDGs), particularly those related to sustainable cities and communities (SDG 11), and climate action (SDG 13 [66]). The findings from Chongqing can serve as a reference for cities facing similar challenges, promoting a global dialogue on sustainable urban development and ecological protection.

2. Methods

2.1. Overview of the Study Area

The central urban area of Chongqing is located in the western part of Chongqing city. It serves as the political, economic, cultural, transportation, and financial center of Chongqing. This area includes Yuzhong District, Yubei District, Jiangbei District, Shapingba District, Nan'an District, Beibei District, Jiulongpo District, Dadukou District, and Banan District (Figure 1). The central urban area covers 5466 km^2, which constitutes 6.63% of the city's total area. As of 2020, the central urban area had a permanent population of 10.34 million, accounting for 32.27% of the city's total population. The regional gross domestic product (GDP) was CNY 982.2 billion, representing 39.28% of the city's total GDP.

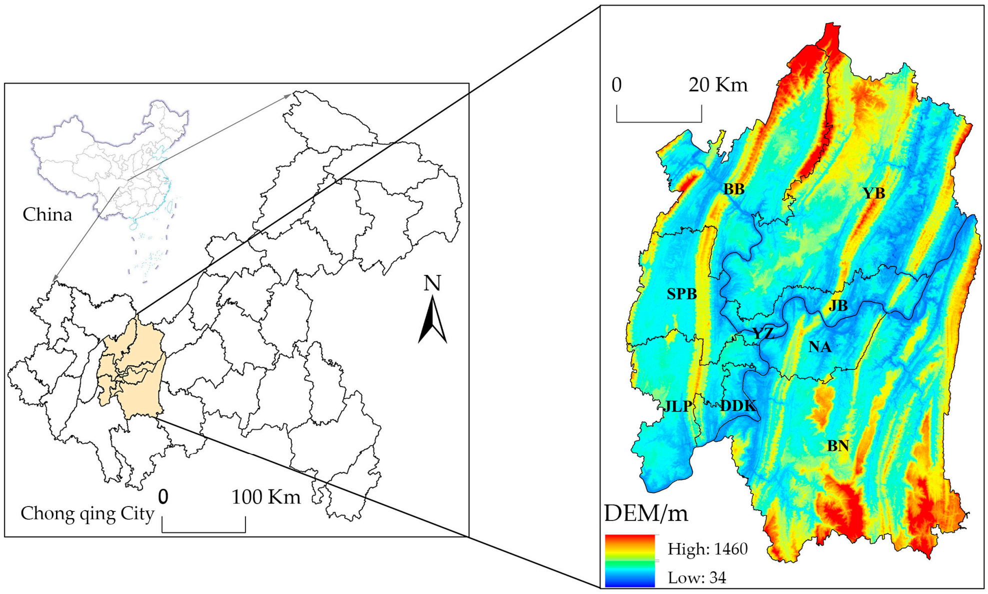

Figure 1. Geographical location and administrative division map of the central urban area. Note: YZ—Yuzhong; YB—Yubei; JB—Jiangbei; SPB—Shapingba; NA—Nanan; BB—Beibei; JLP—Jiulongpo; DDK—Dadukou; BN—Banan.

The terrain of the central urban area is predominantly mountainous and hilly, with relatively few terraces and flatlands. The terrain of Chongqing is predominantly mountainous and hilly, covering 76% of the city's total area. The topography of the urban districts is highly variable, with elevations ranging from 200 to 1400 m. From 2000 to 2020, Chongqing experienced significant land use changes. The built-up area increased by over 30%, primarily at the expense of agricultural and forested lands. These rapid land use changes pose significant challenges for sustainable development and ecological protection, as the rugged terrain complicates infrastructure development and increases the risk of environmental degradation.

This region exemplifies the challenges and opportunities faced by rapidly urbanizing areas globally, especially in the context of sustainable urban development and ecological protection. The mountainous and hilly terrain of Chongqing's central urban area offers a unique case study for understanding how urban expansion interacts with complex topographies, which is relevant to cities in other countries with similar geographical features, such as Kathmandu in Nepal, Rio de Janeiro in Brazil, and Cape Town in South Africa. Specifically, Kathmandu, like Chongqing, is experiencing rapid urban sprawl driven by population growth. The insights gained from this study on managing the expansion of residential areas at the cost of agricultural and forestlands can assist Kathmandu in achieving a balance between urban development and the preservation of agricultural and forested areas. By identifying crucial factors affecting ecological quality, such as the use of pesticides and farming practices, this study can help Kathmandu formulate targeted strategies to enhance environmental sustainability, especially in managing the agricultural zones around the city; similarly, Rio de Janeiro's hilly and mountainous regions face challenges akin to those in Chongqing regarding urban expansion. This study's findings on controlling the spread of industrial and mining areas while conserving ecological spaces are directly applicable to Rio, helping mitigate the environmental impacts of urban growth. Rio also struggles with deforestation and urban encroachment into natural zones. The ecological benefits of converting farmland to forests, as demonstrated in this study, provide practical strategies that Rio can adapt to enhance biodiversity and ecological resilience through improved environmental policies; Cape Town's land use patterns are significantly influenced by its mountainous terrain. The methodologies used in this study for assessing and managing land use changes to protect ecological quality while fostering urban growth can serve as a model for sustainable development in Cape Town. The city's efforts to balance urban expansion with the preservation of its unique biodiversity can greatly benefit from the detailed analysis provided in this study. The findings can inform policies that emphasize the protection of ecological spaces within urban planning frameworks, ensuring both environmental sustainability and urban development.

Moreover, the significant economic and demographic characteristics of Chongqing's central urban area provide valuable insights into the land use changes in mega-cities. As urban planners and policymakers worldwide strive to balance urban growth with environmental sustainability, the findings from this study can inform strategies in other rapidly urbanizing regions, particularly in the Global South. For example, cities in India, Southeast Asia, and Africa can benefit from the lessons learned in Chongqing regarding land use management, the integration of EPLS, and the mitigation of eco-environmental impacts.

2.2. Indicator Selection and Data Sources

For measuring the eco-environment quality considering land use changes, this study adopted the EQI as the dependent variable, a comprehensive quantitative measurement method based on land use changes [67,68]. This study referenced the EQI values assigned to the secondary land use categories by other researchers [69–71]. The land use classification system for the EPLS is based on the second-level classification standard of the National Remote Sensing Monitoring Land Use Classification System, drawing on classification methods from other scholars [72,73].

