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Unraveling the Spatiotemporal Drivers of Sustainable Human Settlement Quality in China: Evidence from Explainable Machine Learning and Panel Econometrics

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Abstract

Human settlement quality is a key dimension of sustainable urban development, yet its spatiotemporal evolution and associated mechanisms remain insufficiently understood, particularly under rapid urbanization and regional inequality. This study aims to evaluate the Human Settlement Quality Index (HSQI) across 31 Chinese provinces from 2012 to 2021 and to examine its nonlinear predictive patterns, average conditional associations, and region-specific pathways. A composite HSQI was constructed using an entropy-weighted multi-criteria decision-making framework based on 25 indicators covering natural, human, social, residential, and supporting systems. XGBoost-SHAP was used to identify global feature importance and nonlinear predictive patterns, while a two-way fixed effects panel model and regional group regressions were employed to estimate average conditional associations and regional heterogeneity. The results show that China's HSQI increased by 12.22% from 2012 to 2021, with an initial decline followed by sustained improvement and narrowing regional disparities. Per capita GDP was the most important predictive factor, while human and supporting systems jointly accounted for more than 60% of the total feature importance. Several core indicators exhibited nonlinear threshold-like response patterns, and regional association patterns differed substantially. Eastern China showed signs of a weaker association between economic growth and HSQI improvement, central China showed stronger associations with digital logistics and infrastructure, and western China remained closely linked to ecological foundation protection. These findings demonstrate the complementarity of interpretable machine learning and panel econometrics and provide evidence for differentiated, sustainability-oriented strategies to improve human settlement quality.



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Keywords: explainable machine learning; human settlement quality; panel econometrics; spatiotemporal heterogeneity; sustainable urban development

1. Introduction

Over the past century, driven by both intensified human activities and global climate change, issues such as climate warming, frequent extreme weather events, and ecological degradation have become increasingly severe [1,2], with profound impacts on human living conditions and quality of life [3,4]. Against this backdrop, research on human settlement environments has gradually developed into a leading interdisciplinary field at the intersection

of environmental science, ecology, and geography [5]. A high-quality human settlement environment not only depends on a sound ecological foundation but also requires the integration of suitable climatic conditions, an adequate level of economic development, and well-established infrastructure, among other multidimensional factors [6–8]. With the sustained growth of China's economy and the acceleration of urbanization, public demand for high-quality living environments has become increasingly urgent [9], while the goals of ecological civilization construction and sustainable development have placed greater demands on urban human settlement environments [10–12]. Scientifically assessing the spatiotemporal evolution of human settlement quality and systematically identifying its core contributing components have become critical prerequisites for formulating region-specific policies and promoting sustainable urban development [13].

Existing studies have made important progress in evaluating human settlement environments and related concepts; however, several issues remain unresolved. Many studies have primarily focused on suitability assessment or index construction, whereas insufficient attention has been paid to the diagnostic decomposition of the multidimensional components underlying the spatiotemporal changes in human settlement quality. In addition, traditional statistical models, spatial models, and stand-alone machine learning approaches remain limited in simultaneously capturing nonlinear predictive patterns, controlling for provincial and temporal heterogeneity, and revealing regional differences. By measuring the objective, multidimensional, and comprehensive performance of provincial human settlement systems, this study seeks to answer the following three research questions: (1) How did provincial human settlement quality in China evolve temporally and spatially from 2012 to 2021? (2) Which indicators contributed more substantially to the model prediction structure of HSQI, and did these indicators exhibit nonlinear response patterns? (3) How did the conditional associations and region-specific pathways differ among the eastern, central, and western regions?

To answer these questions, this study developed an integrated analytical framework that combines a multi-criteria decision-making (MCDM) approach, explainable machine learning, spatial autocorrelation testing, panel econometric modeling, and regional group regression. Specifically, this study first constructed the Human Settlement Quality Index (HSQI) for 31 Chinese provinces from 2012 to 2021 based on 25 indicators from the natural, human, social, residential, and supporting systems. XGBoost-SHAP was then used to identify model-level predictive contributions and nonlinear predictive patterns, and Moran's I was further employed as a spatial dependence pretest to provide empirical evidence for subsequent model selection. On this basis, a two-way fixed-effects panel model was used to estimate average conditional associations after controlling for province-specific fixed characteristics and common-year shocks, while regional group regression was applied to reveal heterogeneous pathways across the eastern, central, and western regions. By embedding XGBoost-SHAP and the two-way fixed effects model within a progressive analytical design, this framework serves distinct inferential purposes and comprehensively examines the spatiotemporal evolution, nonlinear predictive patterns, and regional heterogeneity of human settlement quality. It further provides empirical evidence for formulating differentiated and sustainability-oriented strategies to improve human settlement quality.

The remainder of this paper is organized as follows. Section 2 presents the literature review. Section 3 describes the data sources, data preprocessing procedures, and research methods. Section 4.1 presents the spatiotemporal evolution of HSQI, while Section 4.2 reports the global results of the XGBoost-SHAP analysis. Section 4.3 presents the results of the panel fixed-effects regression and regional heterogeneity analysis; Section 4.4 further compares the regional consistency between the XGBoost-SHAP results and the panel regression results; and Section 4.5 reports the robustness checks. Section 5 discusses

the policy implications and limitations of this study, and Section 6 presents the main conclusions.

2. Literature Review

Human settlement quality overlaps with concepts such as human settlement environments, livability, and residential suitability, although their analytical emphases differ. Human settlement environments generally refer to the integrated natural, social, residential, and infrastructural conditions that support human habitation and development [14]. Livability places greater emphasis on perceived comfort, accessibility, service convenience, and everyday quality of life [15], while residential suitability focuses more on whether a region is suitable for habitation in terms of natural, ecological, climatic, and spatial conditions [16]. In China, Academician Wu Liangyong systematically developed the theoretical framework of human settlement science and divided human settlement environments into five subsystems: natural, human, social, residential, and supporting systems [17]. He emphasized that human settlement environments form the foundation of human survival and development, and that the use of natural resources and construction activities should center on meeting human settlement needs [18]. Building on this theoretical framework, this study evaluates the objective, multidimensional, and comprehensive performance of provincial human settlement systems, rather than focusing solely on subjective livability perceptions or natural residential suitability.

Existing studies have widely used socioeconomic, ecological, infrastructural, and climatic indicators to evaluate human settlement environments [19], with a primary focus on suitability assessment at regional, urban, community, and grid scales [20–22]. Geographic information systems and remote sensing techniques have been widely used to identify spatial patterns and assess the roles of environmental and socioeconomic factors in shaping human settlement conditions [23–25]. International studies on urban livability and healthy cities have shown that high-quality living environments are clearly multidimensional and cannot be evaluated using a single ecological or socioeconomic indicator. Badland et al. [15] systematically identified multiple livability domains related to health and well-being, including employment and income, health services, housing, the natural environment, public open space, and transport. Giles-Corti et al. [26] further noted that urban planning, transport accessibility, density, and active travel are closely related to population health and urban sustainability. These studies suggest that high-quality living environments are closely associated with economic development, public services, infrastructure, ecological conditions, and climatic comfort [27]. These international studies broaden the conceptual basis of human settlement quality and place research on human settlement environments in China within the broader context of sustainable urban development. However, limited attention has been paid to how different dimensions contribute to the spatiotemporal changes in human settlement quality, and integrated frameworks that jointly consider nonlinear prediction, fixed-effects control, and regional heterogeneity remain insufficient. Accordingly, research should move beyond suitability-oriented assessment toward a diagnostic analysis of the multidimensional components of human settlement quality.

Methodologically, traditional statistical models and panel econometric approaches have been widely used to examine the associations between socioeconomic development, environmental conditions, infrastructure, and human settlement outcomes. Panel models, particularly two-way fixed-effects models, help control for time-invariant regional characteristics and common-year shocks [28]. Previous studies have emphasized that simultaneously controlling for time and regional effects can reduce estimation bias arising from omitted macro-level time trends or inherent regional differences [29]. However, these models usually rely on prespecified functional forms and remain limited in cap-

turing complex nonlinear relationships and interaction effects among high-dimensional variables [30]. In recent years, machine learning methods have been increasingly applied to environmental quality assessment, urban heat island analysis, analyses of factors associated with carbon emissions, and urban vitality research because of their strong nonlinear fitting capacity [31–33]. However, stand-alone machine learning models are often regarded as black-box models, making it difficult to directly explain how individual variables contribute to model predictions. The SHapley Additive exPlanations (SHAP) method provides an effective tool for interpreting model-level predictive contributions [34]. Previous studies have used SHAP to reveal nonlinear patterns and interaction effects among variables, and it has been effectively applied in urban vitality analysis [35] and urban-scale analyses of factors associated with carbon emissions [36]. However, using machine learning alone may overlook unobserved regional and temporal heterogeneity, whereas using panel regression alone may miss nonlinear response patterns [37,38]. Recent studies have attempted to combine explainable machine learning with econometric models [39], indicating the growing methodological value of integrating prediction-oriented machine learning with fixed effects control. Building on this line of research, this study embeds XGBoost-SHAP and the two-way fixed effects model within a progressive analytical framework. XGBoost-SHAP is used to identify model-level predictive contributions and nonlinear patterns, while the two-way fixed effects model is used to examine average conditional associations after controlling for provincial and year heterogeneity.

Spatial heterogeneity is another important issue in human settlement research [31,40]. Geographically weighted regression (GWR) and its spatiotemporal extension, geographically and temporally weighted regression (GTWR), have been widely used to characterize the spatial non-stationarity of variable relationships [41–43]. However, when applied to provincial panel data with relatively limited sample sizes, these models may suffer from overfitting, unstable coefficient estimates, and sensitivity to bandwidth or spatial weight specifications. More importantly, the presence of spatial dependence should itself be determined through empirical testing. If residual spatial autocorrelation is weak or non-significant, directly applying complex spatial econometric models may introduce unnecessary model complexity and lead to unstable estimates [44]. Therefore, this study first uses Moran's I as a spatial dependence pretest and then applies regional group regression to examine regional heterogeneity without relying on a prespecified spatial weight matrix.

Overall, existing studies have provided an important basis for understanding human settlement quality through theoretical development, indicator-based evaluation, spatial identification, and methodological extension. As human settlement research increasingly focuses on quality improvement and refined governance, describing spatial patterns or constructing composite indices alone has become insufficient for revealing the relative contributions of different dimensions to human settlement quality. Under rapid urbanization, regional development disparities, and climatic and environmental pressures, changes in human settlement quality are often associated with multiple factors, including economic development, public services, infrastructure, ecological conditions, and climatic comfort. These associations may be nonlinear, condition-dependent, and regionally differentiated. Accordingly, this study constructs the HSQI based on the five-system theoretical framework and combines XGBoost-SHAP, spatial autocorrelation testing, a two-way fixed effects model, and regional group regression to comprehensively analyze the spatiotemporal evolution of provincial human settlement quality in China and its associated components. This framework integrates comprehensive evaluation, nonlinear identification, fixed effects control, and regional heterogeneity analysis, thereby providing evidence for differentiated and sustainability-oriented improvements in human settlement quality.

3. Data and Methods

The empirical analysis proceeded in five steps. First, a theoretically grounded indicator system was established, and the HSQI was calculated using entropy-weighted MCDM. Second, multiple machine learning models were compared, and the best-performing model was selected for SHAP interpretation. Third, SHAP analysis was used to identify global feature importance and nonlinear predictive patterns. Fourth, Global Moran's I was calculated to test whether a spatial econometric model was necessary. Fifth, TWFE and regional group regressions were used to estimate average conditional associations and regional heterogeneity. The overall research framework is illustrated in Figure 1.

