

Article

Dynamic Evolution and Driving Mechanisms of Vulnerability in Coupled Urban Systems in Northeast China, 2000–2020

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Abstract

This study examined urban vulnerability in the three northeastern provinces of China—Heilongjiang, Jilin, and Liaoning—from 2000 to 2020, addressing challenges such as resource shortages, harsh environments, and inadequate education and healthcare. Using the weighted summation method and geographic detector model, this study analyzes the temporal and spatial evolution of urban vulnerability in 34 prefecture-level cities. The results show that overall vulnerability initially increased and then decreased, while economic vulnerability continued to rise. Spatially, vulnerability shifted from weak agglomeration to dispersion by 2020. Key drivers include new fixed assets, local fiscal revenue, and altitude. The findings highlight the need for tailored, coordinated development strategies to reduce urban vulnerability and promote sustainable regional growth, emphasizing the importance of balancing resources, environment, economy, society, and nature.

Keywords: vulnerability in coupled system; temporal and spatial evolution; geographic detector



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1. Introduction

Under rapid urbanization and ecological pressures, China's urban vulnerability research must address multi-system coupling effects, as unidimensional studies focusing solely on economic or environmental factors fail to capture integrated risks. While localized vulnerability profiles can be identified through isolated subsystem analyses of resources, environment, or society, critical gaps persist in understanding coupled vulnerabilities arising from nonlinear interactions. Effective management of such integrated vulnerabilities is pivotal for urban resilience, directly linked to cities' capacity to maintain core functions amid perturbations and avoid systemic collapse [1]. Previous studies have highlighted two limitations: fragmented analyses of subsystems and insufficient dynamic predictions of multi-system interactions. This study aims to bridge these gaps by constructing a coupled-system vulnerability framework, advancing beyond single-subsystem cognitive constraints [2].

The vulnerability concept, first proposed by Margat (1968) for groundwater risk assessment [3], has evolved into a multidisciplinary field [4]. Early studies focused on natural disasters, such as applications of the DPSIR model for wetland ecosystems [5] or the Coastal Vulnerability Index for coastal risks [6]. Later, research expanded to socioeconomic dimensions, including analyses linking mortality rates to urban vulnerability in developing regions [7]. This shift reflects a broader trend from single-factor to multi-dimensional frameworks, exemplified by studies incorporating social, environmental, institutional,

economic, and health dimensions to assess hazard vulnerability [8]. Urban vulnerability research has been further diversified through machine learning applications for flood prediction [9], vulnerability mapping for coastal storm preparedness [10], and integrated land–temperature analyses for megacity risks [11]. However, the dynamic integration of natural, social, and economic factors into operational assessment frameworks remains a challenge, particularly for predictive scenario analysis [12].

Urban vulnerability research in China began later than in some other countries, gaining momentum after the 1990s as scholars adapted the general vulnerability framework to address city-specific complexities, leading to the specialized concept of urban vulnerability [13]. While this field developed rapidly in China, studies have generally adopted systematic research perspectives that classify urban vulnerability into two complementary dimensions [14]: (1) external vulnerability, which examines cities' exposure to exogenous disturbances, such as climate variability impacts and natural hazard exposure and (2) internal vulnerability, which focuses on endogenous systemic weaknesses within urban subsystems. Internal vulnerability encompasses physical subsystems (e.g., natural disaster response capacity [15] and ecological environment fragility [16]) and socio-economic subsystems (e.g., economic system instability [17], social system resilience [18], human–environment interaction risks [19], and social–ecological system dynamics [20]), etc. This dual perspective recognizes that human social and economic activities, as external disturbance factors, interact with cities' inherent structural weaknesses [21]. Therefore, single-model vulnerability approaches cannot adequately address urban vulnerability complexities, creating an urgent need for dynamic simulation and risk prediction under multi-system coupled frameworks.

Early international scholars pioneered urban vulnerability research, achieving significant progress in conceptual definitions, assessment methodologies, and model development. Their work has provided valuable theoretical frameworks for domestic studies. Building on this foundation, domestic research has refined indicator systems through comprehensive urban evaluations [2] and spatial–temporal diagnostics of vulnerability patterns [3]. Yet limitations persist, including subjective weight biases and model applicability issues. To address these, this study proposes: (1) a REESN (resources–environment–economy–society–nature) coupling model with entropy weight–CRITIC integration to reduce subjectivity; (2) SHAP-XGBoost for nonlinear driver identification; and (3) coupling coordination thresholds to diagnose spatial heterogeneity in Northeast China (2000–2022).

The remainder of this paper is structured as follows: Section 2 details the materials and methodology, including the construction of the REESN (resources–environment–economy–society–nature) coupling evaluation framework and the machine learning-driven driver identification approach (SHAP-XGBoost). Section 3 presents the empirical results of vulnerability dynamics in Jilin, Liaoning, and Heilongjiang provinces from 2000 to 2022, using spatial heterogeneity analysis. Section 4 discusses three critical findings: (a) the threshold effects of institutional entropy on coupled system vulnerability, (b) nonlinear drivers revealed by explainable AI, and (c) policy implications for rust-belt revitalization. Finally, Section 5 summarizes theoretical contributions and practical insights for underdeveloped industrial regions globally.

2. General Situation, Research Methods, and Data Processing of the Study Area

2.1. Overview of the Study Area

The three northeastern provinces—Heilongjiang, Jilin, and Liaoning—span 118° E–135° E and 38° N–53° N in Northeast China, share land borders with North Korea and Russia, and are geographically close to South Korea across the Yellow Sea (Figure 1). To

ensure analytical homogeneity in vulnerability mechanisms, we excluded two special regions: (1) the Greater Khingan Mountains due to its distinct natural subsystem drivers, and (2) the Yanbian Korean Autonomous Prefecture, where cross-border demographic flows introduce confounding variables. During 2010–2020, according to data from the National Bureau of Statistics in 2021, this region experienced a net population loss of 11.01 million, driven primarily by: (1) deindustrialization-induced manufacturing collapse, eliminating 23% of industrial employment; (2) selective outmigration of 15–34-year-olds, accounting for 58% of total decline; and (3) capital flight toward eastern service economies. These dynamics triggered cascading vulnerabilities: fiscal capacity contracted by 34% per capita versus the national average, age dependency ratios exceeded critical thresholds ($\geq 25\%$), and spatial mismatches generated over 12,000 ha of urban vacancy. Consequently, 72% of cities transitioned into contraction hotspots, exhibiting systemic fragility through REESN subsystem disintegration—particularly resource depletion, societal aging, and economic structural rigidity.

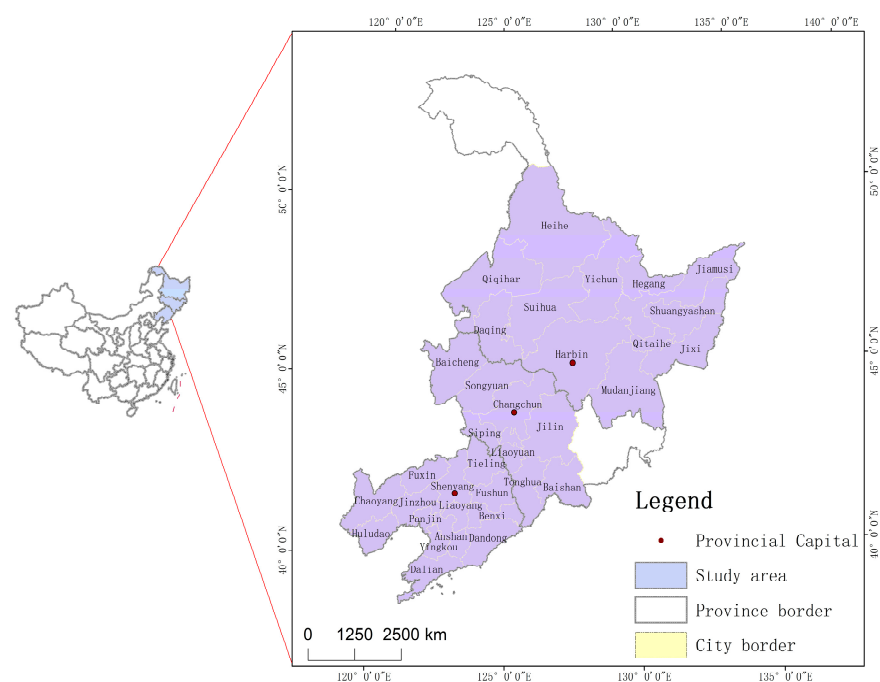


Figure 1. Administrative division map of the study area.