Based on a review of the relevant research literature and a comprehensive range of natural and socio-economic factors [74–80], 16 were selected as independent variables from the 7 dimensions of Population, Economic Development Level, Industrial Structure, Technological Level, Social Consumption Level, Educational and Cultural Level, and Urban Environmental Conditions (Supplementary Table S1). The selection process for these indicators includes the following steps: First, this study included the review of a large body of literature on land use change and ecological environment quality studies to identify widely used and representative indicators [74–80]. Second, this study involved consultation with experts in the relevant fields to discuss and select indicators that are representative and operational in the central urban area of Chongqing. Finally, it was ensured that the data for the selected indicators were available within the study area and time frame. Data were obtained for these independent indicators from the "Chongqing Statistical Yearbook" and statistical reports from relevant government departments. Specifically, the elements of Population include Permanent Population (X1) and Urbanization Rate (X2), which reflect the number of permanent residents in the region and the degree of population concentration in urban areas. X1 is the total number of residents in the region and directly affects the scale and pattern of land use. X2 indicates the proportion of the rural population migrating to urban areas; the urbanization process is usually accompanied by significant changes in land use patterns, having a profound impact on the ecological environment; the elements of Economic Development Level include Total Fixed Asset Investment (X3) and GDP per Capita (X4), which measure the scale of economic construction and infrastructure investment in the region, as well as the average level of economic activity of the residents. X3 directly reflects the intensity of economic development in the region and has an important impact on land use and the ecological environment. X4, as an important indicator of economic development level, and can reflect the quality of life and the intensity of economic activity of the residents; the elements of Industrial Structure include Added Value of the Primary Industry (X5), Added Value of the Secondary Industry (X6), and Added Value of the Tertiary Industry (X7), which reflect the development levels of agriculture, industry, and services, respectively. X5 mainly involves agriculture and forestry, directly affecting the use of agricultural land. X6 reflects the development of industry and manufacturing, where the expansion of industrial land has a significant impact on the ecological environment. X7 reflects the development of the service industry, which plays an important role in urban land use and expansion; the elements of Technological Level include Grain Production (X8), Labor Productivity (X9), and Road Mileage (X10), which measure the efficiency of agricultural production, worker productivity, and the development level of transportation infrastructure, respectively. X8 directly affects the mode and efficiency of agricultural land use. X9 is an important indicator of worker productivity in the region. X10 reflects the development of transportation infrastructure, having an important impact on land use patterns and urban expansion; the elements of Social Consumption Level include Total Retail Sales of Consumer Goods (X11) and General Public Budget Expenditure (X12), which reflect the consumption level of residents in the region and the level of government investment in public services and infrastructure. X11 can indicate market vitality and the demand for commercial land. X12 reflects the government's emphasis on public services and infrastructure, having an important impact on land use and the ecological environment; the elements of Educational and Cultural Level include the Number of Primary and Secondary Schools (X13) and Public Library Collections (X14), which reflect the development levels of educational resources and cultural facilities in the region. X13 directly affects the quality of life of residents and the demand for residential land. X14 reflect the development of cultural facilities, having a certain impact on land use and the quality of life of residents; the elements of Urban Environmental Conditions include CO_2 Emissions (X15) and Pesticide Usage (X16), which measure the environmental pressure from urban industrial activities and agricultural activities, respectively. X15 is an important indicator of the environmental impact of urban industrial activities and transportation, directly indicating the environmental pressure of the city. X16 affects the impact of agricultural activities on the ecological environment, especially on water bodies, soil, and biodiversity, serving as an important indicator of agricultural environmental pressure. In summary, the selected indicators in this study can comprehensively reflect the impact of various elements on the quality of the ecological environment, ensuring the scientific validity and reliability of the data. These indicators not only reflect the specific situation of the central urban area of Chongqing but also have general applicability, providing a reference for other cities with similar terrain and development stages.

The land use raster data for the central urban area for five periods (2000, 2005, 2010, 2015, and 2020) at a resolution of 30 m $\times$ 30 m were obtained from the Resource and Environmental Science Data Center of the Chinese Academy of Sciences (http://www.resde.cn (accessed on 1 October 2023)). These data include six primary land use categories, such as arable land and forestland, and 24 secondary land use categories, including paddy fields and dry land. The data for the independent indicators are sourced from the "Chongqing Statistical Yearbook" and relevant statistical reports from government departments.

2.3. Research Methods

Taking Chongqing as an example, this study first conducts the descriptive analysis of the land use change using a transfer matrix model, evaluating the transfer of land use types in the EPLS. After that, this study applies the EQI to evaluate the ecological quality changes resulting from land use transformation. It further assesses the contributions of specific land use changes on ecological quality using the Ecological Contribution Rate (ECR), which quantifies the contribution of each land use change to the overall ecological status. Finally, using the random forest model, the study analyzes how various natural, socio-economic, and environmental factors impact the EQI to provide target solutions for land use policy.

2.3.1. Land Use Type Transfer in the EPLS

The transfer of land use types in the EPLS was quantitatively analyzed using the transfer matrix model [35].

2.3.2. Eco-Environment Quality Index (EQI)

The EQI is an important method for measuring the quality of the regional eco-environment [81]. The EQI values for the EPLS land categories were assigned using the "area-weighted method" [69–71], as shown in Supplementary Table S2.

2.3.3. Ecological Contribution Rate (ECR)

The ECR refers to the impact of changes in a specific land use type on the regional EQ over a certain period [82].

2.3.4. Random Forest Model

This study employs the random forest model to analyze the impact of land use transformation on EQ in the nine districts of Chongqing's central urban area from 2000 to 2020. It is also utilized to analyze the threshold range of external influencing factors on the dependent variables, thus providing substantial urban development recommendations for city decision makers. The random forest model is an ensemble learning method that improves model stability and accuracy by constructing multiple decision trees and combining their prediction results [63,64].

3. Results

3.1. Evolution Characteristics of EPLS Land Use Transitions

3.1.1. Spatio-Temporal Pattern of EPLS Land Use

Over the past 20 years, as shown in Table 1 and Figures 2 and 3, the living space has increased by 361.53 km^2, especially for urban living spaces. The living space is mainly distributed along the banks of the Jialing River and the Yangtze River, showing a clear trend of concentrated and contiguous distribution, which closely aligns with the scope of urban economic development. Over the past 20 years, the area has continuously expanded outward, increasing to 361.53 km^2. Specifically, the urban living space has significantly increased, with an increase of 182%, while rural living space has slightly increased. The expansion has been towards the western hilly areas between Jinyun Mountain and Zhongliang Mountain, the northern hilly areas towards Tongluo Mountain, the coastal areas along the Yangtze River in the south, and a trend of expansion towards the east.

Table 1. Area statistics of EPLS in the central urban area.

Land Type	Area/km^2				
	2000	2005	2010	2015	2020
Agricultural production space	3923.10	3848.24	3653.90	3527.21	3179.73
Industrial and mining production space	32.09	44.22	145.58	260.36	444.05
Rural living space	53.24	72.64	77.03	79.02	89.32
Urban living space	179.27	222.26	310.30	324.22	504.72
Forest ecological space	1074.64	1074.10	1071.86	1067.79	1031.78
Grassland ecological space	52.29	50.40	51.81	51.31	53.35
Water ecological space	147.53	150.56	153.01	153.58	160.31
Other ecological spaces	4.14	3.88	2.83	2.82	3.06