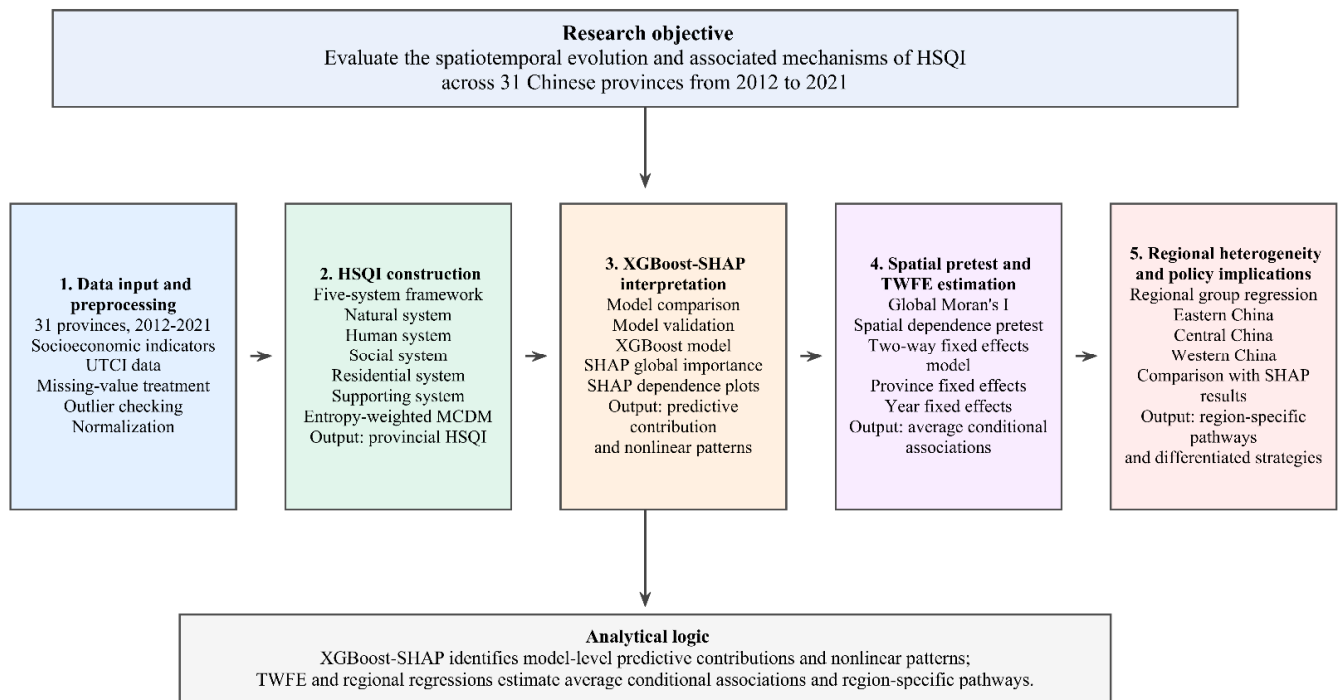


Figure 1. Research framework.

3.1. Data Preprocessing and Quality Control

The indicator system used in this study included socioeconomic data and the Universal Thermal Climate Index (UTCI), covering the period from 2012 to 2021. This period encompassed the late stage of the 12th Five-Year Plan (2012–2015), the entire 13th Five-Year Plan (2016–2020), and the first year of the 14th Five-Year Plan (2021). Socioeconomic data were obtained from the National Bureau of Statistics of China, the China Statistical Yearbook, the China Urban Statistical Yearbook, and relevant provincial statistical yearbooks. To ensure the continuity and completeness of the provincial panel dataset, samples with severe missing information were excluded, whereas sporadic missing observations were filled using linear interpolation. Data quality was further checked by identifying values exceeding three standard deviations. These potential outliers were compared with the original statistical sources. Because most of them reflected real regional differences in socioeconomic development, infrastructure provision, or environmental conditions, they were not automatically removed. Only values caused by obvious input or transcription errors were corrected.

The UTCI, established under the auspices of the World Meteorological Organization's Commission for Climatology (WMO/CCI), is a multi-node thermophysiological model and is widely regarded as one of the most universal models of human thermal balance. It reflects human perception of climate change and thermal comfort [45–47]. In this study,

UTCI data was obtained from the ERA5-HEAT dataset, which was derived from ERA5 reanalysis data provided by the European Center for Medium-Range Weather Forecasts (ECMWF) [48], with a horizontal resolution of $0.25^\circ \times 0.25^\circ$. Daily global UTCI data from 2012 to 2021 were processed using Python 3.13 and aggregated into annual values. The China domain was then extracted, and a small number of missing gridded values were interpolated using neighboring spatial information in ArcGIS 10.7. Provincial UTCI values were finally obtained using zonal statistics.

3.2. Evaluation Method for Human Settlement Quality

The commonly used scientific framework for human settlement environments in China classifies their composition into five major systems [49–51]. Based on this framework and following the principles of scientific rigor, systematization, operability, and data availability [52], this study employed a combination of correlation analysis and the coefficient of variation method to screen indicators. Indicators with data completeness below 90% or a coefficient of variation below 0.10 were excluded. For pairs of indicators with an absolute Pearson correlation coefficient greater than 0.70, we retained the indicator with stronger theoretical relevance, better data availability, and higher variability (Table S1, Note S1). The final indicator system was also checked for consistency with the five-system human settlement framework. This procedure was used to avoid weight dilution and model overfitting caused by an excessive number of indicators, ultimately resulting in a human settlement quality evaluation system comprising five major systems and 25 specific indicators. In the natural system, in addition to traditional ecological endowment indicators such as green space and water resources, the UTCI was introduced to characterize thermal comfort as a dynamic human-perceived factor [53]. The human system focuses on economic development levels and residents' living standards; the social system reflects population vitality, public services, and social security; the residential system represents convenience in daily life and cultural consumption; and the supporting system measures the coverage and capacity of infrastructure provision [49]. Based on a multi-criteria decision-making (MCDM) framework, this study employed the entropy weight method as an objective weighting tool to determine the weight of each indicator [54]. The specific calculation steps were as follows: First, the original data were subjected to min-max normalization to eliminate dimensional effects, as shown in Equations (1) and (2).

For positive indicators:

$$z_{ij} = \frac{(x_{ij} - \min x_{ij})}{(\max x_{ij} - \min x_{ij})} \quad (1)$$

For negative indicators:

$$z_{ij} = \frac{(\max x_{ij} - x_{ij})}{(\max x_{ij} - \min x_{ij})} \quad (2)$$

where x_{ij} is the raw value of the j th indicator for the i th evaluation object, z_{ij} is the standardized value. Subsequently, the information entropy E_j and weight w_j of the j th indicator were calculated using Equations (3)–(5):

$$p_{ij} = \frac{(z_{ij} + \varepsilon)}{\sum_i (z_{ij} + \varepsilon)} \quad (3)$$

$$E_j = -\frac{1}{\ln n} \sum_{i=1}^n p_{ij} \ln p_{ij} \quad (4)$$

$$w_j = \frac{1 - E_j}{\sum_{j=1}^m (1 - E_j)} \quad (5)$$

where p_{ij} is the proportion of the standardized value of the i th object for the j th indicator; ε is a tiny constant used to avoid the $\ln(0)$; n is the number of evaluation objects (province $\times$ year); and m is the number of indicators. The HSQI was calculated using a linear weighting method, as specified in Equation (6), to obtain a comprehensive evaluation value for each province in each year, thereby enabling the ranking and evaluation of human settlement quality from an MCDM perspective.

$$HSQI_i = \sum_{j=1}^m w_j \cdot z_{ij} \quad (6)$$

where z_{ij} is the standardized indicator value, and $HSQI_i$ is the Human Settlement Quality Index of the i th object. The index ranges from 0 to 1, with higher values indicating higher human settlement quality. The complete indicator system and the weight of each indicator are shown in Table 1. Among the indicator attributes, “+” denotes a positive indicator, for which larger values contribute more to human settlement quality, whereas “−” denotes a negative indicator, for which smaller values contribute more to human settlement quality.

Table 1. Indicators of the human settlement quality index.

System	Code	Indicators	Units	Attribute	Weight
Natural	H1	UTCI	°C	+	0.0474
	H2	Green coverage rate of built-up areas	%	+	0.0430
	H3	Per capita park area	m ² /person	+	0.0345
	H4	Per capita park green space	m ² /person	+	0.0431
	H5	Per capita water resources	m ³ /person	+	0.0412
Human	H6	Per capita daily domestic water consumption	L	+	0.0463
	H7	Per capita regional GDP	CNY/person	+	0.0468
	H8	Per capita disposable income of all residents	CNY	+	0.0376
	H9	Urban registered unemployment rate	%	−	0.0445
	H10	Per capita express delivery volume	items/person	+	0.0373
Social	H11	Population natural growth rate	%	+	0.0519
	H12	Proportion of urban employment in the service sector	% of total population	+	0.0404
	H13	Coverage rate of basic medical insurance for urban and rural residents	%	+	0.0339
	H14	Public toilets per 10,000 people	units	+	0.0448
	H15	Hospital beds per 10,000 people	beds	+	0.0331
Residential	H16	Harmless treatment rate of household waste	%	+	0.0495
	H17	Per capita optical cable line length	km/person	+	0.0426
	H18	Per capita private car ownership	vehicles/person	+	0.0334
	H19	Average annual newspaper and magazine subscriptions per 100 people	copies	+	0.0402
	H20	Per capita public library holdings	volumes/person	+	0.0281
Supporting	H21	Urban water supply coverage rate	%	+	0.0468
	H22	Urban gas supply coverage rate	%	+	0.0373
	H23	Internet penetration rate	%	+	0.0302
	H24	Per capita urban road area	m ² /person	+	0.0383
	H25	Public transport vehicles per 10,000 people	standard units	+	0.0279

This study used the calculated HSQI as the target variable for subsequent model analysis to model the mechanisms influencing human settlement quality. Based on the

transparent, reproducible, and theoretically grounded comprehensive evaluation results provided by the MCDM method [55], this study further explored the complex mechanisms through which each indicator is associated with human settlement quality by integrating interpretable machine learning and panel regression models.

Because HSQI is a composite index constructed from the selected indicators, the subsequent XGBoost-SHAP and panel regression analyses were not designed to identify strictly exogenous causal determinants. These analyses were used as a diagnostic decomposition framework to examine the relative contributions, nonlinear response patterns, and conditional associations of different component indicators in relation to the spatiotemporal variation in HSQI. Specifically, XGBoost-SHAP was used to identify the relative contribution of each indicator to HSQI predictions and its potential nonlinear response patterns. The two-way fixed effects model was used to estimate the average conditional association between each indicator and HSQI after controlling for province-specific fixed characteristics and common year shocks. To reduce the potential circular reasoning caused by explaining a composite index using its own component indicators, this study further conducted leave-one-indicator-out robustness checks. For the core indicators with high SHAP rankings, the corresponding indicator was removed, and an alternative HSQI was reconstructed using the same MCDM normalization and entropy-weighting procedures. The association between the omitted indicator and the alternative HSQI, which no longer mechanically included that indicator, was then examined. The results are reported in Section 4.5.2.

3.3. Interpretable Machine Learning Model

3.3.1. Candidate Model Comparison and Selection Method

Machine learning methods, owing to their strong nonlinear fitting capabilities and ability to automatically capture high-dimensional feature interactions, have demonstrated significant advantages in factor simulation and attribution analysis across multiple fields [56–59]. To identify the model that most accurately captured human settlement quality and the complex relationships among its contributing components, and to provide a reliable foundation for subsequent SHAP-based interpretability analysis, eight representative machine learning models spanning linear regression, nonlinear regression, and ensemble learning were selected for performance comparison. The specific models included Lasso regression, support vector machine (SVM), Elastic Net, decision tree, random forest, XGBoost, LightGBM, and AdaBoost. Using the annual HSQI of each province as the target variable and the 25 indicators as feature variables, the dataset was randomly split into a training set (70%) and a testing set (30%). The training-testing split was adopted to balance model training and independent validation, providing sufficient observations for model fitting while retaining an independent testing set for evaluating generalization performance [60,61]. Five-fold cross-validation was then applied to the training set for hyperparameter tuning, and the generalization performance of the final model was evaluated on the testing set. Adjusted R^2 , root mean square error (RMSE), and mean absolute error (MAE) were used as evaluation metrics to compare the predictive accuracy of each model. The formulas for these metrics are given in Equations (7)–(9):

$$R_{adj}^2 = 1 - \left[\frac{(1 - R^2)(N - 1)}{N - k - 1} \right] \quad (7)$$

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (8)$$

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (9)$$

where y_i is the actual value; $\hat{y}_i$ is the predicted value; k is the total number of features ($k = 25$ in this study); and N is the sample size of the testing set.

3.3.2. Interpretation of Machine Learning Model Using SHAP

To interpret how different indicators contributed to HSQI predictions in the selected machine learning model, SHAP was introduced to interpret the selected optimal machine learning model. SHAP was proposed by Lundberg and Lee, and its core concept is derived from the Shapley value in game theory [62]. In machine learning feature attribution, the Shapley value quantifies the contribution of each feature to model predictions, thereby enabling the interpretation of various model outputs [63]. For a single sample, the SHAP value ϕ_i of feature i represents the marginal contribution of that feature to the model prediction relative to the baseline value [64]. The formula is given in Equation (10):

$$\phi_i(f) = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \cdot (|N| - |S| - 1)!}{|N|!} \cdot [f(S \cup \{i\}) - f(S)] \quad (10)$$

where N is the set of all features; S is a subset of features excluding feature i ; $\phi_i(f)$ is the SHAP value for feature i ; $f(S)$ is the model prediction output given feature subset S .

To assess the robustness of the selected model specification and reduce concerns about potential overfitting and data leakage in the provincial panel data, this study further conducted model validation. The robustness checks used the optimal XGBoost hyperparameters obtained from the original five-fold cross-validation grid search, which included 108 candidate parameter combinations and 540 model fits. First, 100 repeated 70/30 train-test splits were performed using different random seeds, and the means and standard deviations of R^2 , RMSE, and MAE were reported. Second, because random splitting may not fully reflect the temporal structure of panel data, leave-one-year-out validation was further conducted. Third, bootstrap resampling was used to evaluate the stability of SHAP-based feature attributions. The results are reported in Section 4.5.1.