2.2. Research Methodology

2.2.1. Entropy Method

In the evaluation index system, there are two ways to determine the weight: the subjective assignment method and the objective assignment method. The objective weighting method, on the other hand, determines weights based on the statistical characteristics or inherent patterns of the evaluation indicator data itself, thereby avoiding direct human intervention and producing results that are more data-driven. The subjective method adopts the method of expert evaluation, and the evaluation results are affected by the subjective judgment of experts. In order to ensure the fairness of the calculation results, this study adopts the entropy method within the objective weighting method to determine the weights of each indicator. The core principle of the entropy method is to allocate weights based on the degree of difference (dispersion) among the data of each indicator: the greater the data difference of an indicator (i.e., the greater the information it provides), the higher its weight in the evaluation system [22]. Therefore, the entropy method is used to calculate the weight values of four subsystems of resources and environment, economy, society, and

nature, and the weight values of each index in each subsystem. These subsystems were selected for their theoretical grounding in established sustainability frameworks [23] and their direct relevance to the following Northeast China's regional challenges: (1) resources–environment captures resource depletion risks (e.g., declining coal reserves in Heilongjiang) and industrial pollution legacies (e.g., Songhua River contamination); (2) economy reflects structural fragility in traditional industries (e.g., SOE-dominated manufacturing in Jilin); (3) society addresses demographic stresses from aging populations and outmigration; and (4) nature accounts for ecological fragility (e.g., black soil degradation in Heilongjiang's farmlands). This configuration recognizes critical interdependencies, where resource constraints amplify economic vulnerability, triggering social displacement and environmental degradation. Specifically, the evaluation system constructed in this paper includes four subsystems: 'resources and environment,' 'economy,' 'society,' and 'nature' (this framework draws on the urban resilience evaluation framework proposed in and is adjusted to suit the characteristics of this study [23], aiming to comprehensively cover the key dimensions of urban comprehensive resilience). We first use the entropy method to calculate the relative weights of these four subsystems within the entire system. Then, for each specific indicator within each subsystem, we apply the entropy method to calculate its local weight within that subsystem. Finally, the global weights of each indicator in the overall evaluation system are obtained by multiplying the weight of its subsystem by its local weight. The calculation formula is as follows:

Proportion of indicator j in year i : (Y_{ij})

$$Y_{ij} = \frac{X_{ij}'}{\sum_{i=1}^m X_{ij}'} \quad (1)$$

where X_{ij}' is the index data after data standardization.

Entropy value of item j : (e_j)

$$e_j = -k \sum_{i=1}^m Y_{ij} \ln(Y_{ij}), \text{ Let } k = \frac{1}{\ln t} \quad (2)$$

where t to evaluate the number of cities, $\ln 0 \leq e_j \leq 1$ is the natural logarithm.

Information redundancy calculation:

$$g_j = 1 - e_j \quad (3)$$

Weight of indicator j : (W_j)

$$W_j = \frac{g_j}{\sum_{j=1}^n g_j} \quad (4)$$

where n is the number of research objects.

2.2.2. Weighted Summation Method and Classification Standard of Vulnerability Assessment Grade

Weighted summation econometric model

According to the standardized values and weight values calculated by Formulas (1)–(4), the comprehensive evaluation functions of the four subsystems of resource and environment vulnerability, economic vulnerability, social vulnerability, and natural vulnerability in the coupling system of cities in the three northeastern provinces are established, respectively. The calculation method is as follows:

$$U(A) = \sum_{i=1}^m a_i \alpha_i^n \quad (5)$$

$$U(B) = \sum_{i=1}^n b_i \beta^n n \quad (6)$$

$$U(C) = \sum_{i=1}^p c_i \gamma^n p \quad (7)$$

$$U(D) = \sum_{i=1}^s d_i \lambda^n s \quad (8)$$

Equations (5)–(8) are the resource and environment evaluation index, economic evaluation index, social evaluation index, and natural evaluation index, respectively. They are the weight coefficients of each subsystem index and are the standardized coordinates of each subsystem index after translation, $U(A)$, $U(B)$, $U(C)$, and $U(D)$, a_i , b_i , c_i and d_i , $\alpha^n m$, $\beta^n n$, $\gamma^n p$ and $\lambda^n s$.

The comprehensive vulnerability index of the urban coupling system in the three northeastern provinces is calculated by the weighted sum of the vulnerability in each subsystem, and the calculation method is as follows:

$$UVI = \sum_{j=1}^m U_k k = A, B, C, D \quad (9)$$

UVI is the comprehensive evaluation index of the vulnerability in the coupled system.

Classification standard of evaluation grade.

The vulnerability index of urban coupling systems ranges between [0 and 1], so this paper divides the vulnerability index of urban coupling systems in the three northeastern provinces into five categories [23]. The larger the index, the more serious the vulnerability in the urban coupling system, and the higher the vulnerability degree (Table 1).

Table 1. Vulnerability in the urban coupling system in the three northeastern provinces.

Exponential Classification	1	2	3	4	5
Vulnerability index	$0 < \text{index} \leq 0.2$	$0.2 < \text{index} \leq 0.4$	$0.4 < \text{index} \leq 0.6$	$0.6 < \text{index} \leq 0.8$	$0.8 < \text{index} \leq 1$
Degree of vulnerability	Very low vulnerability	Low vulnerability	Medium vulnerability	High vulnerability	Very high vulnerability

2.2.3. Spatial Difference Analysis Method

Exploratory spatial data analysis is a spatial statistical method that includes the spatial position relationship, position, and attribute characteristics among variables. Data exploration analysis provides an important reference value for mathematical modeling [24]. Through the spatial distribution pattern of the observed values, the spatial agglomeration and spatial anomaly are found. Exploratory spatial data analysis is mainly divided into global statistics and local statistics, which reveal the evolution of vulnerability spatial patterns under urban coupling systems from both global and local aspects [25]. While multiple methods exist to quantify global spatial autocorrelation (e.g., Geary's C, Getis-Ord General G), this study employs Moran's I for three primary reasons: first, Moran's I index has strong explanatory power. Moran's I provides an intuitive measure of spatial dependence, where values near +1 indicate strong positive autocorrelation (clustering of similar values), values near −1 denote negative autocorrelation (dispersion of dissimilar values), and 0 suggests randomness. Secondly, the data distribution of Moran's I index is robust. Unlike alternatives requiring normality assumptions, Moran's I performs reliably under varied data distributions common in socioeconomic and environmental vulnerability indicators. Finally, Moran's I index methodology is compatible with other methods. Its compatibility with local indicators of spatial association (LISA) allows seamless integration of global patterns and local anomalies, essential for multi-scale urban system analysis. The value range is [−1, 1], where the larger the absolute value, the stronger the spatial

correlation. When $I > 0$, the spatial correlation is positive; the spatial negative correlation when $I < 0$; and there is no spatial correlation when $I = 0$. Moran's I is calculated as follows:

$$I = \frac{\sum_{i=1}^n \sum_{j=1}^n W_{ij} (X_i - \bar{X}) (X_j - \bar{X})}{S^2 \sum_{i=1}^n \sum_{j=1}^n W_{ij}}, \text{ where } S^2 = \sum_{i=1}^n (X_i - \bar{X})^2, \bar{X} = \frac{1}{n} \sum_{i=1}^n X_i \quad (10)$$

In the formula, n represents the number of prefecture-level cities, X_i and X_j represent the vulnerability index of places, respectively, $\bar{X}$ represents the average value of the vulnerability attribute of place, W_{ij} is the spatial weight matrix, and S^2 is the vulnerability variance.

Local spatial autocorrelation is used to describe local spatial aggregation, which can reflect the spatial correlation between the coupling coordination degree of an independent element and adjacent elements. In this paper, cold and hot spot analysis is used to study the local spatial autocorrelation degree [26]. The cold-hot spot analysis can be used to identify the cold spot area and hot spot area of the vulnerability in the coupling system in the three northeastern provinces, and the spatial distribution law of the vulnerability in the urban coupling system in the three northeastern provinces can also be analyzed. The calculation formula is as follows:

$$I_i = (X_i - \bar{X}) \sum_{j=1}^n W_{ij} (X_j - \bar{X}) \quad (11)$$

and represents the normalized weight matrix of space elements I and J , corresponding to $(X_i - \bar{X}) (X_j - \bar{X})$.