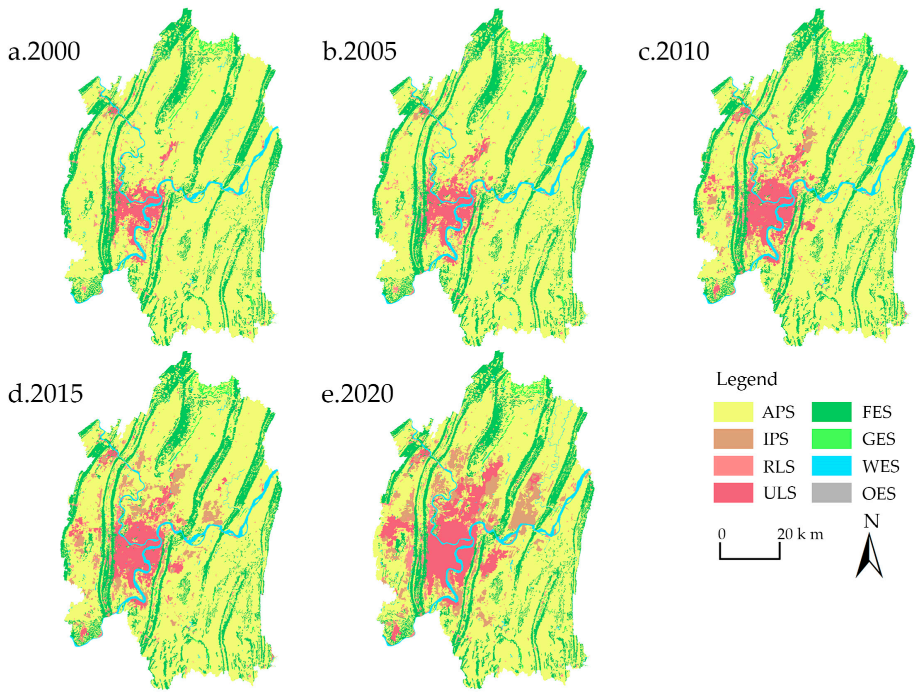

Figure 2. The distribution of EPLS in the central urban area. Note: APS—Agricultural production space; IPS—Industrial and mining production space; RLS—Rural living space; ULS—Urban living space; FES—Forest ecological space; GES—Grassland ecological space; WES—Water ecological space; OES—Other ecological spaces.

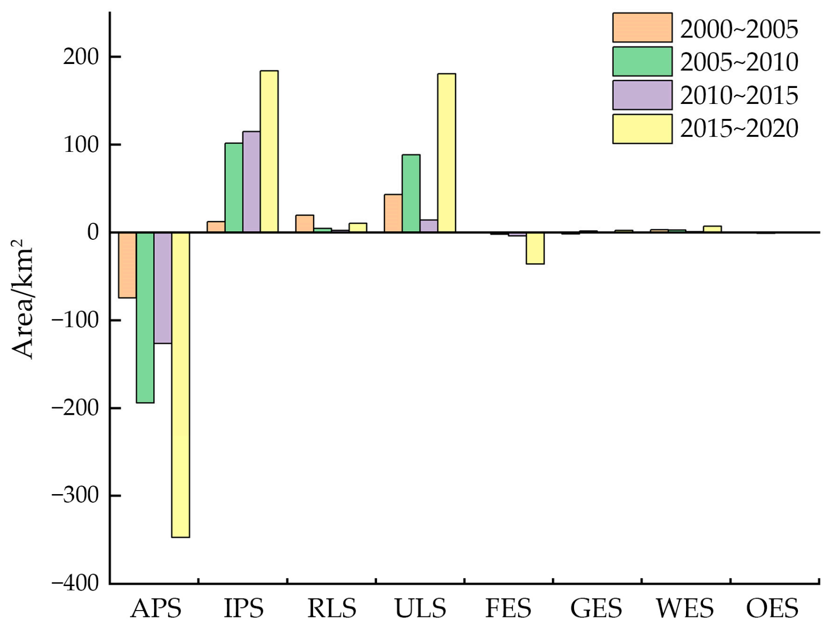

Figure 3. Changes in EPLS in the central urban area. Note: APS—Agricultural production space; IPS—Industrial and mining production space; RLS—Rural living space; ULS—Urban living space; FES—Forest ecological space; GES—Grassland ecological space; WES—Water ecological space; OES—Other ecological spaces.

The production space has decreased by 331.42 km^2, with the industrial and mining production land having the most significant increase. The production space is the most extensive, primarily distributed in the hilly areas between Jinyun Mountain, Zhongliang Mountain, Tongluo Mountain, and Mingyue Mountain. Specifically, the agricultural production space has gradually decreased by 743.37 km^2 over 20 years. In contrast, industrial and mining production land has increased by 411.96 km^2. This trend can be attributed to the significant impact of urban expansion on agricultural production land under rapid urbanization and industrialization, leading to a sharp reduction in agricultural production space. Especially during 2010–2020, industrial and mining production land expanded rapidly, reflecting the increasing demand for industrial development due to the rapid economic growth.

There has been a decreasing trend in ecological spaces, with a reduction of 30.11 km^2. The ecological spaces are mainly distributed along water systems such as the Yangtze River and Jialing River, as well as in mountainous areas such as Jinyun Mountain, Zhongliang Mountain, and Tongluo Mountain. Due to natural conditions such as terrain and climate, grassland, water bodies, and other ecological spaces are relatively less distributed, while forested ecological spaces are more extensive. Over the past 20 years, forested ecological spaces have gradually decreased, particularly during 2010–2020, while the trends for water bodies, grasslands, and other ecological spaces are less pronounced.

3.1.2. Land Use Transition of EPLS

From 2000 to 2020, the EPLS witnessed transformative land use shifts driven by socio-economic strategies, significantly altering the regional landscape (Figure 4). A total reduction of 743.38 km^2 in agricultural spaces highlights the overarching shift towards industrial and urban development. This transition is quantitatively significant, with agricultural land repurposed predominantly for industrial and mining production spaces (475.53 km^2) and urban living spaces (222.53 km^2).

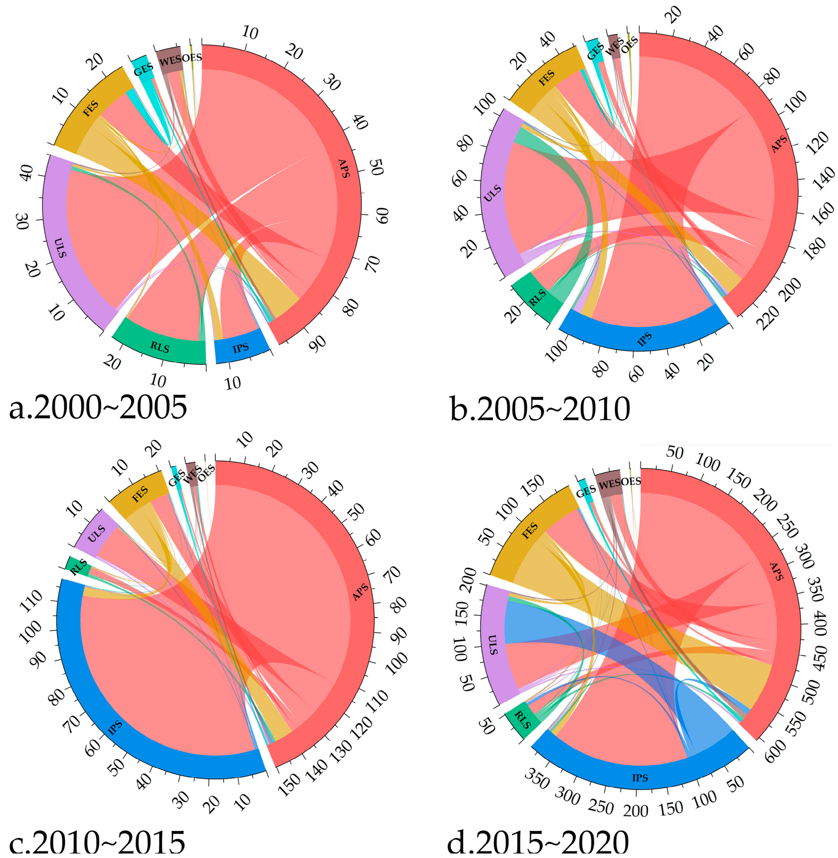

Figure 4. The number of land types transferred for the EPLS in the central urban area.