3.4. Global Moran's I

Before exploring the spatial heterogeneity of contributing components, testing for spatial dependence is a prerequisite for selecting an appropriate econometric model [65,66]. This study used Global Moran's I to examine the annual spatial patterns of the Human Settlement Quality Index (HSQI) across provinces. The formula for Moran's I is shown in Equation (11):

$$I = \frac{n}{S_0} \frac{\sum_{i=1}^n \sum_{j=1}^n w_{ij} (y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^n (y_i - \bar{y})^2} \quad (11)$$

where n is the number of provinces, y_i is the HSQI value of province i , $\bar{y}$ is the national mean, w_{ij} is an element of the spatial weight matrix, and $S_0 = \sum_{i=1}^n \sum_{j=1}^n w_{ij}$ is the sum of all spatial weights. The value of Moran's I generally ranges from -1 to 1 . A significantly positive value indicates that similar HSQI values tend to cluster spatially, whereas a significantly negative value indicates spatial dispersion. A non-significant value ($p > 0.05$) implies that the null hypothesis of spatial randomness cannot be rejected, indicating that no identifiable spatial dependence structure exists [67]. In this study, the results of the spatial autocorrelation test provided a direct statistical basis for subsequent model selection. Specifically, when Moran's I remained non-significant, a panel model without spatial terms was preferentially used, and regional group regression was employed to capture

spatial heterogeneity, thereby avoiding estimation risks associated with complex spatial econometric models under small-sample conditions.

3.5. Two-Way Fixed Effects Panel Model

This study employed a two-way fixed effects panel model (TWFE panel model) to estimate the average conditional associations of each factor on HSQI. By incorporating province and year fixed effects, the TWFE panel model can simultaneously control for time-invariant provincial heterogeneity and annual shocks arising from common macro-level policy adjustments or nationwide technological changes, thereby producing consistent estimates of the explanatory variable coefficients [68]. The model was specified as shown in Equation (12):

$$HSQI_{it} = \beta X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (12)$$

where $HSQI_{it}$ is the HSQI of province i in year t , X_{it} is a vector comprising 25 feature variables, β is the vector of coefficients to be estimated, μ_i is the province fixed effect, λ_t is the year fixed effect, and ε_{it} is the random error term. Model parameters were estimated using the within estimator, and cluster-robust standard errors at the provincial level were employed to address potential within-group serial correlation and heteroscedasticity. In this study, the model achieved an R^2 of 0.88, indicating strong overall explanatory power for the indicator system used.

To assess potential multicollinearity among the explanatory variables, this study further conducted variance inflation factor (VIF) diagnostics. Because the main panel regression model controlled for both province and year fixed effects, VIF tests were conducted not only for the raw variables and MCDM-normalized variables, but also for the variables transformed by two-way fixed effects. The results showed that some variables had high VIF values before the fixed effects transformation, whereas the VIF values decreased substantially after province and year effects were controlled for. After the two-way fixed effects transformation, the maximum VIF was 2.227 and the mean VIF was 1.588, with all variables below the commonly used threshold of 5 (Table S7). This indicates that no severe multicollinearity was detected under the final fixed effects regression specification.

To explore the spatial heterogeneity of associated mechanisms while avoiding the subjectivity and small-sample bias introduced by spatial weight matrices, this study further adopted a regional group panel regression strategy. Specifically, based on the regional classification standards of the National Bureau of Statistics of China, the 31 provinces were divided into three economic zones: eastern, central, and western. The above TWFE panel model was then estimated separately for each zone to compare the direction, magnitude, and significance of the coefficients of the core associated variables. This method indirectly captured regional differences in conditional associations from a geographically grouped perspective without relying on the specification of spatial weight matrices, thereby offering greater robustness and interpretability. The regression results were compared with the previous SHAP-based global interpretability analysis to enhance the multidimensional reliability of the study conclusions.

4. Results

4.1. Spatiotemporal Evolution of Human Settlement Quality in China

Based on the HSQI evaluation results for 31 Chinese provinces (Figure 2a–c), the evolution of human settlement quality in China was systematically analyzed in terms of temporal trends and spatial distribution patterns.

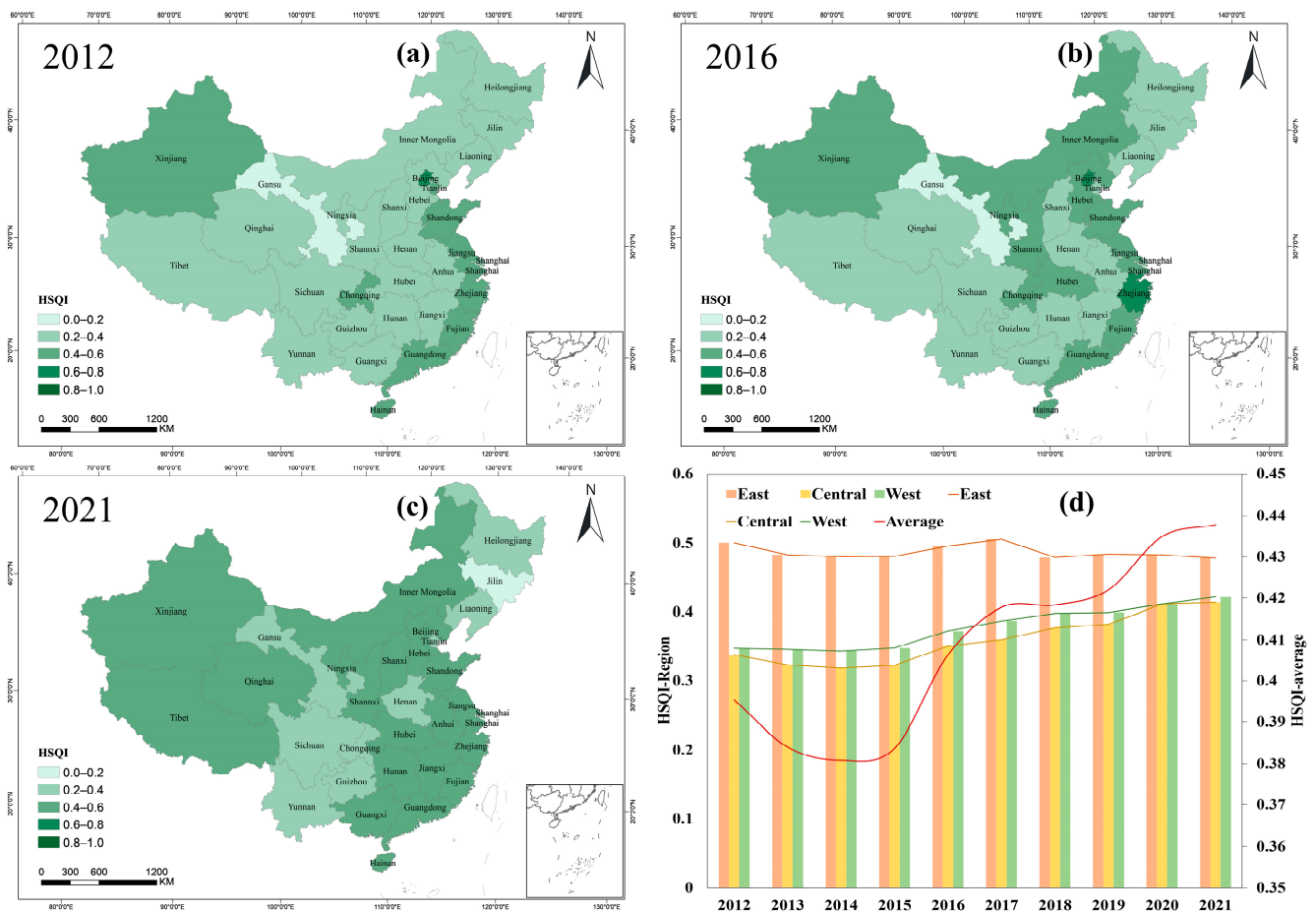


Figure 2. (a–c) Spatial distribution of HSQI in China of 2012, 2016, and 2021. (d) HSQI trends across the three regions from 2012 to 2021.

From the perspective of temporal trends, China's HSQI steadily increased overall between 2012 and 2021. Using 2012 as the baseline, the total increase by 2021 was 12.22%, with the national average rising from 0.3897 to 0.4372. This process exhibited a clear phased pattern, in which the short-term decline during 2012–2015 did not alter the long-term upward trend. From 2012 to 2015, HSQI decreased by 2.51% in total, with an average annual decline of 0.84%; from 2016 to 2021, HSQI increased by 8.33% in total, with an average annual growth rate of 1.62%, indicating a steady upward trajectory as the cumulative effects of human settlement improvement policies gradually became evident.

From the perspective of spatial distribution patterns, regional disparities in HSQI were significant but showed a narrowing trend. Eastern provinces and municipalities, such as Beijing (0.6748), Zhejiang (0.5797), Jiangsu (0.5408), and Shanghai (0.5170), consistently ranked at the top, with averages well above the national mean. Gansu (0.2942), Yunnan (0.3239), and Guizhou (0.3258) remained at the bottom throughout the study period; however, by 2021, they had increased by 61.78%, 29.93%, and 51.10%, respectively, compared with 2012, demonstrating strong late-stage catching-up momentum. Across the three regions (Figure 2d), the eastern region had the highest ten-year average HSQI (0.4784), but its growth rate was only 1.21%, indicating a high-level plateau. In contrast, the central (0.3692) and western (0.3775) regions had similar absolute levels, but their growth rates reached 22.41% and 25.74%, respectively, indicating substantially stronger growth momentum than that of the eastern region. Notably, the gap between the central and western regions narrowed significantly, whereas the absolute gap between the eastern region and the central-western regions remained pronounced, suggesting that regional balance

improved but did not fundamentally alter the basic pattern of higher HSQI in the east and lower HSQI in the central and western regions. Overall, from 2012 to 2021, China's human settlement quality continued to improve, showing a trend of "a slight decline followed by an increase." Significant regional disparities persisted, while the central and western regions exhibited clear late-stage advantages.

4.2. Global Interpretability Analysis

4.2.1. Determination of the Optimal Machine Learning Model

The performance comparison of eight common models (Figure 3) indicates that ensemble learning models (XGBoost, LightGBM, and random forest) generally outperformed linear models (LASSO and Elastic Net) and single learners (decision tree and SVR). XGBoost achieved the best performance among all models (Table 2), demonstrating a significant advantage in capturing the complex nonlinear relationships between human settlement quality and its influencing factors. Therefore, it was selected as the optimal machine learning model for subsequent SHAP-based interpretability analysis in this study. The XGBoost hyperparameter settings are shown in Table S2.

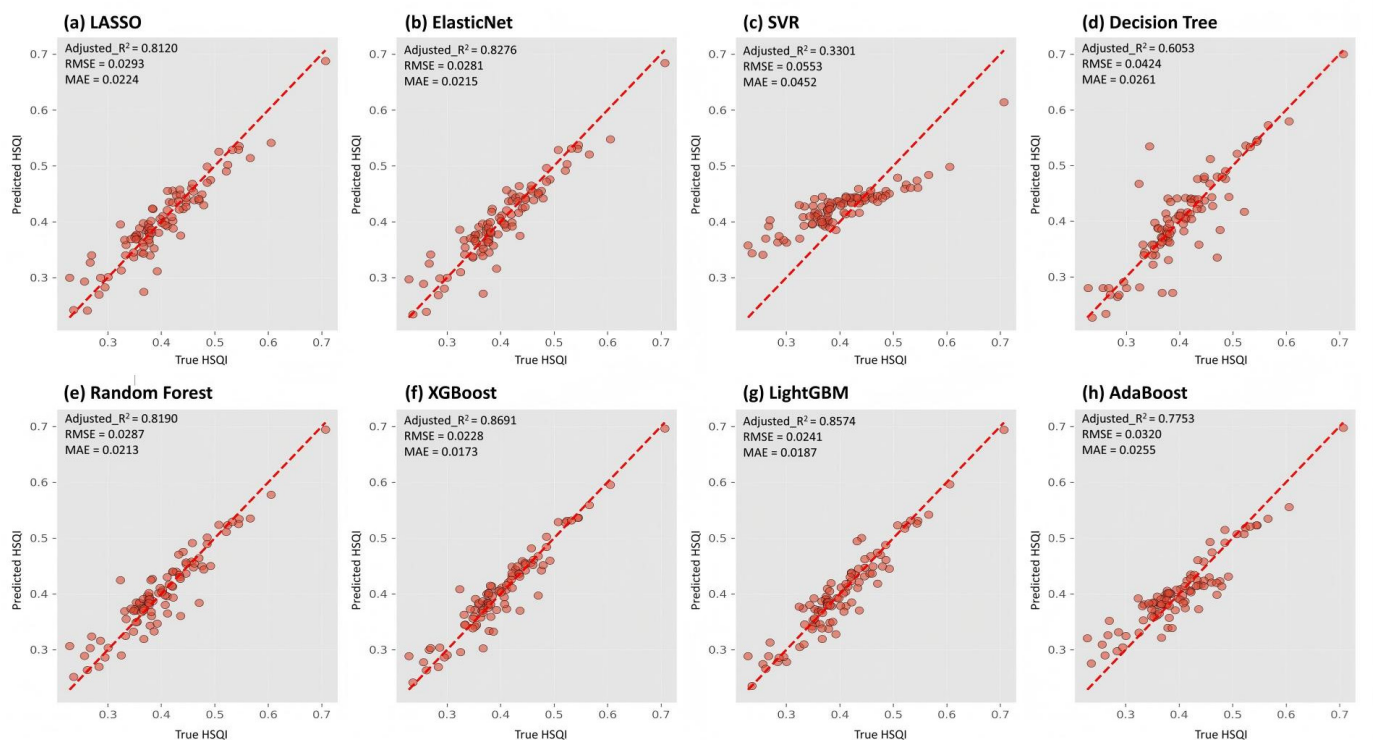


Figure 3. Performance comparison of machine learning models.