2.2.4. Geodetector Model

The geographic detector is a statistical method to find out the driving force behind spatial differentiation [27,28]. The advantage of geographic detectors is that they can detect both numerical data and qualitative data. Another advantage of geographic detectors is to detect the interaction of two factors on dependent variables. The interaction of two factors not only includes a multiplication relationship but also can be detected as long as there is a relationship. Geographic detectors are mainly composed of risk detection, factor detection, ecological detection, and interactive detection. Factor detection is measured by the q value [27], and the model formula is expressed as follows:

$$q = 1 - \frac{1}{N\sigma^2} \sum_{m=1}^L N_m \sigma_m^2 \quad (12)$$

where q is the spatial heterogeneity of an index, and the value range of q is $[0, 1]$; N is the total number of samples in the study area, σ_m^2 is the variance of indicators; and $m = 1, 2, \dots, L$, m represents the number of classifications or partitions. The q value reflects the degree of spatial differentiation. The greater the q value, the stronger the spatial stratification heterogeneity, and the weaker it is. When the q value is 0, it indicates that there is no relationship between the two factors, and when the q value is 1, it indicates perfect spatial heterogeneity.

2.3. Data Acquisition and Processing

2.3.1. Vulnerability Assessment Indicator Data

This paper mainly uses basic geographic data, meteorological data, land use data, and socioeconomic data. Adopting the framework of multi-source data fusion analysis, the overall workflow is shown in Figure 2, covering four stages: data collection → preprocessing → spatial analysis → model construction.

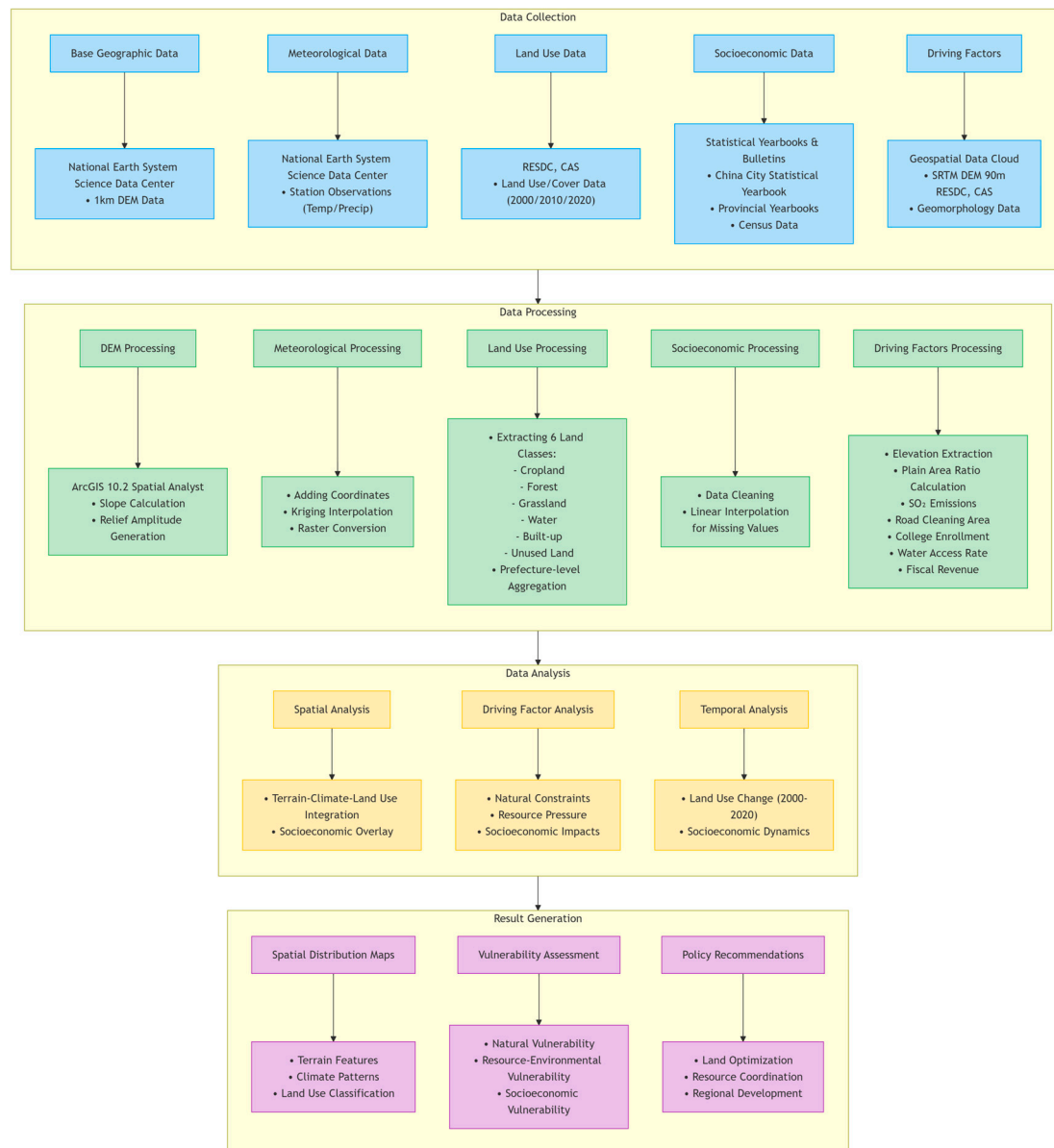


Figure 2. Technical flowchart for urban vulnerability assessment.

(1) Basic geographic data: The DEM data with a spatial resolution of 1 km comes from the National Earth System Science Data [29]. Using the spatial analysis module of ArcGIS 10.2 software, terrain factor indexes of slope and terrain relief are generated from the DEM data.

(2) Meteorological data: This data comes from the National Earth System Science Data [30]. The annual average temperature and annual precipitation data from meteorological stations in three northeastern provinces are collected. Based on the obtained meteorological data, the longitude and latitude coordinates of the stations are added, and the Excel file format is derived. The meteorological data and station data are imported into ArcMap, and the spatial distribution grid data is obtained by the Kriging interpolation method.

(3) Land use data: The land use/cover data in 2000, 2010, and 2020 come from the Data Center of Resources and Environmental Sciences, Chinese Academy of Sciences [31]. Then, from the vector map of land use status in 2000, 2010, and 2020, six first-class types of land, including cultivated land, woodland, grassland, water area, construction land, and unused land, are extracted from each prefecture-level city to prepare for the follow-up study.

(4) Socioeconomic data: This data comes from the China Urban Statistical Yearbook (2001–2021), Statistical Yearbooks of Jilin Province, Liaoning Province, and Heilongjiang Province from 2001 to 2021, and Statistical Bulletin of National Economic and Social Development of Jilin Province, Liaoning Province, and Heilongjiang Province from 2000 to 2020. The population data comes from the 5th, 6th, and 7th national census data.

2.3.2. Driver Factor Data

The driving factor data in this paper include natural data on the altitude and plain area, industrial sulfur dioxide emissions, road cleaning area, other resource and environmental data, and social and economic data, such as the number of students in colleges and universities, water penetration rate, and local general public budget revenue.

(1) Basic geographic data: The altitude data is extracted from elevation data, which comes from SRTMDEMUTM 90 m resolution data products from the geospatial data cloud, the plain area data is extracted from the geomorphic map, and the geomorphic type data comes from spatial distribution data of Chinese geomorphic types in the Resource and Environmental Science Data Center of the Chinese Academy of Sciences.

(2) Socioeconomic data: Statistical yearbooks and statistical bulletins of Jilin Province, Liaoning Province, and Heilongjiang Province from 2000 to 2020, with some missing data, are replaced by the linear interpolation method.