The increase in industrial and mining spaces was particularly notable. From 2000 to 2005, 10.05 km^2 of agricultural land transitioned to these uses. This growth accelerated significantly from 2005 to 2010, with an additional 88.05 km^2 being transformed. From

2010 to 2015, the period saw the largest shift, with 112.06 km^2 of agricultural land being repurposed for industrial activities. The trend continued robustly from 2015 to 2020, with an overwhelming 265.37 km^2 of farmland transformed into industrial zones.

Urban living spaces expanded a lot at the expense of agricultural land. Urban living spaces expanded by 41.99 km^2 from 2000 to 2005, primarily at the expense of agricultural land. This trend continued, with 80.24 km^2 added from 2005 to 2010 and a further 89.30 km^2 from 2015 to 2020, mirroring the region's economic growth and urbanization push. This expansion often occurred in regions proximal to water bodies and less densely populated hilly areas, facilitating the spread of residential and commercial infrastructures.

Despite attempts to reverse this trend, ecological spaces faced a net decrease of 30.11 km^2 over the twenty years. From 2010 to 2020, 75.18 km^2 of agricultural land was designated for ecological purposes. However, the encroachment into these areas was considerable, with agricultural practices diminishing the newly established ecological lands. This resulted in a complex scenario of ecological restoration efforts undermined by ongoing agricultural expansion.

3.2. Ecological Effects of Land Use Transition in EPLS

3.2.1. Temporal Characteristics of Regional EQI

Over the past two decades, the index has exhibited a parabolic decline, decreasing from 0.3665 in 2000 to 0.3501 in 2020 (Figure 5). While there has been an overall deterioration in quality, the magnitude is relatively small. This is because the changes in the eco-environment in the central urban area have simultaneously involved both environmental optimization and degradation, resulting in a certain degree of offsetting.

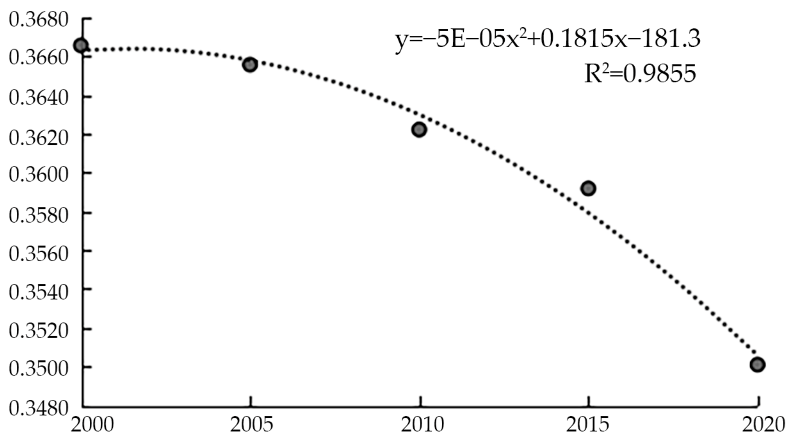

Figure 5. Change curve of EQI in central urban area.

The ECR results indicate that converting agricultural production space to forest ecological space has been the dominant factor in eco-environment optimization from 2000 to 2020 (Table 2). The contribution rates for all four study periods exceeded 50%, with values of 65.30%, 69.21%, 75.44%, and 67.55%, respectively. This demonstrates the ecological benefits of converting farmland to forestland, highlighting the importance of conserving forest and aquatic ecosystems to improve the EQI. The conversion of agricultural production space to industrial and mining production space, as well as the conversion of forest ecological space to agricultural production space, were the main factors contributing to environmental degradation during the study period. This is due to the rapid expansion of industrial and mining production space under conditions of industrialization, as well as ongoing deforestation and land reclamation activities. Therefore, under the "Two Mountains" theory and the new round of national spatial planning, the central urban area should continue to strengthen land use control and orderly development, further implement policies for returning farmland to forests and grasslands, maintain ecological security, and achieve coordinated development between eco-environmental protection and socio-economic development.

Table 2. The main land use transformation and ECR that affect the EQI.

	2000~2005			2005~2010		
	Spatial Transformation	**ECR**	**Percentage of Contribution**	**Spatial Transformation**	**ECR**	**Percentage of Contribution**
Leads to ecological optimization	APS-FES	0.000788	65.30%	APS-FES	0.001746	69.21%
	APS-GES	0.000024	2.03%	APS-GES	0.000147	5.81%
	APS-WES	0.000174	14.43%	APS-WES	0.000168	6.65%
	RLS-FES	0.000011	0.92%	IPS-APS	0.000033	1.33%
	ULS-FES	0.000014	1.16%	ULS-FES	0.000046	1.81%
	GES-FES	0.000121	9.99%	ULS-WES	0.000039	1.56%
				GES-FES	0.000121	4.79%
				OES-FES	0.000136	5.37%
	Total	0.001207	93.82%		0.002522	96.54%
Leads to ecological degradation	APS-IPS	−0.000219	9.95%	APS-IPS	−0.001917	32.67%
	APS-RLS	−0.000259	11.77%	APS-RLS	−0.000215	3.67%
	APS-ULS	−0.000530	24.09%	APS-ULS	−0.001013	17.26%
	FES-APS	−0.000717	32.59%	ULS-IPS	−0.000051	0.87%
	FES-IPS	−0.000236	10.75%	FES-APS	−0.001164	19.84%
	FES-RLS	−0.000052	2.34%	FES-IPS	−0.000911	15.53%
	FES-ULS	−0.000061	2.77%	FES-RLS	−0.000102	1.74%
	WES-APS	−0.000041	1.88%	FES-ULS	−0.000330	5.62%
	Total	−0.0022	96.13%		−0.005867	97.20%
	2010~2015			**2015~2020**		
	Spatial Transformation	**ECR**	**Percentage of Contribution**	**Spatial Transformation**	**ECR**	**Percentage of Contribution**
Leads to ecological improvements	APS-FES	0.000665	75.44%	APS-FES	0.006460	67.55%
	APS-GES	0.000020	2.23%	APS-GES	0.000187	1.95%
	APS-WES	0.000064	7.23%	APS-WES	0.001100	11.50%
	IPS-APS	0.000020	2.23%	IPS-APS	0.000248	2.59%
	IPS-FES	0.000026	2.90%	IPS-ULS	0.000764	7.99%
	RLS-APS	0.000012	1.41%	IPS-FES	0.000195	2.04%
	RLS-FES	0.000016	1.76%	RLS-FES	0.000100	1.04%
	ULS-FES	0.000016	1.78%	ULS-FES	0.000094	0.99%
	Total	0.000881	94.98%		0.009564	95.65%
Leads to ecological degradation	APS-IPS	−0.002448	62.35%	APS-IPS	−0.005798	31.04%
	APS-RLS	−0.000034	0.87%	APS-RLS	−0.000256	1.37%
	APS-ULS	−0.000180	4.57%	APS-ULS	−0.001131	6.06%
	FES-APS	−0.000672	17.10%	FES-APS	−0.008171	43.74%
	FES-IPS	−0.000393	10.02%	FES-IPS	−0.001218	6.52%
	FES-RLS	−0.000046	1.17%	FES-RLS	−0.000206	1.10%
	FES-ULS	−0.000040	1.01%	FES-ULS	−0.000605	3.24%
	WES-APS	−0.000043	1.10%	WES-APS	−0.000508	2.72%
	Total	−0.003927	98.18%		−0.018683	95.78%