Table 2. Comparison of machine learning models.

Model	Train R2	Test R2	adj R2	RMSE	MAE
LASSO	0.9314	0.8631	0.8120	0.0293	0.0224
ElasticNet	0.9361	0.8745	0.8276	0.0281	0.0215
SVR	0.6497	0.5122	0.3301	0.0553	0.0452
Decision Tree	1.0000	0.7126	0.6053	0.0424	0.0261
Random Forest	0.9880	0.8682	0.8190	0.0287	0.0213
XGBoost	0.9998	0.9047	0.8691	0.0228	0.0173
LightGBM	0.9966	0.8962	0.8574	0.0255	0.0191
AdaBoost	0.9491	0.8364	0.7753	0.0320	0.0255

4.2.2. Global Feature Importance and Nonlinear Response Patterns

Based on the XGBoost-SHAP results, this study systematically analyzed the influence mechanisms of various factors on human settlement quality from two perspectives: global feature contribution and nonlinear response patterns. From the perspective of individual feature contributions (Figure 4), economic development level (H7) was the dominant driving factor, with an importance approximately twice that of the second-ranked factor, indicating that the stage of economic development remained the most fundamental explanatory variable for provincial disparities in human settlement quality in China during the study period. Municipal infrastructure (H22 and H24), public services and cultural consumption (H19), domestic water supply security (H6), and ecological greening (H2 and H4) together formed the core influencing layer. From a system-level perspective (Table 3), the human system had the strongest explanatory power for HSQI, with a contribution rate of 37.62%. The supporting and natural systems followed, contributing 22.57% and 15.14%, respectively. Within the supporting system, the core indicator H22, which had the highest contribution within the system, ranked second among all indicators, revealing that the coverage of hardware infrastructure, such as municipal pipelines, remained key to improving environmental quality. The residential and social systems had relatively lower contributions, indicating that ecological greening and cultural information services had not yet surpassed the economic and infrastructure dimensions to form independent driving forces. The core indicator of the social system (H11) ranked only eighth, suggesting that social vitality may exert its influence primarily through nonlinear interactions or long-term indirect pathways.

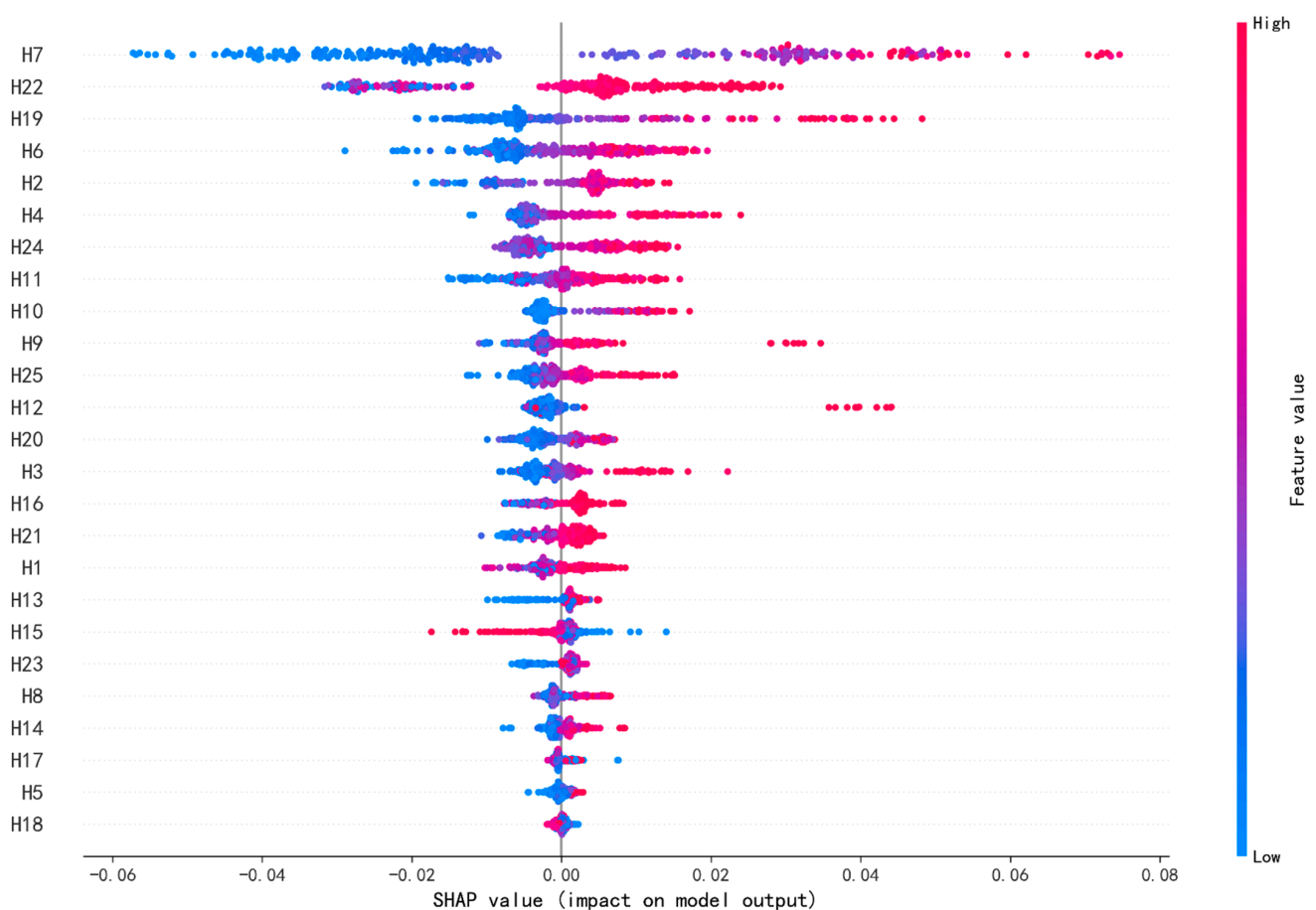
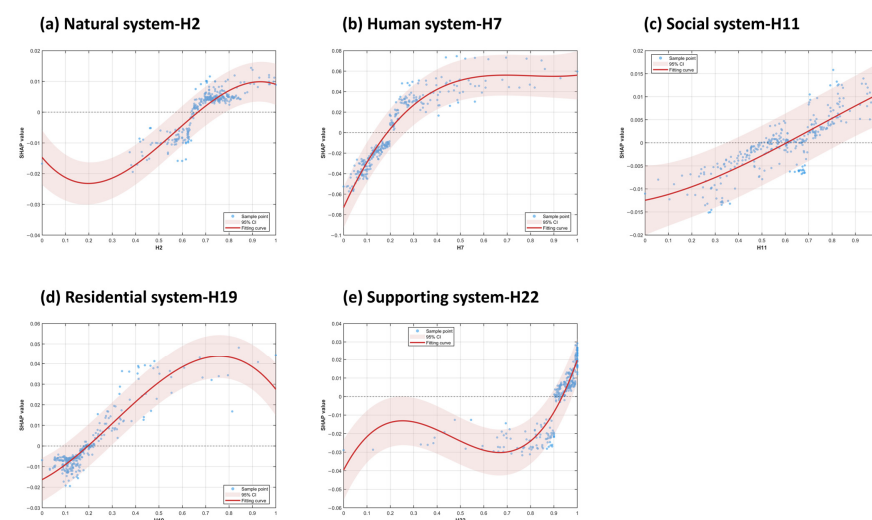


Figure 4. SHAP analysis results from the XGBoost model. “High” and “Low” indicate the relative values of each feature across samples, with red representing high values and blue representing low values. Points farther to the right indicate a stronger positive effect of the feature on the model output, whereas points farther to the left indicate a stronger negative effect.

Table 3. Results of system-level feature contribution analysis.

System	Total System Importance	Proportion (%)	Core Indicator	Contribution of the Core Indicator	Overall Ranking of the Core Indicator
Natural	0.0186	15.14%	H2	0.0062	5
Human	0.0463	37.62%	H7	0.0295	1
Social	0.0129	10.50%	H11	0.0045	8
Residential	0.0174	14.17%	H19	0.0098	3
Supporting	0.0278	22.57%	H22	0.0140	2

To verify the presence of nonlinear response patterns, this study further analyzed the core indicators of each system, including H2 (natural system), H7 (human system), H11 (social system), H19 (residential system), and H22 (supporting system), thereby revealing the complex nonlinear response patterns of these indicators with respect to HSQI (Figure 5a–e). The results showed that the SHAP curve of H2 exhibited an N-shaped fluctuation: within the range of [0, 0.2], the SHAP value was negative and declined; within the range of [0.2, 0.8], the contribution increased rapidly and shifted from negative to positive, demonstrating strong marginal gains; when H2 exceeded 0.8, the curve leveled off and entered a saturation stage. The SHAP curve of H7 increased continuously with higher feature values, but its growth rate gradually slowed, exhibiting a nonlinear pattern of diminishing marginal contributions. When H7 was below 0.4, it showed a strong positive driving effect and then gradually leveled off, entering a plateau at approximately 0.6. This indicated that H7 had a significant effect at the early stage, but its marginal contribution became limited as input increased further. The SHAP values of H11 exhibited near-linear growth with slight convexity, increasing slowly in the low-value range and rising steadily in the medium-to-high-value range above approximately 0.6. This indicated that H11 had a continuous and relatively balanced driving effect. The SHAP curve of H19 exhibited an inverted U-shaped relationship, showing a clear rise-then-decline trend. Within the range of [0, 0.8], the contribution increased continuously and reached its peak positive value at the threshold of 0.8, after which it declined. This indicated that H19 had a significant threshold effect, and excessively high values may even have negative effects. H22 exhibited clear multi-stage fluctuations, forming a complex trajectory of initial increase, subsequent decrease, and renewed increase, thereby demonstrating a pronounced late-stage effect. The above analysis consistently showed that the core indicators of each system had nonlinear dependencies with HSQI, displaying differentiated contribution patterns and effect intensities.

**Figure 5.** Nonlinear characteristics of the core indicators across the five systems.

4.2.3. Regional Heterogeneity of Mean SHAP Values

Based on the mean SHAP values of the top ten indicators ranked by importance in the SHAP analysis (Figure 6), this study revealed the regional differentiation characteristics of the drivers of human settlement quality. The results showed that in the eastern region, the economic foundation was dominant, with the importance of H7 far exceeding that of other variables and its mean SHAP value being positive (0.027). This indicated that in the economically developed eastern provinces, a strong material base remained the strongest support for high-quality human settlements. In addition, H2 and H10 also exhibited significant positive contributions in the eastern region, reflecting comprehensive and balanced development in the material, ecological, and convenience dimensions of this region. The most prominent feature in the central region was H10, whose SHAP value was significantly higher than the national average, demonstrating that central provinces compensated for shortcomings in traditional public services through digital logistics. Notably, H7 exhibited a negative mean SHAP value (-0.013) in the central region, indicating that in this area, mere economic expansion did not automatically translate into improvements in human settlement quality. In the western region, H22 and H4 ranked at the top, revealing the logic for improving human settlement environments in the western region: prioritizing ecological protection while maintaining living quality. This highlighted the core value of the ecological foundation in enhancing residents' well-being.