2.3.3. Construction of the Vulnerability Index System for the Urban Coupling System

This study proposes a reconceptualized framework for urban vulnerability assessment that resolves prior ambiguities in subsystem classification through rigorously defined operational boundaries. Urban vulnerability emerges from four interdependent yet distinct domains: (1) resource security vulnerability, characterized by deficits in engineered resource inputs essential for urban operations (e.g., water/energy availability); (2) environmental stress vulnerability, defined by anthropogenic degradation exceeding ecological carrying capacity (e.g., PM_{2.5} emissions and waste assimilation failure); (3) socioeconomic stability vulnerability, encompassing institutional capacities and structural resilience factors (e.g., economic diversification, infrastructure robustness, and social equity); and (4) natural hazard vulnerability, reflecting exposure to exogenous geophysical/climatological threats (e.g., flood susceptibility and seismic risk). This restructuring critically differentiates human-induced stressors (subsystems 1–3) from biophysical threats (subsystem 4), while integrating social and economic dimensions under a unified socioeconomic domain due to empirically observed feedback loops—economic instability exacerbates social vulnerability, which in turn undermines recovery capacity.

The indicator system was systematically realigned to ensure conceptual consistency across 8 first-level factors and 33 s-level indicators (Table 2). Operational definitions govern component assignment: resource security incorporates strictly supply-side metrics (water availability indices, energy reserve ratios); environmental stress comprises pollution-output metrics (ambient pollutant concentrations, waste treatment efficiency); socioeconomic stability integrates structural-capacity metrics (employment diversification indices, healthcare accessibility, infrastructure reliability coefficients); and natural hazard employs exposure-sensitivity metrics (hazard probability indices, climate impact projections). The indicator weights were derived through entropy methods, objectively prioritizing variables while eliminating categorical ambiguities that plagued prior frameworks. This holistic approach establishes a causally coherent assessment model where subsystem boundaries align with discrete vulnerability mechanisms.

Table 2. Frailty index system of the urban coupling system in the three northern provinces.

Target Layer	First-Class Index	Secondary Index	Weight
Vulnerability of resources and environment	Resource vulnerability	X1 Per capita park green area (square meters)	0.0327
		Green coverage rate of X2 built-up area (%)	0.0319
		X3 Power consumption per unit GDP (10,000 yuan/10,000 kWh)	0.0518
		X4 Bioabundance index (ind/m ³)	0.0275
	Environmental vulnerability	X5 Per capita land resources (m ² /10,000 people)	0.0286
		X6 Total carbon emissions (10,000 tons)	0.0471
		X7 Average PM2.5 content in air (μg/m ³)	0.0273
Economic vulnerability	Fragility of economic structure	X8 Proportion of GDP of primary industry to GDP of the city (%)	0.0393
		X9 Proportion of GDP of secondary industry to GDP of the city (%)	0.0224
		X10 Proportion of tertiary industry GDP to municipal GDP (%)	0.0229
		X11 Investment in fixed assets (RMB 10,000)	0.0151
		X12 Total sales of wholesale and retail commodities (RMB 10,000)	0.0140
	Vulnerability of economic efficiency	X13 GDP growth rate (%)	0.0626
		X14 GDP per capita (yuan)	0.0187
	Vulnerability of economic innovation	X15 Fiscal self-sufficiency rate (%)	0.0242
		X16 Proportion of education expenditure to fiscal expenditure (%)	0.0276
		X17 Proportion of science and technology expenditure to fiscal expenditure (%)	0.0168
Social vulnerability	Vulnerability of social life	X18 Population density (people/km ²)	0.0469
		X19 Natural population growth rate (%)	0.0236
		X20 Number of doctors per 10,000 people (people)	0.0238
		X21 Per capita daily domestic water consumption (L)	0.0292
		Book collection of X22 hundred people library (Volume)	0.0172
	Infrastructure vulnerability	Total passenger transport on X23 highway (10,000 people)	0.0188
		X24 Total road freight (10,000 tons)	0.0284
		X25 Computer service and software employees (%)	0.0198
		X26 Per capita road area (square meters)	0.0217
		X27 Number of industrial enterprises above designated Size (Units)	0.0148
Natural vulnerability	Vulnerability of natural environment	X28 Gradient	0.0519
		X29 Topographic relief (km)	0.0523
		X30 Annual average rainfall (mm)	0.0537
		X31 Annual average temperature (°C)	0.0394
		X32 Proportion of water area to total area (%)	0.0211
		X33 Proportion of vegetation area (%)	0.0268

2.3.4. Selection of Driving Factors

The selection of driving factor indicators in this paper is shown in Table 3, in which indicators such as sewage discharge and industrial sulfur dioxide discharge have an impact on resources and environment, indicators such as local general public budget revenue reflect economic development, indicators such as the number of road lighting lamps and the actual public steam (electric) vehicles operating at the end of the year reflect human social life, and altitude has an impact on climate and vegetation growth. The plains in the three northeastern provinces account for a large area, which is conducive to farming and convenient for travel. The dependent variables of this paper are the urban coupling system vulnerability index, resource and environment vulnerability index, economic vulnerability index, social vulnerability index, and natural vulnerability index from 2000 to 2020. The

altitude of the independent variables is expressed by the average value, and the rest of the data are of a numerical type. The geographic detector data based on the R language in this paper should be of a numerical type.

Table 3. Driver factor indicators.

Type	Driving Factor	Indicators
Vulnerability of resources and environment	X1	Domestic garbage removal amount
	X2	Total water supply
	X3	Industrial sulfur dioxide emissions
	X4	Road cleaning area
	X5	Sewage discharge
Economic vulnerability	X6	New fixed assets
	X7	Total retail sales of social consumer goods
	X8	Current assets of industrial enterprises above the designated size
	X9	Local general public budget revenue
Social vulnerability	X10	Water penetration rate
	X11	Density of drainage pipeline in built-up area
	X12	Number of road lighting lamps
	X13	At the end of the year, there were public buses (electric vehicles) operating vehicles
Natural vulnerability	X14	Number of students in institutions of higher learning
	X15	Proportion of plain area
	X16	Altitude

3. Spatial and Temporal Pattern Analysis of Vulnerability in Urban Coupling System in Three Northeastern Provinces

3.1. The Temporal Evolution Characteristics of the Vulnerability in the Urban Coupling System

3.1.1. Analysis of Temporal Evolution Characteristics of Resource and Environmental Vulnerability Subsystem

The vulnerability indices of four subsystems of the coupling system of cities in north-east China in 2000, 2010, and 2020 are calculated by Formulas (5)–(8), including resource and environment vulnerability, economic vulnerability, social vulnerability, and natural vulnerability. According to Figure 3, in 2000, the resource and environmental vulnerability indexes of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0632 to 0.1959, with the maximum value being Shenyang, followed by Liaoyuan (the provincial affiliation of prefecture-level cities is shown in Figure 1, and the same applies below), with a value of 0.1938. Because the average value of the total carbon emissions and PM2.5 content in the air in Liaoyuan and Shenyang is too high, industrial development, carbon dioxide content in the air, and urban air quality will pollute the urban environment, making the urban vulnerability index high. The minimum vulnerability value is Dandong City, followed by Benxi City, with a value of 0.0635, which is mainly because Dandong City has more per capita land resources and less electricity consumption per unit GDP. Benxi has a large amount of land resources per capita and a high green coverage rate in built-up areas. In 2010, the vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0728 to 0.1871, and the maximum value was Siping City, followed by Changchun City, with a value of 0.1790. Because of the small total resources, the small number of parks, and the low biological abundance index in Siping City, the air pollution and biodiversity in Changchun City were serious, which led to the high vulnerability in the city. The smallest vulnerability value is Heihe City, followed by Tieling City, with a value of 0.0730. Heihe City has more per capita

land resources and less power consumption per unit GDP, while Tieling City has less total carbon emissions and more per capita land resources, which makes the vulnerability value lower. In 2020, the vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0505 to 0.1995, with the maximum value being Siping City, followed by Harbin, with a value of 0.1860. The main reason is that the air pollution in Siping City and Harbin City is serious, and the green coverage rate in Harbin City is low. The smallest vulnerability value is Heihe City, followed by Fushun City, with a value of 0.0551. Benxi City has a small population and abundant forest resources and biological resources, which makes its resources fully distributed. Fushun has low total carbon emissions and a low vulnerability index.