3.2.2. Spatial Characteristics of Regional EQI

Over the period of this study, the EQI has shown a consistent decline each year, with the exception of Beibei District, which has remained unchanged (Figure 6). The decline is particularly notable in other districts. For instance, Shapingba District has seen its EQI drop from a very-high-quality category to a low-quality category over the past 20 years. Initially, Shapingba's slower pace of development did not significantly impact the eco-environment. However, as development accelerated, the negative impacts, including pollution, intensified. Despite some investments in eco-environmental regulation and management, these efforts were insufficient, leading to a lag in the EQI. Conversely, Beibei District has maintained a consistently very high EQI. This can be attributed to its advantageous geographical features: it is surrounded by mountains and water bodies, including Huaying Mountain and the central area bisected by the Jialing River. The district's industrial and mining development is constrained by its topography, which has helped preserve its high EQI.

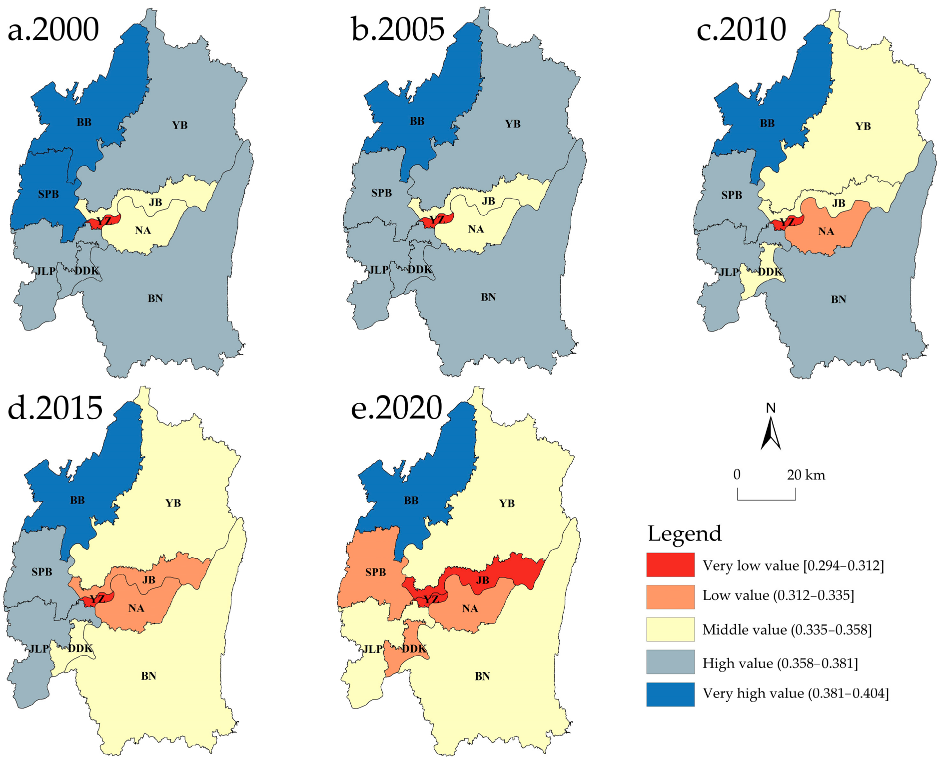

Figure 6. The spatial pattern of EQI in the central urban area.

3.3. Analysis of Factors Influencing Regional EQI Changes

This study, considering various factors including natural and socioeconomic aspects, employed a random forest model to reveal the mechanisms influencing the evolution of the EQI. Before conducting the random forest model analysis, this study first validated the model to ensure its accuracy and stability in predicting the target variable (Y). The data was split into training and testing sets, with 70% of the data used for training and 30% for testing. The random forest model was trained on the training set and then used to predict on the test set. Evaluation metrics such as the Root Mean Squared Error (RMSE), Coefficient of Determination (R-squared), and Mean Absolute Error (MAE), among others, were used to assess the predictive performance of the model. The results indicated an RMSE of approximately 0.0173, MAE of approximately 0.0153, and R-squared of approximately 0.7036. These metrics demonstrate that the random forest model performed well in predicting the target variable Y, with relatively low prediction errors and reasonable explanatory power. The model's performance can explain about 70.36% of the variance in the target variable Y. These results confirm the effectiveness and stability of the model on the test set.

3.3.1. Significance and Relative Importance of Feature Variables

Eight influencing variables significantly affect regional EQI changes. Among them, Pesticide usage (X16), grain production (X8), and added value of the primary industry (X5) collectively contribute 17.08%, 11.45%, and 11.32%, respectively. Specifically, among all variables with significant effects, X16 ranks first, and is significantly higher than other variables (Figures 7 and 8). Furthermore, its higher value has a notably positive effect on regional EQI changes. Secondly, X8 and X5, representing technological level and industrial structure, respectively, have the second- and third-highest relative importance. Both are generally positively correlated with the EQI. Thirdly, permanent population (X1: 7.84%), public library collections (X14: 7.10%), and road mileage (X10: 7%) have relatively moderate explanatory power with similar magnitudes. However, X1 mostly exhibits a negative correlation with EQI changes, while X14 and X10 generally show positive correlations. Finally, urbanization rate (X2) and CO_2 emissions (X15) have weaker explanatory power at 5.99% and 5.67%, respectively. Interestingly, although X15 has a low impact on EQI changes, it also exhibits a positive correlation.

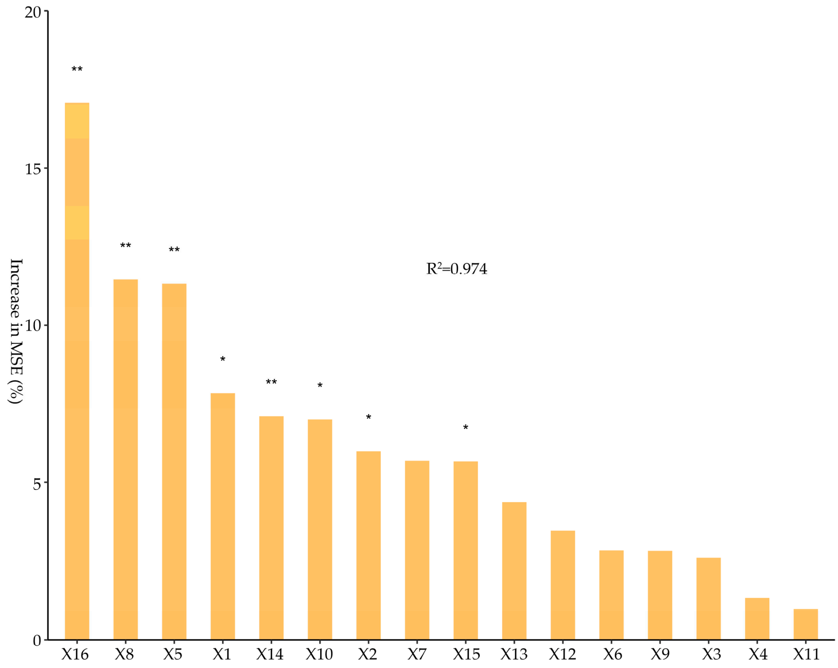

Figure 7. The result of RF model. **, * means significant at 1%, 5% level, respectively.