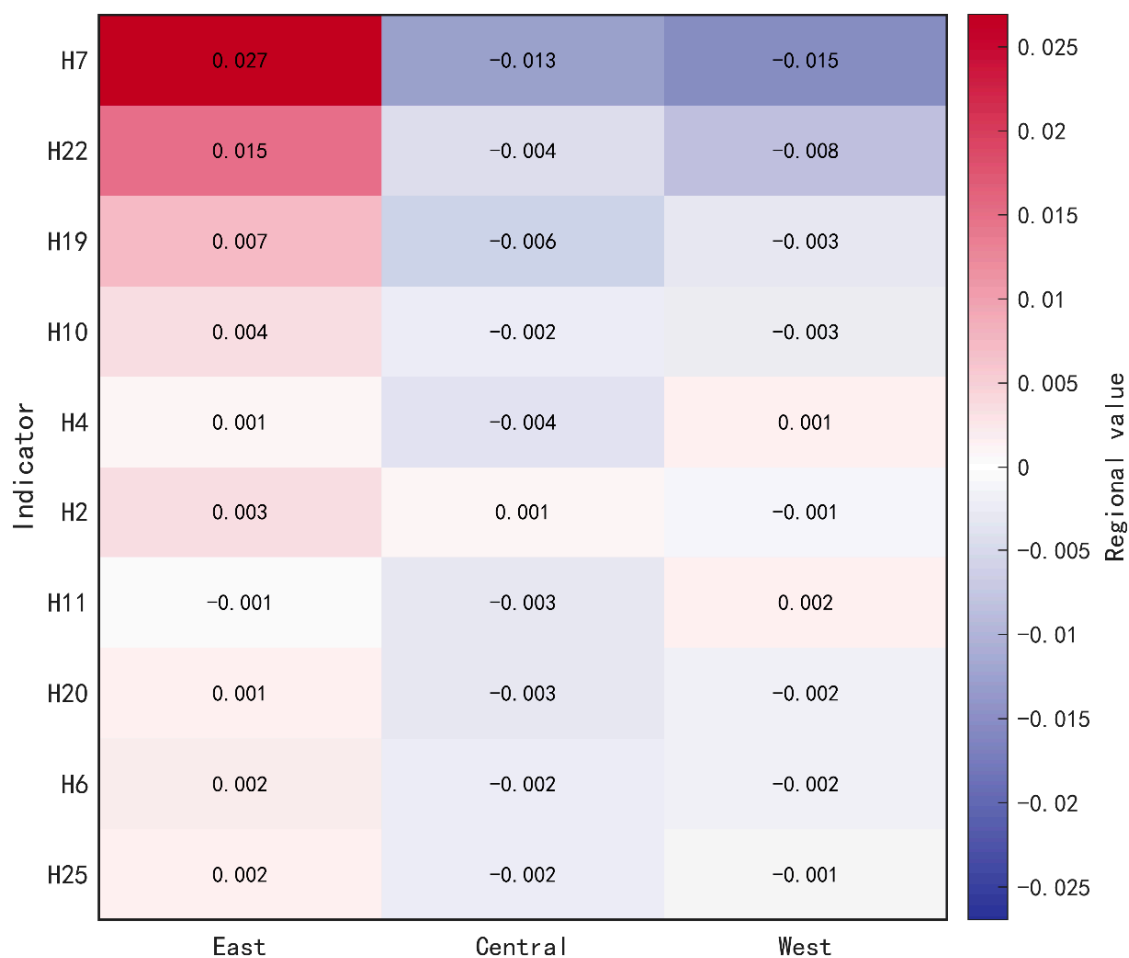


Figure 6. Regional comparison of the top 10 indicators across eastern, central, and western China. Indicators are ranked according to the maximum absolute value across the three regions. Positive and negative values indicate the direction of regional differences, while the color intensity represents the magnitude of the value.

4.3. The Fixed Effects Regression and Regional Heterogeneity

4.3.1. Spatial Correlation Analysis

The Moran's I results for provincial HSQI in China from 2012 to 2021 are shown in Table 4. The spatial correlation test results indicated that from 2012 to 2020, Moran's I values were not statistically significant ($p > 0.05$), suggesting that human settlement quality during this period was relatively spatially balanced or randomly distributed. Although Moran's I was significant in 2021, this significance occurred in only one year of the study period, and provincial fixed effects in the full-panel estimation absorbed long-term spatial differences. Therefore, the TWFE panel model remained a robust choice.

Table 4. Moran's I results.

Year	Moran's I	<i>p</i> Value
2012	−0.03028	0.481837
2013	−0.03392	0.503492
2014	−0.03785	0.52691
2015	−0.07861	0.752794
2016	−0.10925	0.873403
2017	0.061882	0.081828
2018	−0.12067	0.901089
2019	0.047573	0.117635
2020	−0.06613	0.683865
2021	0.106881	0.021133 **

Note: ** indicate significance at the 5% levels.

4.3.2. Average Conditional Associations from the TWFE Panel Model

The results of the TWFE panel regression are presented in Table 5. The results showed that among the 25 explanatory variables, most indicators had significant positive conditional associations. Indicators of the natural system demonstrated strong and robust positive associations. Specifically, the coefficient of H4 was 0.098 ($p < 0.01$), and that of H5 was 0.153 ($p < 0.05$), indicating that the expansion of green space and the abundance of water resources contributed substantially to improving human settlement quality. In the supporting and residential systems, H24 and H23 had significantly positive coefficients, indicating that well-developed infrastructure was key to maintaining high-quality human settlements. In addition, the significant coefficients of indicators such as H21, H23, and H24 suggested that China may have reduced gaps in basic living conditions through improvements in infrastructure and public services during the study period. Notably, H10 showed a significant positive conditional association, demonstrating the implicit enhancement in living quality through digitalized logistics. The positive coefficient of H9 should be interpreted as a conditional association between the original urban registered unemployment rate and HSQI, rather than as evidence that unemployment improves human settlement quality.

Table 5. Results of the TWFE panel regression.

Indicator	Estimate	Std. Error	<i>p</i> -Value
H1	0.0535	0.0146	<0.001 ***
H2	0.0347	0.0179	0.053
H3	0.0253	0.0110	0.022 **
H4	0.0985	0.0154	<0.001 ***
H5	0.1535	0.0694	0.028 **
H6	0.0768	0.0142	<0.001 ***

Table 5. Cont.

Indicator	Estimate	Std. Error	p-Value
H7	−0.0172	0.0474	0.718
H8	−0.0282	0.0725	0.698
H9	0.0527	0.0075	<0.001 ***
H10	0.0560	0.0164	<0.001 ***
H11	0.0793	0.0137	<0.001 ***
H12	0.0376	0.0473	0.428
H13	0.0539	0.0048	<0.001 ***
H14	0.0647	0.0118	<0.001 ***
H15	0.0544	0.0181	0.0030 ***
H16	0.0385	0.0078	<0.001 ***
H17	0.0267	0.0130	0.041 **
H18	0.0145	0.0246	0.557
H19	0.0558	0.0138	0.001 ***
H20	0.0667	0.0385	0.084
H21	0.0703	0.0143	<0.001 ***
H22	−0.0001	0.0247	0.997
H23	0.0877	0.0131	<0.001 ***
H24	0.0472	0.0134	<0.001 ***
H25	0.0506	0.0143	<0.001 ***

Note: ** and *** indicate significance at the 5% and 1% levels.

4.3.3. Regional Heterogeneity Analysis

This section presents a regional heterogeneity analysis of the regional group panel regression results for the ten indicators discussed in Section 4.2.3 (Figure 7). The results indicated that the driving logic of human settlement quality across Chinese provinces exhibited pronounced geographic differentiation. In the eastern region, H7 showed a significant negative conditional association on human settlement quality ($-0.108, p < 0.05$), suggesting that, as China's economic frontrunner, the eastern region had moved beyond the stage in which environmental improvement was primarily associated with GDP growth. Dense economic activity may have led to traffic congestion, rising living costs, and ecological carrying pressures, causing GDP growth to exert a negative conditional association with human settlement quality. In contrast, the eastern region showed a stronger association with H24 ($0.201, p < 0.01$), reflecting that urban management had shifted its focus toward refined spatial optimization. The central region exhibited a distinctly different association structure, with H10 having a coefficient as high as $0.877 (p < 0.01)$, far exceeding the full-sample estimate. This suggested that over the past decade, the central region had substantially alleviated the relative deficiency of traditional offline commercial facilities by rapidly integrating into the digital economy and logistics networks. In addition, H2 ($0.185, p < 0.05$) was also significant in the central region, indicating that the central region was undergoing a rapid improvement phase characterized by simultaneous infrastructure completion and ecological optimization. The regression results for the western region were the most distinctive and challenging. H7 exerted a negative conditional association on human settlement quality in the western region ($-0.330, p < 0.01$), and H10 also had a significantly negative coefficient ($-0.477, p < 0.05$). This suggested that the fragile ecological barriers in the western region could not support traditional high-energy-consumption development models. In contrast, H4 ($0.187, p < 0.01$) had a strong positive conditional association in the western region, indicating that, for western provinces, maintaining the ecological baseline was an effective pathway for improving human settlement quality.

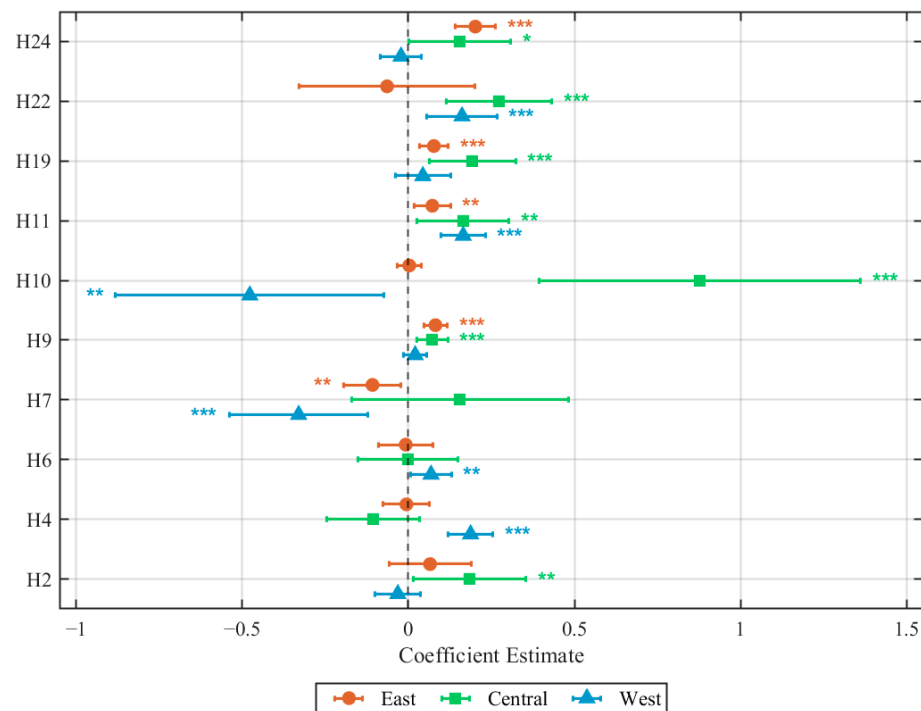


Figure 7. Forest plot of regression coefficients. *, **, and *** indicate significance at the 10%, 5%, and 1% levels.

4.4. Comparative Analysis of XGBoost-SHAP and the TWFE Panel Model from a Regional Perspective

To further clarify the relationship between the XGBoost-SHAP results and the panel fixed effects results, this study compared the indicators with high SHAP importance rankings with their corresponding fixed effects regression results in Tables 6 and 7. In the full-sample results, most indicators with high SHAP importance also showed significant positive conditional associations in the fixed effects model, including H19, H6, H4, H24, H11, H10, and H9. This suggests that these variables contributed to the model prediction structure and were statistically associated with within-province temporal changes in HSQI. By contrast, although H7 and H22 had high SHAP importance, their coefficients were not significant in the full-sample fixed-effects model. This indicates that these two indicators may primarily capture cross-provincial structural differences or nonlinear predictive information, whereas their average linear associations were not stable after province and year fixed effects were controlled for. When regional differences, threshold patterns, or nonmonotonic relationships exist, the full-sample average coefficient may be offset by opposing associations across regions or feature ranges.

Table 6. Comparison of SHAP-based predictive importance and fixed-effect regression results.

Indicator	SHAP Value	TWFE Coefficient	Interpretation
H7	0.029466	−0.017	Inconsistent
H22	0.013966	≈0	Not Significant
H19	0.009815	0.056	Consistently Positive
H6	0.007419	0.077	Consistently Positive
H2	0.006192	0.035	Consistently Positive
H4	0.00572	0.098	Consistently Positive
H24	0.005634	0.047	Consistently Positive
H11	0.004532	0.079	Consistently Positive
H10	0.003947	0.056	Consistently Positive
H9	0.003855	0.053	Consistently Positive

Table 7. Regional comparison of mean SHAP values and fixed-effect coefficients.

Indicator	Eastern		Central		Western	
	SHAP	Coef.	SHAP	Coef.	SHAP	Coef.
H7	0.02694	−0.108 **	−0.01278	0.156	−0.01517	−0.330 ***
H22	0.0148	−0.064	−0.00443	0.273 ***	−0.00826	0.162 ***
H19	0.00724	0.077 ***	−0.00596	0.193 ***	−0.00301	0.044
H6	0.00195	−0.008	−0.00247	−0.001	−0.00178	0.068 **
H2	0.00334	0.065	0.00088	0.185 **	−0.00097	−0.032
H4	0.00078	−0.006	−0.00352	−0.106	0.00147	0.187 ***
H24	0.00125	0.201 ***	−0.00212	0.155 *	0.00082	−0.022
H11	−0.00057	0.072 **	−0.00324	0.164 **	0.00168	0.165 ***
H10	0.00369	0.003	−0.00223	0.877 ***	−0.00262	−0.477 **
H9	0.00035	0.082 ***	−0.00141	0.072 ***	−0.00084	0.02

Note: *, **, and *** indicate significance at the 10%, 5% and 1% levels.