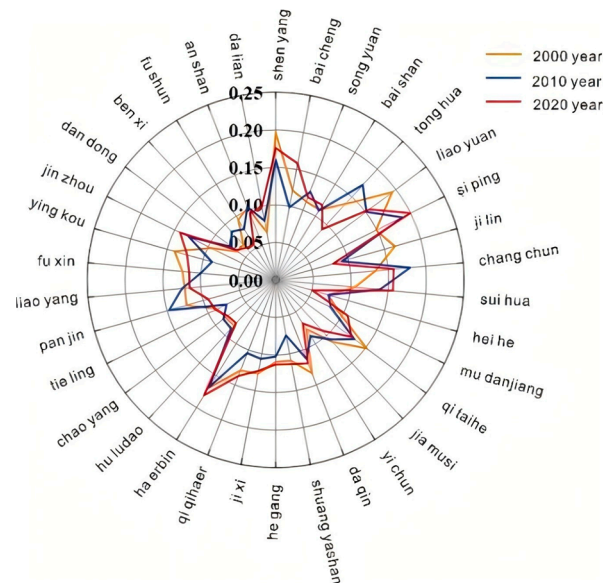


Figure 3. Time change diagram of the resource and environmental vulnerability in the prefecture-level cities in the urban coupling system in the three northeastern provinces.

3.1.2. Analysis of Time Evolution Characteristics of Economic Vulnerability Subsystem

According to Figure 4, in 2000, the economic vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0921 to 0.1710, with the maximum value being Yichun, followed by Chaoyang, with a value of 0.1665. Due to the small scale of investment in fixed assets and the overall single economic structure in Yichun City, the vulnerability is high. Chaoyang City's per capita GDP and financial self-sufficiency rate are lower. The minimum value of vulnerability is Changchun City, followed by Jilin City, with a value of 0.1087. Changchun City has a great improvement in economic investment and economic system reform compared with other cities. Jilin City has a large proportion of tertiary industry GDP and a high growth rate of GDP. In 2010, the economic vulnerability index of each prefecture-level city in the coupling system of cities in the three northeastern provinces ranged from 0.0723 to 0.1835, and the maximum value was Yichun, followed by Heihe, with a value of 0.1735. The economic system reform in Yichun was not obvious during the decade from 2000 to 2010, and the economic efficiency in Heihe was low, resulting in less investment in scientific research and education, and a high vulnerability index. The smallest vulnerability value is Shenyang, followed by Changchun, with a value of 0.0771. Shenyang and Changchun strive to expand investment, actively promote the upgrading of industrial structure, and improve independent innovation ability, such as scientific research. In 2020, the economic vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0732 to 0.1770, with the maximum value being Siping

City, followed by Yichun City, with a value of 0.1768. In 2020, Siping City was affected by several policies. After Gongzhuling was under the jurisdiction of Changchun, the number of permanent residents dropped sharply, and the total GDP also dropped significantly. At the same time, it was affected by the epidemic, resulting in a higher vulnerability index. The minimum vulnerability value is Changchun City, which has a good economic development trend, adjusts its economic policies and industrial development direction in time, and its per capita GDP surpasses Shenyang.

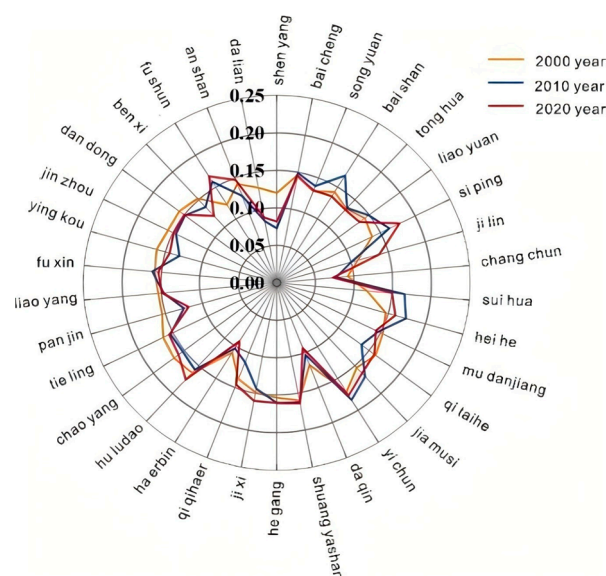


Figure 4. Time change chart of the economic vulnerability in the prefecture-level cities in the urban coupling system in the three northeastern provinces.

3.1.3. Analysis of Temporal Evolution Characteristics of Social Vulnerability Subsystem

According to Figure 5, in 2000, the social vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranged from 0.0744 to 0.2147, with the maximum value being Yingkou City, followed by Qitaihe City, with a value of 0.2103. A large number of people in Yingkou City and Qitaihe City began to gather in cities, and the urbanization phenomenon was obvious, which brought a certain burden to society and led to higher vulnerability. The smallest vulnerability value is Harbin, followed by Shenyang, with a value of 0.0784. Harbin has more passenger transport and freight transport, and more enterprises above the designated size, making it more vulnerable. Shenyang has more enterprises above the designated size, which solves people's employment problems, and has more computer service personnel and software employees. Compared with other cities, social development is more advanced. From 2010 to 2020, the highest vulnerability was Qitaihe City, which is mainly due to the high population density and the small total amount of road passenger transport and freight transport. The lowest vulnerability was Shenyang in 2010 and Changchun in 2020, which have a moderate population and perfect infrastructure. From 2000 to 2020, Shenyang, Dalian, Dandong, Jinzhou, Harbin, Hegang, and Heihe have continuously had a high social vulnerability index, Jilin, Yingkou, Liaoyang, and Huludao have continuously reduced their social vulnerability index, and other prefecture-level cities are in fluctuation.

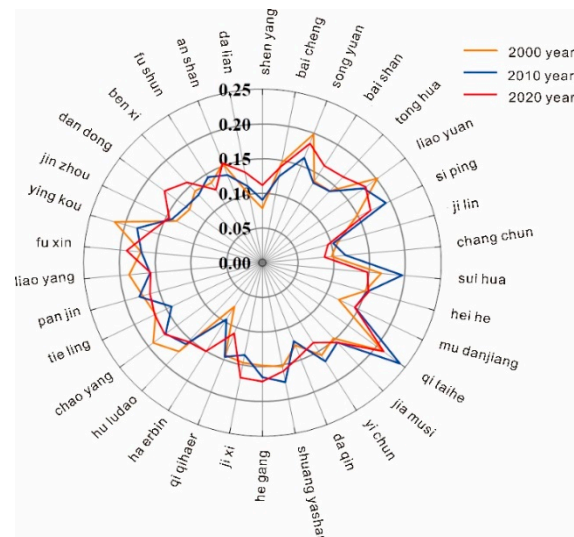


Figure 5. Time change chart of the social vulnerability in the variable prefecture-level cities in the urban coupling system in the three northern advantages.

3.1.4. Analysis of Temporal Evolution Characteristics of Natural Vulnerability Subsystem

According to Figure 6, from 2000 to 2020, the natural vulnerability index of each prefecture-level city in the urban coupling system in the three northeastern provinces ranges from 0.0228 to 0.2486, with the highest value being Liaoyang City and the lowest value being Daqing City. Liaoyang City experienced a rare rainstorm under the influence of a typhoon in 2012, and rare extreme weather occurred in 2020. The rainfall was more than usual in the same period, resulting in relatively more annual average rainfall and a higher vulnerability value. Daqing City is located in the Songnen Plain, with vast wetlands, so the water area is relatively large, and the average annual rainfall and temperature are relatively moderate, which makes its vulnerability index low. From 2000 to 2020, Jilin, Baishan, Mudanjiang, and Suihua have had a continuously high natural vulnerability index, while Changchun, Songyuan, Baicheng, Dandong, Yingkou, Fuxin, Tieling, Chaoyang, Hegang, and Yichun have continuously reduced their natural vulnerability index. Compared with the resources and environment vulnerability index, economic vulnerability index, and social vulnerability index, the natural vulnerability index of prefecture-level cities changes greatly.