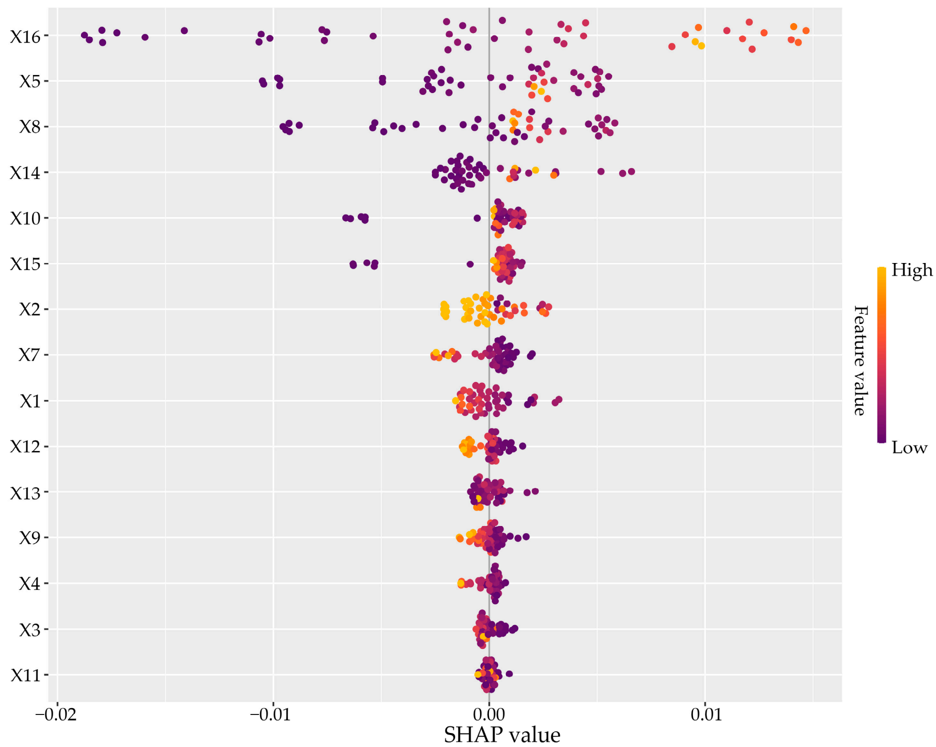

Figure 8. The SHAP summary plot.

3.3.2. Nonlinear Relationships of Influence Forces of Regional EQI Changes

Partial dependence plots (PDP) can provide a fine-grained analysis of the relationship between independent variables and the dependent variable. Single dependence analysis illustrates the impact of individual factors on the prediction of the regional EQI [83,84]. Figure 9 shows the individual dependence of the eight most important factors in the model. The *X*-axis represents the attribute values of the factors, while the *Y*-axis represents the Shaple values associated with these attribute values. The results indicate a clear nonlinear relationship between the selected influence factors and the threshold values for changes in the regional EQI.

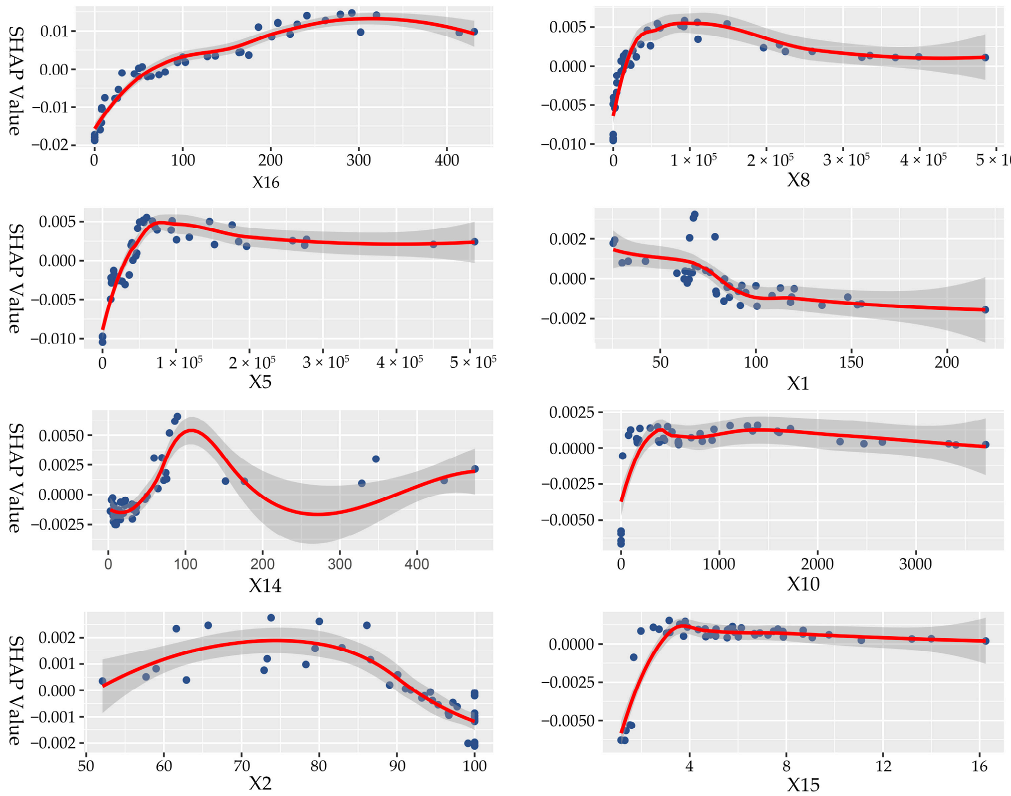

Figure 9. SHAP value of key factors.

As is shown in Figure 9, the relationship between X16 and the regional EQI shows a negative to positive correlation trend. As the feature value increases, the positive correlation strengthens until it reaches a threshold of 300, after which the positive correlation weakens. The X8, X5, X10, and X15 variables exhibit a common pattern. Initially, there is a negative correlation with regional EQI. As the feature values increase, the correlation shifts to a pronounced positive trend. Beyond a certain threshold, the positive correlation diminishes and approaches zero, indicating that the impact of these factors becomes very limited once they reach an ideal state. The relationship between X1 and the regional EQI shows a clear monotonic decrease, indicating a significant negative correlation. X14 shows substantial variability in its relationship with the regional EQI, characterized by noticeable peaks and troughs. The quality initially increases sharply within the range of 0 to 100. However, between 100 and 250, there is a significant decrease, followed by another increase as the feature value rises. The relationship between X2 and the regional EQI is relatively clear. When X2 is between 52 and 75, the positive correlation strengthens with increasing feature values. However, once X2 exceeds 75, the correlation turns negative with further increases in the feature value.

4. Discussion

4.1. Main Characteristics of EPLS Land Use Transition in the Central Urban Area

This study analyzed the transition of EPLS land use in Chongqing's central urban area from 2000 to 2020, revealing the characteristics of its spatiotemporal patterns and transitions. The results indicate significant expansion of living spaces, particularly urban living spaces. This phenomenon is closely related to the rapid urbanization process in Chongqing and aligns with existing studies describing land use changes in rapidly urbanizing areas of China [85]. Corresponding to the expansion of living spaces, agricultural production space significantly decreased, with a cumulative reduction of 743.37 km^2 from 2000 to 2020. In contrast, urban living space and industrial and mining production space showed an increasing trend. The rapid expansion of industrial and mining production land, in particular, indicates that the demand for industrial development driven by economic growth has dominated the land use structure [86].