The regional results further show that the differences between SHAP and fixed effects regression have clear methodological implications (Table 7). The regional mean SHAP value indicates the average contribution direction of a variable relative to the model baseline prediction within a given region, whereas the coefficient from the region-specific fixed effects model represents the average conditional association between within-region changes in that variable and HSQI. Taking H7 as an example, its mean SHAP value was positive in the eastern region, whereas its fixed effects coefficient was significantly negative. This suggests that a higher level of economic development helped the model identify the higher baseline HSQI in the eastern region, but after fixed effects were controlled for, further economic expansion may have been constrained by high-density development, congestion costs, resource consumption, and environmental burdens. In the western region, both the mean SHAP value and the fixed-effects coefficient of H7 were negative, indicating that the conversion of economic growth into improvements in human settlement quality may be limited by ecological constraints and infrastructure deficiencies. For H22, the fixed effects coefficients were significantly positive in the central and western regions, while the regional mean SHAP values were negative. This suggests that the current level of H22 in these regions had not yet formed a positive predictive advantage, but its incremental improvement was still significantly and conditionally associated with HSQI improvement.

Overall, the comparison shows that SHAP importance and fixed effects coefficients capture different dimensions of information. SHAP reflects model-level predictive contribution, whereas fixed-effects coefficients reflect within-province conditional associations after province and year heterogeneity are controlled for.

4.5. Robustness Checks

4.5.1. Model Validation and SHAP Stability

To address the potential overfitting concern associated with the high training performance of XGBoost, additional validation analyses were conducted using the optimal hyperparameters obtained from the original five-fold cross-validation grid search. The 70/30 training-testing split was repeated 100 times using different random seeds. The repeated validation results showed stable out-of-sample performance, with a mean test R^2 of 0.966 ± 0.016 , RMSE of 0.0179 ± 0.0037 , and MAE of 0.0112 ± 0.0016 (Table S3). Because random splitting may not fully capture the temporal structure of panel data, leave-one-year-out validation was further conducted. The results remained stable, with a mean R^2 of 0.966 ± 0.028 , RMSE of 0.0166 ± 0.0070 , and MAE of 0.0109 ± 0.0034 (Table S4). These results indicate that the predictive performance of the XGBoost model was not driven by a single random data partition.

Bootstrap SHAP analysis was further used to examine whether the selected core indicators were sensitive to sample perturbation. The results showed that H7, H10, H23, H17, and H13 appeared in the top 10 in at least 98% of the bootstrap samples (Table S5). H19 and H8 also showed high selection stability, whereas H6, H9, and H20 showed relatively lower stability. These results indicate that several core indicators retained stable model-based predictive relevance across bootstrap samples. Nevertheless, SHAP values were interpreted only as model-based predictive contributions rather than causal effects.

4.5.2. Robustness Against Circularity in HSQI Construction

The leave-one-indicator-out results showed that several selected core indicators, including H7, H10, H23, H17, and H13, remained positively and significantly associated with the reconstructed HSQI after being excluded from the index construction (Table S6). This suggests that the identified associations were not entirely driven by the mechanical inclusion of these indicators in the composite index. However, some indicators became statistically insignificant after exclusion, indicating that the results should be interpreted as diagnostic associations rather than strict causal effects. Therefore, the XGBoost-SHAP and panel regression results in this study were used to reveal contribution structures and conditional associations rather than to draw strong causal conclusions.

5. Discussion

5.1. Regional Differentiation in the Relationship Between Economic Development and Human Settlement Quality

The results indicate that the relationship between economic development and human settlement quality is characterized by clear regional differentiation and stage-specific features. Per capita GDP (H7) was an important predictor in the XGBoost-SHAP analysis, suggesting that economic development remains an important background factor for explaining provincial differences in human settlement quality. In the two-way fixed effects model and regional group regressions, the marginal association of H7 differed across regions, indicating that the relationship between economic growth and improvements in human settlement quality was not uniform. This finding is broadly consistent with studies on the environmental Kuznets curve (EKC) in China [69], which suggests that the relationship between economic growth and environmental quality is often nonlinear and stage-specific. This relationship also varies substantially across provinces, cities, and development levels [70,71]. More developed eastern provinces may have reached or crossed certain environmental pressure thresholds earlier, whereas the central and western regions remain at different development stages [72,73]. This study further extends this nonlinear relationship from the traditional fields of pollution emissions and energy intensity to the comprehensive evaluation of human settlement quality [74]. Unlike a single indicator, HSQI includes multiple dimensions, such as ecological conditions, public services, residential conditions, and supporting systems. Therefore, the relationship between economic growth and HSQI may be jointly conditioned by urban congestion, service provision, spatial development intensity, and ecological constraints.

Therefore, the negative or statistically insignificant marginal association of H7 in the eastern region may be understood as the offsetting role of congestion costs, resource consumption, spatial development intensity, and environmental burdens under conditions of high economic density. The positive association in the central region suggests that its human settlement quality may still be in an upward stage, jointly supported by economic development and infrastructure improvement. Economic growth may contribute to improvements in human settlement quality through enhanced fiscal capacity, better public service provision, and improved transport and residential infrastructure. In the

western region, the association of economic variables with HSQI may be more strongly conditioned by ecological endowments, resource constraints, and infrastructure deficiencies. Economic expansion, therefore, does not necessarily translate into improved human settlement quality.

5.2. Interpretation of Digital Transformation, Public Services, and Employment Indicators

Digitalization-related indicators showed relatively high importance in explaining human settlement quality. Indicators such as per capita express delivery volume (H10), Internet penetration rate (H23), and per capita optical cable line length (H17) showed relatively stable predictive associations in the model. This suggests that digital logistics, information infrastructure, and digital service capacity have become important components related to provincial human settlement quality. In the central region in particular, digital logistics and information infrastructure may contribute to human settlement quality by improving daily convenience, enhancing consumption accessibility, and partly compensating for spatial inequalities in traditional public services [75,76]. Previous studies have shown that digital services may play a compensatory role in regions where infrastructure has not yet reached the level of the eastern region [77–79]. The association between digital activities and human settlement quality is not necessarily positive. The expansion of logistics activities may be accompanied by increased traffic pressure, energy consumption, packaging waste, and carbon emissions [80]. In ecologically fragile regions or areas with limited infrastructure carrying capacity, the expansion of digital activities should be coordinated with resource and environmental carrying capacity. These findings suggest that digitalization should be coordinated with green logistics, low-carbon infrastructure, and public service equalization.

The positive coefficient of the urban registered unemployment rate (H9) requires cautious interpretation. H9 was directionally adjusted as a negative indicator only during HSQI construction, whereas the original urban registered unemployment rate was used in the subsequent XGBoost-SHAP and panel regression analyses. Its positive conditional association with HSQI may reflect the registration system, access to social security, and the development of public employment services, rather than any beneficial role of unemployment itself. Previous studies have shown clear discrepancies between China's official registered unemployment rate and the actual unemployment rate, with such discrepancies shaped by statistical coverage, the household registration system, registration eligibility, and unemployment registration behavior [81,82].

5.3. Complementarity Between XGBoost-SHAP and Two-Way Fixed Effects Results

This study uses XGBoost-SHAP and a two-way fixed effects model to characterize the component structure and conditional associations of human settlement quality from different perspectives. XGBoost-SHAP measures variable contributions to HSQI predictions in a nonlinear machine learning model and can capture nonlinear responses, threshold patterns, and potential interactions among variables [83]. The two-way fixed effects model estimates within-province average conditional associations after time-invariant provincial characteristics and common year shocks are controlled for [84]. Because the two approaches have different inferential aims, differences in direction, statistical significance, or importance ranking between the SHAP analysis and fixed effects regression do not necessarily indicate conflicting results.

A variable may have high SHAP importance because it explains structural differences or nonlinear distributional patterns across provinces. Once province-fixed effects absorb long-standing regional differences, the average marginal association with within-province temporal variation may weaken or become statistically insignificant. Per capita GDP (H7)

provides a clear example. Its high predictive contribution in the SHAP analysis indicates that economic development is an important background variable for distinguishing provincial differences in human settlement quality. In the region-specific fixed effects regressions, its marginal association varied substantially across regions, suggesting that further economic expansion does not necessarily translate into synchronous improvements in human settlement quality. Therefore, SHAP results are more suitable for identifying model-level predictive contributions and nonlinear responses, whereas fixed effects regression is more suitable for examining average conditional associations after regional and temporal heterogeneity are controlled for [39]. The former reveals the role of variables in the overall prediction structure, while the latter examines their statistical associations along the within-province variation dimension.

SHAP dependence plots further provide context for interpreting the average linear coefficients from the fixed effects regressions. Taking H2 as an example, its SHAP dependence pattern showed nonlinear fluctuations, indicating that its predictive contribution may vary in direction across different value ranges. Accordingly, the coefficient of H2 was only marginally significant in the full-sample panel regression, and the direction and significance of its coefficients also differed across regional regressions. This may reflect differences in the development stage of built-up area green coverage across regions, with some regions not yet reaching the range in which stable positive marginal associations emerge [85]. H19 also illustrates the complementarity of the two approaches. Its SHAP dependence plot showed an inverted U-shaped pattern, suggesting that its predictive contribution may reach a relatively high level in the intermediate range and then decline at higher levels. In the panel regressions, H19 showed significant positive associations in the full sample and in some regions, suggesting that most provinces may still have been within the positive-return range during the study period. The SHAP analysis further suggests that this relationship may have an upper limit and that the marginal contribution may weaken once related cultural and information services reach a relatively high level. These differences therefore do not indicate a simple conflict between the two approaches but reflect distinct information dimensions related to predictive contribution, nonlinear response, and average conditional association.

5.4. Differentiated Governance Implications

Based on the above results, region-specific pathways should be adopted to improve human settlement quality. The eastern region generally has a relatively high level of human settlement quality, although it faces constraints such as high-density development, traffic congestion, resource consumption, and environmental burdens. Policy priorities should shift from incremental expansion to stock optimization and quality improvement. More specifically, urban renewal, compact and orderly spatial governance, improved public transport, blue-green space restoration, and low-carbon infrastructure construction should be promoted to mitigate the negative externalities of intensive urbanization. The central region may still be in a stage in which human settlement quality is jointly supported by economic development, infrastructure improvement, and the expansion of digital services. Policies should continue to promote coordinated development among digital infrastructure, logistics networks, public services, and residential systems, using digital services to improve daily convenience and public service accessibility. At the same time, traffic, energy, and environmental pressures associated with the expansion of digital logistics should be reduced by developing green logistics and low-carbon delivery systems. Improvements in human settlement quality in the western region depend more strongly on the protection of ecological endowments and the enhancement of basic service capacity. Given its fragile ecological environment and stronger resource constraints, the western region should avoid

simply replicating the high-intensity development path of the eastern region. Priority should be given to water resource security, ecological space stability, and the provision of basic public services. While infrastructure and digital services are being developed, ecological conservation redlines, resource carrying capacity assessments, and low-impact development models should be strengthened to achieve coordinated improvements in ecological security and residential well-being.

From a broader sustainable development perspective, the region-specific pathways described above are closely aligned with sustainable urban development, equalized public services, efficient resource use, and ecological conservation [27,86]. Stock optimization and low-carbon renewal in the eastern region correspond to improved urban resource efficiency and reduced environmental burdens. In the central region, coordination between digital infrastructure and public services can enhance service accessibility and regional inclusiveness. In the western region, ecological priority and resource carrying-capacity constraints can help maintain a balance between development needs and ecological security. Therefore, improving human settlement quality should be embedded in regional sustainable development and high-quality urban governance frameworks [87].

5.5. Limitations

This study has several limitations. First, owing to the availability of provincial panel data, the indicator system was mainly based on objective statistical and climatic data, and it did not fully incorporate environmental exposure and subjective perception indicators, such as fine particulate matter, noise pollution, traffic exposure, perceived community safety, sense of belonging, and residential satisfaction. Future studies could combine high-resolution remote sensing data, street-view imagery, social media text, mobile phone signaling data, and questionnaire surveys to develop a more refined measurement system for human settlement quality. Second, this study was conducted mainly at the provincial scale. Although regional group regression can reveal broad differences among the eastern, central, and western regions, it may mask heterogeneity at the scales of urban agglomerations, metropolitan areas, and intra-urban spaces. When city-level or finer-scale panel data become available, future research could combine multiscale geographically weighted regression (MGWR), dynamic spatial models, or multilevel models to further characterize the spatial differentiation of factors associated with human settlement quality. Third, the interpretation of the SHAP and panel regression results should remain cautious. SHAP results reflect model-level predictive contributions, and fixed effects regression results reflect conditional associations after regional and year heterogeneity are controlled for. Neither can be directly equated with strict causal effects. Future studies could further test the stability and generalizability of these findings using longer time series, finer spatial scales, and richer variable systems.