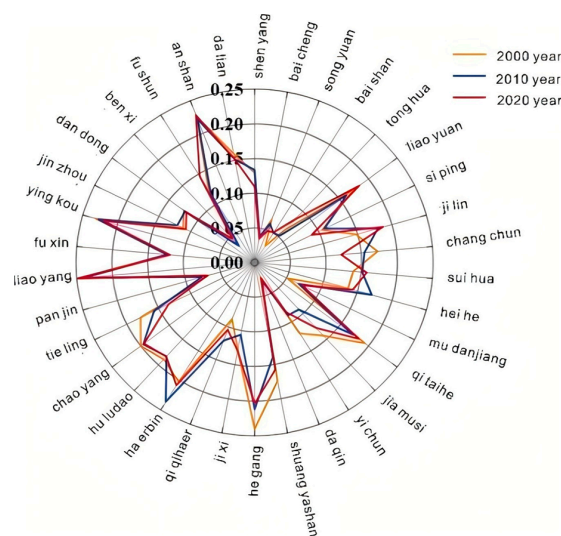


Figure 6. Time change diagram of the natural vulnerability of the prefecture-level cities in the urban coupling system in the three northeastern provinces.

3.1.5. Analysis of Time Evolution Characteristics of Comprehensive Vulnerability in Urban Coupling System

According to Formula (9), the comprehensive vulnerability evaluation indexes of 34 prefecture-level cities in three northeastern provinces in 2000, 2010, and 2020 are calculated and sorted, and the results are shown in Table 4. From 2000 to 2020, the average values of the vulnerability index of the urban coupling system were 0.5423, 0.5334, and 0.5383, respectively, showing a trend of first decreasing and then rising. In 2000, Benxi City had the lowest comprehensive vulnerability index, Yingkou City had the highest comprehensive vulnerability index, and Daqing City had the lowest comprehensive vulnerability index in 2010. Qitaihe City had the highest comprehensive vulnerability index, and Daqing City had the lowest comprehensive vulnerability index in 2020. There are obvious ranking changes in the degree of vulnerability in the urban coupling system in the three northeastern provinces. According to the changing trend of the vulnerability index, 34 prefecture-level cities in the three northeastern provinces are mainly divided into three categories: vulnerability rising cities, vulnerability declining cities, and vulnerability fluctuating cities.

Table 4. Comprehensive evaluation index of urban coupled system vulnerability.

City	2000	Sort	2010	Sort	2020	Sort
Changchun	0.4949	25	0.5269	18 ↑	0.4391	32 ↓
Jilin	0.5300	16	0.4730	27 ↓	0.4994	20 ↑
Siping	0.5372	15	0.6519	3 ↑	0.6344	6 ↓
Liaoyuan	0.7099	4	0.6385	5 ↓	0.6542	3 ↑
Tonghua	0.4743	26	0.4972	22 ↑	0.4742	26 ↓
Baishan	0.4182	31	0.4622	28 ↑	0.4687	28 →
Songyuan	0.5061	21	0.4858	24 ↓	0.4828	23 ↑
Baicheng	0.4516	30	0.4109	32 ↓	0.4782	24 ↑
Shenyang	0.5229	19	0.4559	29 ↓	0.4778	25 ↑
Dalian	0.4522	29	0.4268	31 ↓	0.4718	27 ↑
Anshan	0.6229	7	0.5852	11 ↓	0.6230	8 ↑
Fushun	0.4739	27	0.4995	21 ↑	0.4913	22 ↓
Benxi	0.3896	34	0.3883	33 ↑	0.3814	33 →
Danton	0.4734	28	0.4770	26 ↑	0.5069	19 ↑
Jinzhou	0.4987	23	0.5363	15 ↑	0.5430	16 ↓
Yingkou	0.7468	1	0.6272	7 ↓	0.6489	4 ↑
Fuxin	0.5765	11	0.5540	13 ↓	0.5782	14 ↓
Liaoyang	0.7105	3	0.6687	2 ↑	0.6687	2 →
Panjin	0.5173	20	0.5274	17 ↑	0.4439	31 ↓
Tieling	0.5960	9	0.5254	19 ↓	0.5470	15 ↑
Sunrise	0.6401	6	0.6042	8 ↓	0.6038	10 ↓
Huludao	0.6064	8	0.5866	10 ↓	0.5897	12 ↓
Harbin	0.5550	12	0.6021	9 ↑	0.6302	7 ↑
Qiqihar	0.4976	24	0.4841	25 ↓	0.4957	21 ↑
Chicken West	0.5497	14	0.4914	23 ↓	0.5811	13 ↑
Hegang	0.6503	5	0.6385	6 ↓	0.6466	5 ↑
Shuangyashan	0.5944	10	0.5509	14 ↓	0.5935	11 ↑
Daqing	0.4008	33	0.3652	34 ↓	0.3812	34 →
Yichun	0.5250	18	0.5278	16 ↑	0.4640	30 ↓
Jiamusi	0.5547	13	0.5238	20	0.5376	17 ↑
Qitaihe	0.7146	2	0.6812	1 ↑	0.6787	1 →
Mudanjiang	0.4155	32	0.4406	30 ↑	0.4680	29 ↑
Heihe	0.5041	22	0.5690	12 ↑	0.5070	18 ↓
Suihua	0.5278	17	0.6518	4 ↑	0.6108	9 ↓

‘↑’ indicates an increase in the vulnerability index, indicating a worsening of vulnerability; ‘↓’ indicates a decrease in the vulnerability index, indicating a reduction in vulnerability; ‘→’ indicates a stable vulnerability index, indicating that the vulnerability status remains unchanged.

There are four cities with rising vulnerability, mainly Baishan, Jinzhou, Harbin, and Mudanjiang. Baishan and Mudanjiang are ranked lower, Jinzhou is ranked between 15 and 23, and Harbin is ranked between 7 and 12, which is ranked higher. The vulnerability in the urban coupling system is severe. There are 25 cities with fluctuating vulnerability, including Changchun, Jilin, Siping, Liaoyuan, Tonghua, Baicheng, Shenyang, Dalian, Anshan, Fushun, Dandong, Yingkou, Fuxin, Panjin, Tieling, Huludao, Qiqihar, Jixi, Hegang, Shuangyashan, Daqing, Yichun, Jiamusi, Heihe, and Suihua. The vulnerability degree of Jilin, Siping, Shenyang, Tieling, Jixi, and Heihe fluctuated obviously from 2000 to 2010. In 2010, the degree of vulnerability in the Siping and Heihe urban coupling systems increased, ranking third and 12th. In 2010, the vulnerability in the Jilin, Shenyang, Tieling, and Jixi urban coupling systems decreased obviously. Shenyang proposed to transform into an innovative city in 2010, which accelerated the economic transformation mode. From 2010 to 2020, the vulnerability ranking of the urban coupling systems in Changchun, Panjin, and Yichun decreased significantly. From 2000 to 2020, the vulnerability in the urban coupling systems in Changchun, Jilin, Siping, Shenyang, Dandong, Panjin, Tieling, Jixi, Yichun, Heihe, and Suihua fluctuated violently during the whole study period, and the vulnerability in the urban coupling systems showed an unstable state. There are five cities with decreased vulnerability, mainly Songyuan, Benxi, Liaoyang, Chaoyang, and Qitaihe. Among them, Songyuan's vulnerability is in a low state as a whole, ranking between 21 and 24, Benxi's vulnerability ranks between 33 and 34, and the vulnerability in the urban coupling system is in a low state as a whole. Liaoyang and Qitaihe are always in the top three, and the vulnerability in the urban coupling systems is serious (Table 4).

3.2. Spatial Evolution Characteristics of the Vulnerability in the Urban Coupling System

By using ArcGIS 10.2 software, this paper analyzes the vulnerability in the urban coupling systems in the three northeastern provinces and obtains Z and P values of the vulnerability indexes from 2000 to 2020. The vulnerability index is divided into hot spots, sub-hot spots, warm spots, sub-cold spots, and cold spots by the natural segment method, and finally, the spatial cold-hot spots distribution map of the comprehensive vulnerability in each subsystem and urban coupling system in the three northeastern provinces.

3.2.1. Cold-Hot Spot Analysis of Spatial Difference of Resource and Environment Vulnerability Subsystem

Spatial changes in resources and environment subsystems are quite drastic. In 2000, hot spots of the vulnerability of resources and environment subsystems formed in the center of the three northeastern provinces, with most of the sub-hot spots in the periphery of hot spots, while cold spots formed in the northern and southwestern parts of the three northeastern provinces, with all the sub-cold spots around cold spots. The temperature spots were large and contiguous, and distributed in a "1" shape in the north and south of the three northeastern provinces. By 2010, hot spots spread around, and finally, there was a contiguous aggregation where the sub-hot spots increased slightly, temperature points gradually decreased and gradually increased to the southeast, sub-cold spots increased in the northeast, and cold spots showed spatial dispersion. In 2020, the hot spots are concentrated in the central part to form a contiguous gathering area, the sub-hot spots spread around the hot spots, and the temperature points gradually shift eastward from Qiqihar and Daqing City. Compared with 2010, the sub-cold spot area showed a decreasing trend in the east, and the cold spot area gradually decreased, leaving only Heihe and some areas in Liaoning Province, as shown in Figure 7.