The changes in production space are characterized by a reduction in agricultural production space and an increase in industrial and mining production land. As Chongqing's industrialization progressed, industrial and mining production land increased by 411.96 km^2, reflecting the growing demand for industrial land driven by economic development. This result is consistent with the land use change trends observed in other rapidly industrializing regions in China. For example, Huang et al. (2020) systematically analyzed the increase in land development intensity in western China, driven by economic factors, comparable to the increase in industrial land use in Chongqing [87]. However, the reduction in ecological space, especially the sharp decline in forestland, highlights the conflict between ecological protection and economic development. This result suggests that despite implementing policies such as returning farmland to forest by the national and local governments, the encroachment of urban expansion and industrialization on ecological space persists, putting greater pressure on the eco-environment. Similar conflicts have been observed internationally, where urbanization and land use changes have led to significant environmental impacts, including the degradation of ecosystem services and increased carbon emissions [18,88]. Delphin et al. (2016) employed a scenario spanning 2003 to 2060 that simulated urbanization and land use changes based on land cover data and a population distribution model. They utilized the Integrated Valuation and Ecosystem Services Tradeoffs model to quantify alterations in ecosystem services, revealing how urbanization influences the spatial and temporal dynamics of ecosystem services and their associated trade-offs [88]. This underscores the need for more robust measures to balance urban and industrial development with ecological conservation efforts to mitigate environmental degradation.

4.2. Ecological Environmental Effects of Land Use Transition

By calculating and analyzing the EQI in the central urban area from 2000 to 2020, this study reveals the significant impact of land use transition on EQ. Although the overall EQI shows a downward trend, the magnitude of change is relatively small, indicating a partial offset between ecological optimization and degradation processes. This result is consistent with the conclusions of some international studies, demonstrating the dual impact of land use change on the environment [13,89].

Specifically, the conversion of agricultural production space to forest ecological space contributes the most to the optimization of the EQI, especially under the implementation of the returning farmland to forest project. This transformation significantly enhances the regional EQI, which is consistent with the results of other researchers. Balthazar et al. (2015) found in their study of the Andes that converting farmland into forests not only improves the quality of ecosystem services but also enhances biodiversity and carbon storage at the local scale. Their study highlights the positive impact of reforestation on the eco-environment [90]. Li et al. (2021) examined agricultural land conversion in Chongqing from a multiscale perspective, discussing the policy rationale behind these changes and their implications for sustainable rural–urban transformation [91]. Benalcazar et al. (2022) researched the impact of converting coniferous forests into agricultural land on soil health, finding that this conversion significantly reduces soil organic matter and the soil health index, while also negatively affecting ecosystem services [92]. These studies collectively support the conclusion that converting agricultural production spaces into forest ecological spaces significantly enhances the quality of the eco-environment, emphasizing the importance of this process on a global scale. However, the conversion of agricultural production space to industrial and mining production space, as well as the conversion of forest ecological space to agricultural production space, has negative impacts on EQ. The increase in industrial and mining production land is closely related to the industrialization process, while the existence of deforestation and land reclamation reveals deficiencies in the implementation of ecological protection policies.

Furthermore, this study found significant spatial differentiation in the EQI of the central urban area, particularly strong trend differences in Shapingba District and Beibei District. Shapingba District experienced a decrease in ecological quality due to excessive urbanization, while Beibei District maintained the EQI due to its geographical and policy protection. This difference indicates that regional ecological protection policies need to consider geographical and socio-economic differences, and implement differentiated management strategies. For example, Bhatti et al. (2017) studied the spatial dynamic relationship between quality of life (QOL), land use/land cover (LULC), and population density in Lahore, Pakistan. The study found that urbanization and land use changes significantly impact the quality of the eco-environment, emphasizing the importance of considering spatial heterogeneity in regional planning [93]; Korpilo et al. (2018) examined the relationship between landscape value, visitor use, and biodiversity in urban forests of Helsinki, Finland, finding low spatial consistency between social and ecological variables, which highlights the importance of integrating multiple stakeholder perspectives and data sources in urban planning [94]; Samoli et al. (2019) investigated the spatial association between nitrogen dioxide (NO_2) and socioeconomic indicators in nine metropolitan areas of Europe, discovering that traffic pollution is significantly associated with socioeconomic factors such as population density and the unemployment rate. This indicates that socioeconomic factors play a crucial role in influencing urban environmental quality [95]; Yu et al. (2021) examined urban expansion patterns across the Yangtze River Delta, noting significant expansion along the river and coastal areas driven by the region's economic development [96]. These studies show that the impact of urbanization and geographical factors on ecological quality is universal and significant globally, necessitating the formulation and implementation of differentiated ecological protection strategies tailored to the specific geographical and socioeconomic conditions of each region to achieve sustainable development goals. In contrast, this study shows that the expansion of urban living space in Chongqing's central urban area has a more extensive spatial distribution, involving multiple regions in the west, north, south, and east. This expansion pattern reflects the uniqueness of Chongqing as a key area for the Western Development strategy.

In summary, since the reform and opening up, China has vigorously developed its economy, leading to significant changes in land use driven by rapid industrialization and urbanization. With extensive economic growth and inadequate protection of the land ecosystem, a large number of land types with higher ecological quality have undergone transformation, which is the main reason for the decline in ecological quality in the central urban area during the study period. Subsequently, the implementation of strategies such as the "Western Development" strategy, the "Belt and Road Initiative", and the "Ecological Protection and High-Quality Development of the Yangtze River Basin" has provided new opportunities for the central urban area, gradually emphasizing eco-environmental protection. Measures such as natural forest protection, returning farmland to forests, and the restoration of key ecological function areas have alleviated the trend of ecological quality deterioration. In the future, the central urban area should continue to promote the concept of ecological civilization and coordinate the construction of an organic land use pattern integrating "mountains, rivers, forests, fields, lakes, and grasses", to achieve harmony among production, living, and ecology.

4.3. Analysis of Influencing Factors and Mechanism Exploration

This study utilized a random forest model to analyze the factors influencing changes in the regional EQI. The results indicate that pesticide usage, grain production, and the added value of the primary industry have the most significant impacts on EQ. Among these, the increase in pesticide usage is strongly correlated with the decline in the EQI, as also reported in the existing literature [97,98]. Larsen, AE and Noack, F. (2021) observed an increase in pesticide usage, highlighting its potentially detrimental effects on the environment and human health [97]. Tudi et al. (2021) noted that one third of agricultural products depend on pesticide application, which leads to chemical residues affecting human health through environmental and food contamination [98]. This suggests that excessive pesticide usage in agricultural production is a key factor leading to the deterioration of EQ. The impacts of grain production and the added value of the primary industry are more complex, exhibiting both positive and negative effects on EQ. This complexity may be related to the sustainability of production methods and resource management. Adjusting the industrial structure and optimizing production methods could be potential strategies for improving EQ in the future.