6. Conclusions

Based on panel data for 31 Chinese provinces from 2012 to 2021, this study constructed the Human Settlement Quality Index (HSQI) and combined XGBoost-SHAP, spatial autocorrelation testing, a two-way fixed effects model, and regional group regression to analyze the spatiotemporal evolution of provincial human settlement quality in China and its associated component indicators. The results showed that provincial HSQI in China increased by 12.22% during the study period, while the central and western regions showed a catching-up trend, and regional disparities narrowed to some extent. The XGBoost-SHAP results showed that indicators related to economic development, municipal infrastructure, cultural services, and supporting systems made relatively high contributions to the model

prediction structure, and that some core indicators exhibited nonlinear response patterns with HSQI.

Regionally, eastern China should prioritize stock optimization and low-carbon renewal, central China should strengthen coordination between digital infrastructure and public services, and western China should balance ecological protection, water resource security, and basic service provision. Methodologically, XGBoost-SHAP and the two-way fixed effects model provided complementary perspectives. The former helped identify model-level predictive contributions and nonlinear characteristics, whereas the latter was used to estimate conditional associations after provincial and year heterogeneity were controlled for. It should be emphasized that the findings should be understood as a diagnostic analysis based on provincial panel data and a composite index framework, rather than as strict causal identification. Future research could further incorporate city-level or finer-scale data and include indicators such as air pollution, noise exposure, resident perceptions, and community services. Stronger causal identification strategies or dynamic spatial models could also be used to test the stability and applicability of these findings.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su18147106/s1>, Table S1: Initial indicator pool; Note S1: Indicator quality check and screening procedure; Table S2: XGBoost hyperparameter settings; Table S3: Repeated 70/30 split validation; Table S4: Leave-one-year-out validation; Table S5: Bootstrap selection stability of selected core indicators; Table S6: Leave-one-indicator-out robustness check for selected core indicators; Table S7: Variance inflation factor diagnostics after two-way fixed-effect transformation.

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References

1. Sethi, S.S.; Vinoj, V. Urbanization and regional climate change-linked warming of Indian cities. *Nat. Cities* **2024**, *1*, 402–405. [CrossRef]
2. Cheng, Y.; Yu, Z.; Xu, C.; Manoli, G.; Ren, X.; Zhang, J.; Liu, Y.; Yin, R.; Zhao, B.; Vejre, H. Climatic and Economic Background Determine the Disparities in Urbanites' Expressed Happiness during the Summer Heat. *Environ. Sci. Technol.* **2023**, *57*, 10951–10961. [CrossRef] [PubMed]
3. Jiang, G.; Ji, W.; Tian, Y.; Luo, Y.; Ma, W. Compact and livable? Identifying and managing the relationships between intensive land use and urban livability: Evidence from 337 cities in China. *Ecol. Econ.* **2025**, *232*, 108562. [CrossRef]
4. Yue, T.; Wu, C.; Shi, W.; Tian, Y.; Wang, Q.; Lu, Y.; Zhang, L. Progress in models for coupled human and natural systems. *Sci. China Earth Sci.* **2024**, *67*, 3631–3637. [CrossRef]
5. Huang, X.; Liu, Y. Livability assessment of 101,630 communities in major Chinese cities: A remote sensing perspective. *Sci. Sin. Terrae* **2022**, *52*, 1283–1298. (In Chinese)
6. Tan, Y.; Zhou, Y.; Zhou, H.; Gao, L.; Shi, L. Analysis of the coordinated development and influencing factors between urban population and environment: A case study of 35 metropolises in China. *Sustain. Cities Soc.* **2025**, *121*, 106160. [CrossRef]

7. Yang, Y.; Jing, T.; Wang, H.; Zhong, Y.; Yu, W.; Zhou, H. Causal network of high-quality development and urban resilience in Chinese cities based on transfer entropy: Structure and determinants. *Sustain. Cities Soc.* **2025**, *133*, 106875. [\[CrossRef\]](#)
8. Ye, S.; Wei, C.; Wang, Z. Coupling coordination between resource and environmental carrying capacity and social development quality and its influence mechanism. *Ecol. Indic.* **2025**, *179*, 114151. [\[CrossRef\]](#)
9. Marans, R.W. Quality of urban life & environmental sustainability studies: Future linkage opportunities. *Habitat Int.* **2015**, *45*, 47–52. [\[CrossRef\]](#)
10. Xu, Y.; Chen, C.; Deng, W.; Dai, L.; Yang, T. Spatial eco-socio-economic trade-offs inform differentiated management strategies in mega-urban agglomerations. *npj Urban Sustain.* **2025**, *5*, 43. [\[CrossRef\]](#)
11. Zhang, C.; Zhao, L.; Song, X.; Zhang, Q.; Zhang, X. Spatial-temporal coupling characteristics and interaction effects of economic resilience and people's livelihoods and well-being: An analysis of 78 cities in the Yellow River Basin. *Sustain. Cities Soc.* **2024**, *112*, 105638. [\[CrossRef\]](#)
12. Ma, M.; Tang, J. Nonlinear impact and spatial effect of tourism urbanization on human settlement environment: Evidence from the Yellow River Basin, China. *J. Clean. Prod.* **2023**, *428*, 139432. [\[CrossRef\]](#)
13. Han, S.; Li, C.; Li, M.; Lenzen, M.; Chen, X.; Zhang, Y.; Li, M.; Yin, T.; Li, Y.; Li, J.; et al. Prospects for global sustainable development through integrating the environmental impacts of economic activities. *Nat. Commun.* **2024**, *15*, 8424. [\[CrossRef\]](#) [\[PubMed\]](#)
14. Wu, F.; Liu, Y.; Zeng, Y.; Yan, H.; Zhang, Y.; Li, L. Evaluation of the Human Settlements Environment of Public Housing Community: A Case Study of Guangzhou. *Sustainability* **2020**, *12*, 7361. [\[CrossRef\]](#)
15. Badland, H.; Whitzman, C.; Lowe, M.; Davern, M.; Aye, L.; Butterworth, I.; Hes, D.; Giles-Corti, B. Urban liveability: Emerging lessons from Australia for exploring the potential for indicators to measure the social determinants of health. *Soc. Sci. Med.* **2014**, *111*, 64–73. [\[CrossRef\]](#) [\[PubMed\]](#)
16. Yang, X.; Ma, H. Natural Environment Suitability of China and Its Relationship with Population Distributions. *Int. J. Environ. Res. Public Health* **2009**, *6*, 3025–3039. [\[CrossRef\]](#) [\[PubMed\]](#)
17. Wu, L. Exploration of the science of human settlements. *Planners* **2001**, *17*, 5–8. (In Chinese)
18. Wu, L. A brief review and prospect of the science of human settlements. *J. Urban Reg. Plan* **2016**, *8*, 1–9. (In Chinese) [\[CrossRef\]](#)
19. Liu, H.; Li, X.; Guan, Y.; Li, S.; Sun, H. Comprehensive Evaluation and Analysis of Human Settlements' Suitability in the Yangtze River Delta Based on Multi-Source Data. *Int. J. Environ. Res. Public Health* **2023**, *20*, 1354. [\[CrossRef\]](#) [\[PubMed\]](#)
20. Jun, S.; Jung, J. Urban Livability Assessment in South Korea: Incorporating Climate Change Vulnerability. *Urban Sci.* **2024**, *8*, 181. [\[CrossRef\]](#)
21. Zhang, H.; Liu, J.; Guo, Q. Evaluation of rural human settlements in China based on the combined model of DPSIR and PLS-SEM. *Environ. Impact Assess.* **2024**, *108*, 107617. [\[CrossRef\]](#)
22. Long, Y.; Wu, Y.; Huang, L.; Aleksejeva, J.; Iossifova, D.; Dong, N.; Gasparatos, A. Assessing urban livability in Shanghai through an open source data-driven approach. *npj Urban Sustain.* **2024**, *4*, 7. [\[CrossRef\]](#)
23. Li, Z.; Zhao, Z.; Zhang, T. Livability evaluation of urban environment based on Google Earth Engine and multi-source data: A case study of Kunming, China. *Ecol. Indic.* **2024**, *169*, 112968. [\[CrossRef\]](#)
24. Najafi, E.; Hosseinali, F.; Najafi, M.M.; Sharifi, A. A GIS-based Evaluation of Urban Livability using Factor Analysis and a Combination of Environmental and Socio-economic Indicators. *J. Geovisualization Spat. Anal.* **2024**, *8*, 27. [\[CrossRef\]](#)
25. Chen, Q.; Yang, Y.; Xu, Z.; Huang, S. Construction and application of a regional human settlement environment index based on remote sensing. *Environ. Monit. Manag. Technol.* **2024**, *36*, 19–24+31. (In Chinese) [\[CrossRef\]](#)
26. Giles-Corti, B.; Vernez-Moudon, A.; Reis, R.; Turrell, G.; Dannenberg, A.L.; Badland, H.; Foster, S.; Lowe, M.; Sallis, J.F.; Stevenson, M.; et al. City planning and population health: A global challenge. *Lancet* **2016**, *388*, 2912–2924. [\[CrossRef\]](#) [\[PubMed\]](#)
27. Lowe, M.; Adlakha, D.; Sallis, J.F.; Salvo, D.; Cerin, E.; Moudon, A.V.; Higgs, C.; Hinckson, E.; Arundel, J.; Boeing, G.; et al. City planning policies to support health and sustainability: An international comparison of policy indicators for 25 cities. *Lancet Glob. Health* **2022**, *10*, e882–e894. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Yan, Y.; Zhang, H.; Zhang, M. Study on the Impact of Digital Financial Inclusion on Low-Carbon Agricultural Development in Guizhou Province—Empirical analysis based on two-way fixed effects model and mediated effects model. *Procedia Comput. Sci.* **2024**, *242*, 428–435. [\[CrossRef\]](#)
29. Kim, N.; Jeong, W.C.; Kim, H.; Ha, R.; Jung-Choi, K. Adverse Impact of Nonstandard Working Hours on Mental Health: An Analysis Using Two-way Fixed Effects Model. *Saf. Health Work* **2026**, *17*, 262–269. [\[CrossRef\]](#) [\[PubMed\]](#)
30. Koga, K.; Kayo, C.; Quevedo, J.M.D.; Kohsaka, R. What drives mangrove forest gains? Evidence from six Southeast Asian countries using fixed effects panel data models. *For. Ecol. Manag.* **2026**, *601*, 123330. [\[CrossRef\]](#)
31. Li, T.; Liu, Y.; Zheng, Z.; Li, S.; Zheng, X.; Wei, G.; He, B. The mitigating effects of urban resilience on surface urban heat islands: Nonlinear responses, threshold effects, and spatial heterogeneity. *Sustain. Cities Soc.* **2025**, *131*, 106722. [\[CrossRef\]](#)
32. Wang, A.; Liu, D.; Li, Z.; Liu, S.; Nie, Y.; Zhang, Q. Spatiotemporal decoupling of land surface temperature driving mechanisms using ensemble learning. *Sustain. Cities Soc.* **2025**, *133*, 106868. [\[CrossRef\]](#)