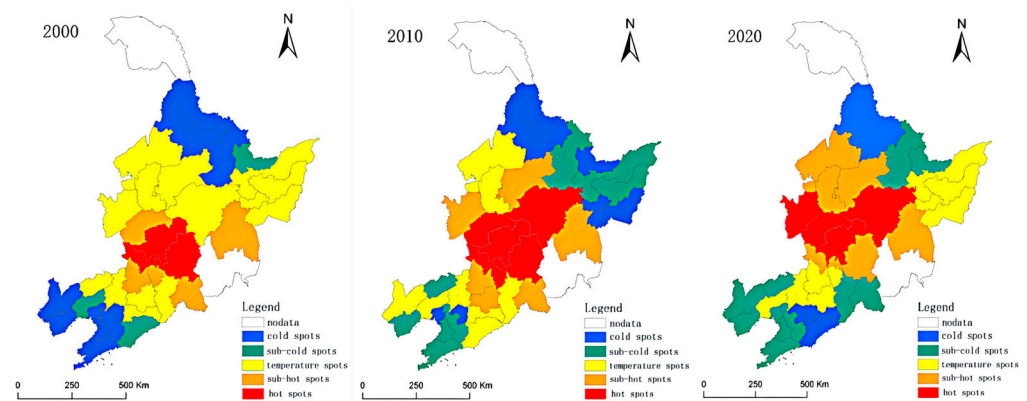


Figure 7. Analysis of fragile cold-hot spots of resource and environment subsystems in urban coupling systems in three northeastern provinces.

3.2.2. Cold-Hot Spot Analysis of Spatial Difference of Economic Vulnerability Subsystem

The fragility of the economic subsystem changed dramatically in the whole space. In 2000, the hot spot area was small and scattered, concentrated in individual cities in Heilongjiang Province and Liaoning Province, and all the sub-hot spots, except Heihe River, contiguously gathered around the hot spot area, while most of the temperature points contiguously gathered in the southeast part of the three northeastern provinces. Some cities in Heilongjiang Province had temperature points and cold points continuously gathered in the central region of the three northeastern provinces, and most of the sub-cold points spread to the northwest along the cold points. By 2010, the hot spots gradually expanded from the southwest to the northeast of the three northeastern provinces, forming an L-shaped contiguous gathering area, and the sub-hot spots gradually decreased, leaving Jixi City in the southeast, and the southwest gradually shifted to the north, and the temperature points changed from gathering to dispersing in space. The secondary cold spots gradually shifted to the central and southwestern parts of the three northeastern provinces, and finally formed an L-shaped gathering area in the central part, while the cold spot gathering area decreased in the southwestern part, with Changchun in the central part and Dandong in the southwestern part. In 2020, compared with 2010, the change range of the hot spots is not obvious, the area of sub-hot spots is reduced, the spatial distribution of temperature points is scattered compared with 2010, the sub-cold spots gradually spread from “L” to the northwest, and the cold spots mainly gather in the central region. Generally speaking, the area of the hot spot area gradually increases, the area of the sub-hot spot area gradually decreases, and the cold spot area shows a trend of first greatly decreasing and then greatly increasing, as shown in Figure 8.

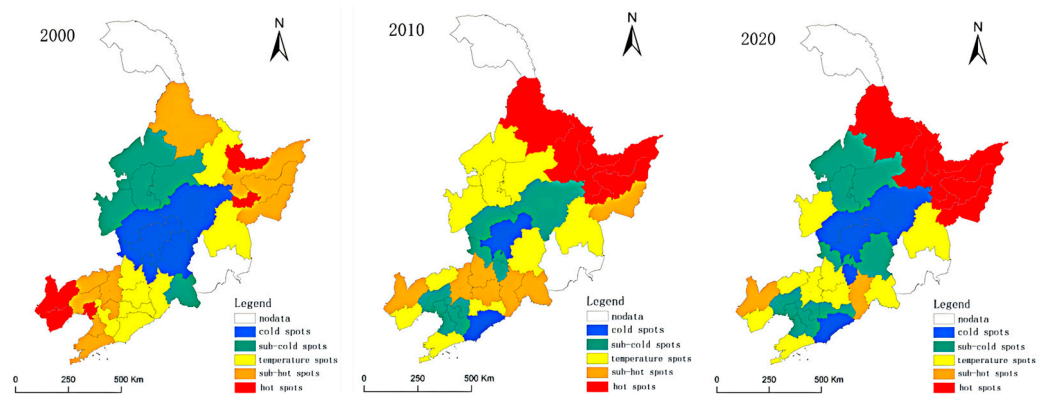


Figure 8. Analysis diagram of the cold-hot spots of the vulnerability in the urban coupling system in the three northern provinces.

3.2.3. Spatial Cold-Hot Spot Analysis of Social Vulnerability Subsystem Difference

The spatial distribution of vulnerability in the social subsystems has changed greatly. In 2000, the hot spots were mainly distributed in southwestern Liaoning and Hegang (northeastern Heilongjiang). By 2010, the hot spot gathering areas shifted from southwest to northeast and finally gathered in most of the cities in Heilongjiang Province. By 2020, the hot spots were scattered in Chaoyang City and Fushun City, Liaoning Province, and most of the rest were contiguous and gradually spread to the east, mainly distributed in Heilongjiang Province. In 2000, the sub-hot spots were mainly distributed in Heilongjiang Province and gathered in the southeast. By 2010, only Heihe City in the north, Chaoyang City, and Huludao City in Liaoning Province were left in the sub-hot spots. By 2020, the area of sub-hot spots will increase slightly, and the number of sub-hot spots will increase from three to five. In 2000, the temperature point region appeared in the central region and the western edge region of Jilin Province and Heilongjiang Province, and in 2010, the spatial variation range of the temperature point region was large. By 2020, most of the temperature points will surround the hot spots. In 2000, the sub-cold spot region formed a trend of spreading outward, with Harbin as the center. By 2010, the number of sub-cold spots increased, showing contiguous aggregation in the middle and south. By 2020, the sub-cold spots were mainly concentrated in most areas in Jilin Province, and the rest of the cold spots were distributed in Heihe and Dandong. In 2000, there were two cold spots, Harbin and Liaoyuan. By 2010, the cold spot area shifted from the central part of the three northeastern provinces to the southwest, and by 2020, the area of the cold spot increased, and the spatial distribution shifted from southwest to northwest, as shown in Figure 9.

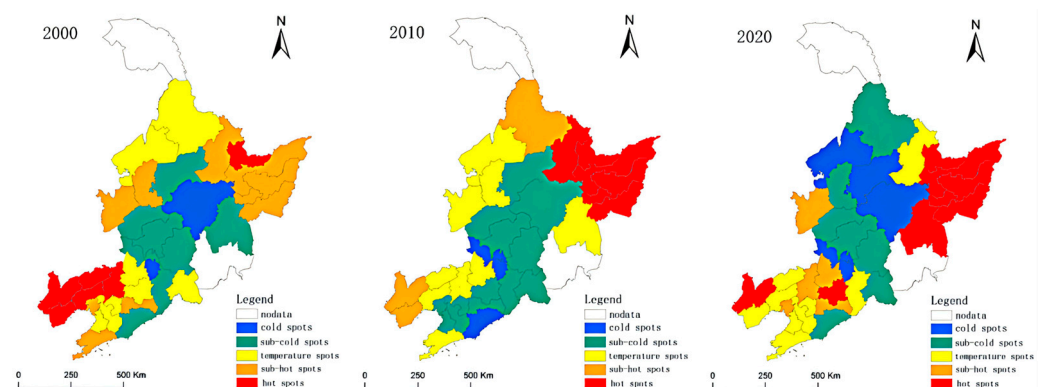


Figure 9. Cold-hot spot analysis diagram of social subsystem vulnerability in urban coupling system in three northern provinces.