Specifically, the negative impact of pesticide usage on the eco-environment is closely related to soil and water pollution. This not only disrupts soil biodiversity but also pollutes water sources through surface runoff and infiltration, affecting the broader ecosystem health [99]. Raffa and Chiampo (2021) observed that pesticides are employed to safeguard and enhance the yield and quality of crops. However, the excessive application of these chemicals, coupled with their environmental persistence, has led to significant issues, including soil and water pollution, and to a lesser degree, air pollution. These pollutants have detrimental effects on the ecosystem and the food chain [99]. In addition, improving pesticide usage efficiency and adopting more environmentally friendly alternatives should be the direction for future agricultural development. The impact of pesticide usage on ecological quality is a universal concern. Studies from various regions, such as those by Lechenet et al. (2017) in France, demonstrate the feasibility of reducing pesticide use while maintaining productivity, which is crucial for sustainable agriculture worldwide [100]. The dual effects of grain production and the added value of the primary industry reflect the varying impacts of different agricultural practices on the environment. On one hand, increased agricultural production intensifies land use, potentially leading to soil degradation and the overuse of water resources [97]. On the other hand, the application of modern agricultural techniques and improved agricultural management can enhance EQ. For example, Lechenet et al. (2017) indicated that adopting new production strategies not only reduces pesticide use, but also does not reduce the productivity and profitability of arable farms [100]. That shows that adopting organic and ecological farming techniques can reduce environmental pollution and protect ecosystem functions [100–102].

The results also indicate that socio-economic factors such as a permanent population, public library collections, and road mileage significantly influence changes in EQ. Notably, the permanent population shows a negative correlation with EQ, consistent with studies that highlight the increased environmental pressure in densely populated urban areas. Population growth typically accompanies increased resource consumption and waste production, escalating environmental pressure. This finding suggests the need for enhanced population and resource management during urbanization to promote the construction of green cities [103,104]. The fluctuating impact of public library collections reflects the complex relationship between cultural and educational resource distribution and EQ. Koziuk et al. (2019) aimed to evaluate the influence of a country's population's educational level and the development of science and technology on the overall environmental condition. They discovered that, for underdeveloped countries, investments in education and science have a more substantial impact on the ecological situation compared to highly developed countries [105]. Improving cultural and educational levels can potentially enhance public environmental awareness, indirectly improving EQ [105,106].

Additionally, CO_2 emissions show a positive correlation with EQ up to 400 tons, indicating that initial CO_2 emissions associated with economic growth may lead to increased environmental investments and regional greening. Local ecosystems can effectively absorb this amount of CO_2 [107,108]. However, beyond 400 tons, EQ declines as CO_2 emissions increase. This is because the absorption capacity of regional ecosystems reaches saturation, and additional pollutants may also increase [109]. Sustained high CO_2 emissions can lead to broader climate change impacts, such as increased temperatures and altered precipitation patterns, further stressing existing ecosystems [110–112]. Solomon et al. (2010) showed carbon dioxide displays exceptional persistence that renders its warming nearly irreversible for more than 1000 years [111]. This phenomenon suggests that environmental policies need to consider CO_2 emission thresholds and adjust measures to address the ecological pressures associated with increased emissions, ensuring a balance between environmental protection and economic development.

Overall, the insights from this study align with global efforts to achieve the United Nations Sustainable Development Goals, particularly SDG 2 (Zero Hunger), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). By addressing the environmental impacts of agricultural practices and urbanization, this research supports global sustainability initiatives. The findings of this study provide valuable lessons for international scholars and policymakers. The methodologies and insights can be applied to other contexts, facilitating the development of targeted strategies to enhance ecological quality and promote sustainable development globally.

4.4. Limitations and Future Outlook

While this study has made progress in revealing the land use transformation of the EPLS in the central urban area of Chongqing and its eco-environmental effects, there are still some limitations. Firstly, the time span of the land use data is five years, which may not reflect more detailed annual changes. Future research could utilize higher-temporal-resolution data to reveal the finer processes of land use transformation. Secondly, although the random forest model has high explanatory power in revealing influencing factors, its nonlinear nature may overlook some complex interactive effects. Future research could combine and compare various modeling methods, such as the GeoDector, to further explore the complex relationships between influencing factors. Additionally, this study primarily relies on remote sensing data and statistical yearbook data, and the accuracy and timeliness of the data may affect the reliability of the research results. Future studies could combine field surveys and finer spatial data to improve the accuracy and applicability of the results.

In summary, this study has revealed the profound impact of land use changes on the eco-environment through analyzing the land use transformation of the EPLS in the central urban area of Chongqing and its eco-environmental effects. The research results not only provide a scientific basis for regional land and space development and eco-environmental protection but also offer references for sustainable development and ecological civilization construction in similar regions. Future research should continue to deepen the exploration of land use transformation and its eco-environmental effects to support the realization of higher-quality eco-environment governance.

5. Conclusions

This study, focusing on the central urban area of Chongqing, explores the eco-environmental effects and influencing factors of the land use transformation of the EPLS from 2000 to 2020. Based on remote sensing data and the random forest model, the following main conclusions are drawn:

1. Over the past 20 years, the living space in the central urban area has significantly expanded, with the increase in urban living space being the most pronounced. Agricultural production space has decreased substantially, with a cumulative reduction of 743.37 km^2. The expansion of industrial and mining production land reflects the strong demand for industrial development driven by economic growth. Overall, there is a trend of reduction in ecological space, particularly a sharp decrease in forestland, highlighting the contradiction between ecological protection and economic development.
2. Land use transformation significantly affects EQ, with a downward trend in the overall EQI. The conversion of agricultural production space to forest ecological space contributes the most to the optimization of the eco-environment, validating the ecological benefits of the policy of returning farmland to forests. However, the conversion of agricultural production space to industrial and mining production space, as well as the conversion of forest ecological space to agricultural production space, has negative impacts on EQ, revealing shortcomings in the implementation of ecological protection policies.
3. The random forest model analysis shows that pesticide usage, grain production, and the added value of the primary industry are the main factors affecting EQ. Among them, pesticide usage has a significant negative impact on EQ, indicating the need for the judicious use of chemicals in agricultural production. The impact of grain production and the added value of the primary industry on EQ is complex, reflecting the importance of agricultural production methods and resource management.
4. There are significant spatial differences in EQ. Shapingba District experienced a decline in EQ due to excessive urbanization, while Beibei District maintained a relatively high level of EQ due to its topography and policy protection. This indicates that regional ecological protection policies need to be tailored, implementing differentiated management strategies.

The findings of this study have broader implications beyond China. Rapid urbanization and industrialization are global phenomena, and the environmental challenges identified in Chongqing are mirrored in many other rapidly developing regions around the world. The study's insights into the effects of land use transformation on ecological quality provide valuable lessons for international policymakers and urban planners. Specifically, this research highlights the critical need for balanced strategies that reconcile economic growth with ecological sustainability. The policy recommendations for converting agricultural land to forests and managing industrial expansion can be adapted to other countries facing similar issues. Moreover, the methodology combining remote sensing data with the random forest model offers a robust approach for assessing land use impacts on the environment, which can be applied in diverse geographical contexts to enhance global environmental governance. In addition, deepening the understanding of the theory of EPLS in practical applications, this study emphasizes the core role of ecological space protection in maintaining regional EQ, providing theoretical support for future land use planning.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land13081196/s1, Table S1: Influencing Indicators; Table S2: Land use classification system and their corresponding EQI results.

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