33. Wang, Z.; Zhou, R.; Rui, J.; Yu, Y. Revealing the impact of urban spatial morphology on land surface temperature in plain and plateau cities using explainable machine learning. *Sustain. Cities Soc.* **2025**, *118*, 106046. [[CrossRef](#)]
34. Lundberg, S.M.; Lee, S. A Unified Approach to Interpreting Model Predictions. In *Advances in Neural Information Processing Systems 30 (NIPS 2017)*; NeurIPS Proceedings: San Diego, CA, USA, 2017.
35. Gao, S.; Ge, X.; Li, H.; Zhou, H. Analysis of urban vitality and its driving factors in Zhengzhou's main urban area based on multi-source data and XGBoost. *Ecol. Indic.* **2025**, *179*, 114187. [[CrossRef](#)]
36. Li, Y.; He, Y.; Yang, F.; An, H.; Li, J.; Xie, Y. An XGBoost-SHAP analysis of the driving factors of carbon emissions in China's first-tier cities. *Sci. Rep.* **2025**, *16*, 1659. [[CrossRef](#)] [[PubMed](#)]
37. Liu, Q.; Wang, J.; Bai, B. Unveiling nonlinear effects of built environment attributes on urban heat resilience using interpretable machine learning. *Urban Clim.* **2024**, *56*, 102046. [[CrossRef](#)]
38. Liu, Q.; Hang, T.; Wu, Y. Unveiling differential impacts of multidimensional urban morphology on heat island effect across local climate zones: Interpretable CatBoost-SHAP machine learning model. *Build. Environ.* **2025**, *270*, 112574. [[CrossRef](#)]
39. Jiang, P.; Yu, Z.; Lu, S.; Cong, L. Interaction effects and threshold analysis of enterprise digital service innovation on environmental performance: Evidence from interpretable machine learning models. *J. Clean. Prod.* **2025**, *520*, 146113. [[CrossRef](#)]
40. Xu, Y.; Li, C. Investigating the heterogeneity of driving mechanisms and multi-dimensional policy pathways in ecosystem service supply-demand relationships: A case study of the Shandong Peninsula urban agglomeration. *J. Clean. Prod.* **2025**, *512*, 145523. [[CrossRef](#)]
41. Shi, F.; Liao, X.; Shen, L.; Meng, C.; Lai, Y. Exploring the spatiotemporal impacts of urban form on CO₂ emissions: Evidence and implications from 256 Chinese cities. *Environ. Impact Assess.* **2022**, *96*, 106850. [[CrossRef](#)]
42. Wang, N.; Qu, Z.; Li, J.; Zhang, Y.; Wang, H.; Xi, H.; Gu, Z. Spatial-temporal patterns and influencing factors of carbon emissions in different regions of China. *Environ. Res.* **2025**, *276*, 121447. [[CrossRef](#)] [[PubMed](#)]
43. Hou, H.; Guo, Q.; Guo, J.; Lian, G.; Zhang, D.; Zhang, Y. The temporal effect of urban landscape pattern on the spatiotemporal heterogeneity of water-related ecosystem services: Evidence from Suzhou, China (2004–2022). *Ecol. Indic.* **2026**, *182*, 114589. [[CrossRef](#)]
44. Kelejian, H.H.; Prucha, I.R. Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *J. Econom.* **2010**, *157*, 53–67. [[CrossRef](#)] [[PubMed](#)]
45. Brunt, D. Climate and Human Comfort. *Nature* **1945**, *155*, 559–564. [[CrossRef](#)]
46. Peng, J.; Wang, Q.; Yang, Z.; Dong, J.; Yu, X.; Corcoran, J. Anthropogenic climate change drives rising global heat stress and its spatial inequality. *Nat. Commun.* **2026**, *17*, 2310. [[CrossRef](#)] [[PubMed](#)]
47. Wu, F.; Yang, X.; Shen, Z. Regional and seasonal variations of outdoor thermal comfort in China from 1966 to 2016. *Sci. Total Environ.* **2019**, *665*, 1003–1016. [[CrossRef](#)] [[PubMed](#)]
48. Di Napoli, C.; Barnard, C.; Prudhomme, C.; Cloke, H.L.; Pappenberger, F. ERA5-HEAT: A global gridded historical dataset of human thermal comfort indices from climate reanalysis. *Geosci. Data J.* **2021**, *8*, 2–10.
49. Guo, Y.; Chen, P.; Zhu, Y.; Zhang, H. Study on comprehensive evaluation of human settlements quality in Qinghai Province, China. *Ecol. Indic.* **2023**, *154*, 110520. [[CrossRef](#)]
50. Yang, Q.; Yang, X.; Gao, Y. Temporal evolution of vulnerability in the rural human settlement environment system in the semi-arid region of the Loess Plateau since 1980: A case study of Jiaxian County, Shaanxi Province. *Prog. Geogr.* **2019**, *38*, 756–771. (In Chinese)
51. Ge, D.; Zheng, Y.; Zhang, S.; Fu, J.; Su, F. Spatio-Temporal Pattern and Influence Mechanism of Rural Human Settlements System Resilience: Case from China. *Sustainability* **2022**, *14*, 14533. [[CrossRef](#)]
52. Tang, L.; Huang, Y.; Jiang, Y.; Feng, D. The Spatial Association of Rural Human Settlement System Resilience with Land Use in Hunan Province, China, 2000–2020. *Land* **2023**, *12*, 1524. [[CrossRef](#)]
53. Kong, F. Multi-temporal-scale evaluation and regional differences of climatic comfort in China's human settlement environment. *J. Arid Land Resour. Environ.* **2020**, *34*, 102–111. (In Chinese)
54. Jing, X.; Tao, S.; Hu, H.; Sun, M.; Wang, M. Spatio-temporal evaluation of ecological security of cultivated land in China based on DPSIR-entropy weight TOPSIS model and analysis of obstacle factors. *Ecol. Indic.* **2024**, *166*, 112579. [[CrossRef](#)]
55. Chen, Y.; Cai, S.; Zhang, D.; Wang, L.; Sun, Y. An interpretable machine learning-assisted urban resilience evaluation and determinants identification: A case study of the Yangtze River Economic Belt, China. *Sustain. Cities Soc.* **2025**, *134*, 106930. [[CrossRef](#)]
56. Lesinger, K.; Tian, D. Skillful subseasonal soil moisture drought forecasts with deep learning-dynamic models. *Nat. Commun.* **2025**, *16*, 7461. [[CrossRef](#)] [[PubMed](#)]
57. Li, L.; Sun, S.; Zhong, L.; Han, J.; Qian, X. Novel spatiotemporal nonlinear regression approach for unveiling the impact of urban spatial morphology on carbon emissions. *Sustain. Cities Soc.* **2025**, *125*, 106381. [[CrossRef](#)]
58. Zhong, Z.; Chen, H.W.; Dai, A.; Zhou, T.; He, B.; Su, B. Sub-diurnal asymmetric warming has amplified atmospheric dryness since the 1980s. *Nat. Commun.* **2025**, *16*, 8247. [[CrossRef](#)] [[PubMed](#)]

59. Chen, H.; Liu, L.; Wang, L.; Zhang, X.; Du, Y.; Liu, J. Key indicators of high-quality urbanization affecting eco-environmental quality in emerging urban agglomerations: Accounting for the importance variation and spatiotemporal heterogeneity. *J. Clean. Prod.* **2022**, *376*, 134087. [[CrossRef](#)]
60. Xia, J.; Zhang, G.; Ma, S.; Pan, Y. Spatial Heterogeneity of Driving Factors in Multi-Vegetation Indices RSEI Based on the XGBoost-SHAP Model: A Case Study of the Jinsha River Basin, Yunnan. *Land* **2025**, *14*, 925. [[CrossRef](#)]
61. Liang, T.; Zhan, J.; Su, Y.; Deng, W. Examining the nonlinear effects of multidimensional land use efficiency on ecological resilience using the XGBoost-SHAP and GTWR model in Guangdong province. *Front. Environ. Sci.* **2025**, *13*, 1697381. [[CrossRef](#)]
62. Yang, C.; Chen, M.; Yuan, Q. The application of XGBoost and SHAP to examining the factors in freight truck-related crashes: An exploratory analysis. *Accid. Anal. Prev.* **2021**, *158*, 106153. [[CrossRef](#)] [[PubMed](#)]
63. Zhang, J.; Ma, X.; Zhang, J.; Sun, D.; Zhou, X.; Mi, C.; Wen, H. Insights into geospatial heterogeneity of landslide susceptibility based on the SHAP-XGBoost model. *J. Environ. Manag.* **2023**, *332*, 117357. [[CrossRef](#)]
64. Yuan, Y.; Guo, W.; Tang, S.; Zhang, J. Effects of patterns of urban green-blue landscape on carbon sequestration using XGBoost-SHAP model. *J. Clean. Prod.* **2024**, *476*, 143640. [[CrossRef](#)]
65. Zhang, L.; Fang, C.; Zhao, R.; Zhu, C.; Guan, J. Spatial-temporal evolution and driving force analysis of eco-quality in urban agglomerations in China. *Sci. Total Environ.* **2023**, *866*, 161465. [[CrossRef](#)] [[PubMed](#)]
66. Feng, D.; Meng, X.; Zhang, H.; Zhou, M.; Chai, Y.; Liu, M. The progress and spatiotemporal heterogeneity evaluation of China's ecological civilization. *Ecol. Indic.* **2026**, *185*, 114746. [[CrossRef](#)]
67. Shi, Y.; Li, C.; Shi, Y. Revealing spatiotemporal dynamics and driving mechanisms of ecological vulnerability under climate and human pressures using multi-source remote sensing in the dryland of China. *J. Arid Environ.* **2026**, *232*, 105526. [[CrossRef](#)]
68. Li, Q.; Zheng, R.; Ji, A.; Ma, H. Fixed effects spatial panel interval-valued autoregressive models and applications. *Spat. Stat.* **2025**, *65*, 100875. [[CrossRef](#)]
69. Hu, Y.; Guan, K.; Wang, S. Challenging the Environmental Kuznets Curve in China: Evidence from a dynamic panel threshold model with cross-sectional dependence. *J. Environ. Manag.* **2026**, *398*, 128432. [[CrossRef](#)]
70. De Groot, H.L.F.; Withagen, C.A.; Minliang, Z. Dynamics of China's regional development and pollution: An investigation into the Environmental Kuznets Curve. *Environ. Dev. Econ.* **2004**, *9*, 507–537. [[CrossRef](#)]
71. Ahmad, M.; Jabeen, G.; Wu, Y. Heterogeneity of pollution haven/halo hypothesis and Environmental Kuznets Curve hypothesis across development levels of Chinese provinces. *J. Clean. Prod.* **2021**, *285*, 124898. [[CrossRef](#)]
72. Cui, X.; Deng, X.; Wang, Y. Evolution characteristics and driving factors of rural regional functions in the farming-pastoral ecotone of northern China. *J. Geogr. Sci.* **2023**, *33*, 1989–2010. [[CrossRef](#)]
73. Li, W. Development patterns of central cities: Livability and economies of scale based on panel data from 26 provincial capital cities. *Urban Insight* **2010**, *6*, 142–149. (In Chinese)
74. He, L.; Zhang, X.; Yan, Y. Heterogeneity of the Environmental Kuznets Curve across Chinese cities: How to dance with 'shackles'? *Ecol. Indic.* **2021**, *130*, 108128. [[CrossRef](#)]
75. Guo, Q.; Ma, X. How Does the Digital Economy Affect Sustainable Urban Development? Empirical Evidence from Chinese Cities. *Sustainability* **2023**, *15*, 4098. [[CrossRef](#)]
76. Bai, X.; Shen, Q. Exploring impact of digital economy on sustainable urban development by panel data of 30 underdeveloped cities in China. *Sci. Rep.* **2025**, *15*, 13325. [[CrossRef](#)] [[PubMed](#)]
77. Duanmu, X.; Yu, J.; Yuan, X.; Zhang, X. How Does Digital Infrastructure Mitigate Urban–Rural Disparities? *Sustainability* **2025**, *17*, 1561. [[CrossRef](#)]
78. Cai, X.; Li, M. The impact of digital inclusive finance on rural ecological livability. *Chongqing Soc. Sci.* **2023**, *6*, 47–62. (In Chinese) [[CrossRef](#)]
79. Huang, X.; Lan, F. The impact and moderating mechanisms of digital inclusive finance on public services in Chinese counties. *Sci. Rep.* **2025**, *15*, 25771. [[CrossRef](#)] [[PubMed](#)]
80. Duan, H.; Song, G.; Qu, S.; Dong, X.; Xu, M. Post-consumer packaging waste from express delivery in China. *Resour. Conserv. Recycl.* **2019**, *144*, 137–143. [[CrossRef](#)]
81. GILES, J.; PARK, A.; ZHANG, J. What is China's true unemployment rate? *China Econ. Rev.* **2005**, *16*, 149–170. [[CrossRef](#)]
82. Wang, X.; Sun, W. Discrepancy between Registered and Actual Unemployment Rates in China: An Investigation in Provincial Capital Cities. *China World Econ.* **2014**, *22*, 40–59. [[CrossRef](#)]
83. Wu, N.; Zhou, Y.; Yin, S.; Gong, H.; Zhang, C. Revealing the nonlinear impact of environmental regulation on ecological resilience using the XGBoost-SHAP model: Evidence from the Yangtze River Delta region, China. *J. Clean. Prod.* **2025**, *514*, 145700. [[CrossRef](#)]
84. Dang, H.H.; Hallegatte, S.; Nguyen, M.C.; Trinh, T. Impacts of global warming on subnational poverty and inequality. *Nat. Clim. Change* **2026**, *16*, 207–213.
85. Fu, J.; Fu, H.; Zhu, C.; Sun, Y.; Cao, H. Assessing the health risk impacts of urban green spaces on air pollution—Evidence from 31 China's provinces. *Ecol. Indic.* **2024**, *159*, 111725. [[CrossRef](#)]

86. Fang, X.; Li, J.; Ma, Q. Integrating green infrastructure, ecosystem services and nature-based solutions for urban sustainability: A comprehensive literature review. *Sustain. Cities Soc.* **2023**, *98*, 104843. [[CrossRef](#)]
87. Babuna, P.; Han, C.; Li, M.; Gylbag, A.; Dehui, B.; Awudi, D.A.; Tulcan, R.X.S.; Yang, S.; Yang, X. The effect of human settlement temperature and humidity on the growth rules of infected and recovered cases of COVID-19. *Environ. Res.* **2021**, *197*, 111106. [[CrossRef](#)] [[PubMed](#)]

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