3.2.4. Space Cold-Hot Spot Analysis of Natural Vulnerability Subsystem Difference

The spatial distribution of the vulnerability in the natural subsystems changed dramatically. In 2000, the hot spots were concentrated in some cities in northeast Heilongjiang Province and Fuxin, Jinzhou, Panjin, and Dalian in Liaoning Province. From 2010 to 2020, the area of hot spots decreased, leaving only four cities in Liaoning Province compared with 2000. In 2000, the sub-hot spots were distributed around the hot spots. By 2010, the area of the sub-hot spots increased obviously, showing an “X” distribution in the southeast. By 2020, the sub-hot spots changed from “X” to “Y” and gathered in some areas of Heilongjiang Province. In 2000 and 2010, the temperature point area was mainly distributed around the sub-hot spot area, and by 2020, the temperature point area was significantly reduced compared with that in 2000. In 2000, the sub-cold spot area was concentrated in most parts of Jilin Province in the middle, and in Heilongjiang Province, it was mainly Qiqihar City and Suihua City. In 2010, the contiguous area in the south of the central part of the sub-cold spot area increased, Jixi increased in the northeast, and by 2020, the sub-cold

spot area in the central part decreased, and some cities in Heilongjiang Province increased in the north. From 2000 to 2020, the cold spot area had no obvious change, and gathered in the central edge area, as shown in Figure 10.

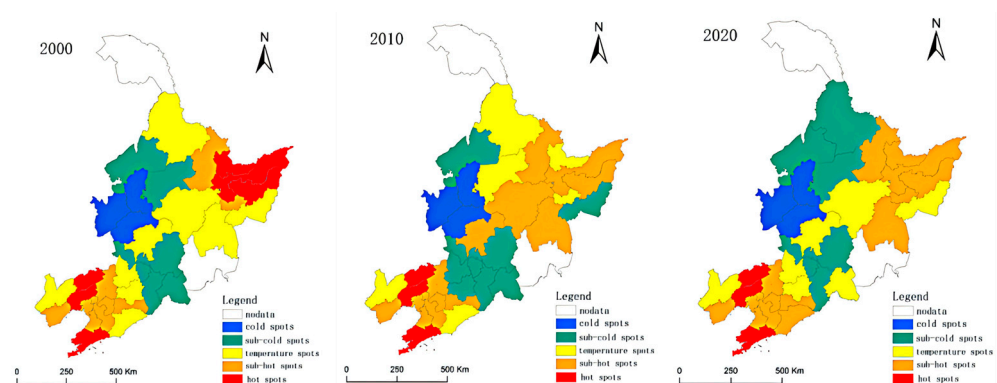


Figure 10. Cold-hot spot analysis diagram of the natural subsystem vulnerability in the urban coupling system in the three northern provinces.

3.2.5. Cold-Hot Spot Analysis of Spatial Difference of Comprehensive Vulnerability in Urban Coupling System

Using the spatial autocorrelation function of ArcGIS software, the global Moran's I index of the vulnerability in the urban coupling systems in three northeastern provinces from 2000 to 2020 is calculated, and the calculated results are shown in Table 5. From 2000 to 2020, Moran's I values are all negative, and Z values have not passed the significance test, which shows that the vulnerability in the urban coupling system in the three northeastern provinces has a strong negative correlation in space. From the numerical point of view, the overall correlation shows a downward trend first and then an upward trend, with weak spatial autocorrelation and scattered spatial distribution.

Table 5. Global autocorrelation test of the vulnerability in the urban coupling systems in the three northern provinces.

Year	Moran's	Z	p
2000	−0.0003	0.3381	0.7353
2010	−0.0626	−0.3626	0.7168
2020	−0.0564	−0.2926	0.7698

From 2000 to 2010, from the spatial distribution of the comprehensive vulnerability index of the urban coupling system in the three northeastern provinces, the change range of hot spots, warm spots, and sub-cold spots is small, while the sub-hot spots increase obviously in the central region and the cold spots decrease in a large area. From 2010 to 2020, the area of hot spots decreased, leaving only the northeast. The sub-hot spots shifted from the southeast to the central region, and the temperature spots changed from a scattered state to a concentrated distribution in a “one” shape. From the northeast to the southwest, the area of sub-cold spots gathered in the marginal areas of Heilongjiang Province, while the other sub-cold spots did not change obviously, and the cold spots increased in Liaoyuan City (Figure 11).

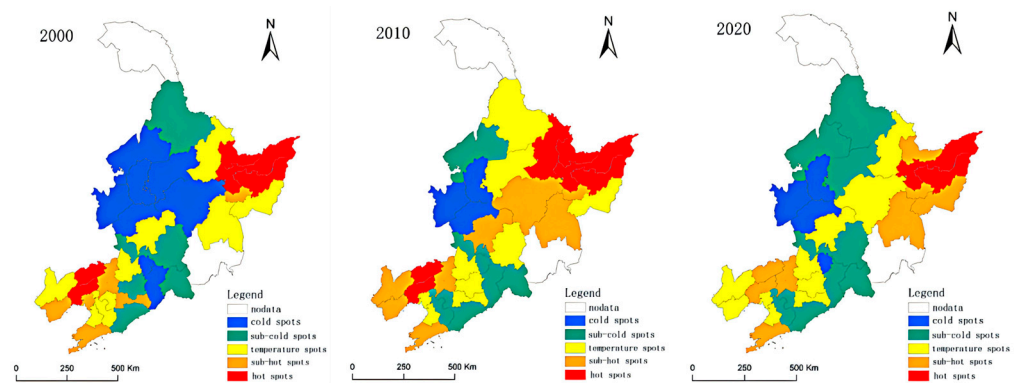


Figure 11. Analysis of cold-hot spots in urban coupling system in three northern provinces.

4. Vulnerability Driving Force Analysis of Urban Coupling System in Three Northeastern Provinces

4.1. The Detection and Analysis of the Leading Driving Factors of the Vulnerability in the Urban Coupling System

In this paper, the geographic detector is constructed by RStudio 4.3.2, and the data are dispersed into 3–7 categories. The detection results of the vulnerability driving factors of the urban coupling systems in 2000, 2010, and 2020 are shown in Table 6. In the table, the Q value is the influence. The larger the Q value, the stronger the explanatory power of the driving factor to the comprehensive vulnerability index of the urban coupling system vulnerability, and vice versa.

Table 6. Results of the vulnerability driver detection in the three northeastern provinces. (See Table 3 for the indicator definitions).

Driving Factor	Q Value					
	2000	Ordering of Explanatory Power	2010	Ordering of Explanatory Power	2020	Ordering of Explanatory Power
X1	0.4136	2	0.1535	16	0.1283	14
X2	0.2075	13	0.2474	8	0.2123	9
X3	0.3727	4	0.1584	15	0.1278	15
X4	0.3992	3	0.2023	11	0.2143	8
X5	0.2704	9	0.3169	6	0.1896	12
X6	0.2485	11	0.3268	5	0.0882	16
X7	0.3567	5	0.3802	3	0.2819	3
X8	0.1476	15	0.1731	14	0.2793	4
X9	0.1649	14	0.1979	12	0.1904	11
X10	0.3191	7	0.3130	7	0.2299	7
X11	0.2694	10	0.2135	9	0.1874	13
X12	0.2719	8	0.2054	10	0.2037	10
X13	0.2109	12	0.3550	4	0.2746	5
X14	0.1422	16	0.1863	13	0.2333	6
X15	0.4450	1	0.4380	1	0.5057	1
X16	0.3493	6	0.3883	2	0.4415	2

From the time series point of view, the top five main driving factors of urban coupling system vulnerability in 2000 are plain area (X15), domestic garbage removal (X1), road cleaning area (X4), industrial sulfur dioxide emission (X3), and total retail sales of social consumer goods (X7). It can be seen that the proportion of plain area (X15) has the strongest explanatory power to the vulnerability in the urban coupling system, and the explanatory power Q value reaches 0.4450 and passes the significance test of 5%, which is the key factor

affecting the vulnerability in the urban coupling system, indicating that natural factors play a central role in reducing the vulnerability in the urban coupling system. The explanatory power of the altitude (X16) and water use penetration rate (X10) is second only to the total retail sales of social consumer goods (X7), with Q values of 0.3493 and 0.3191, respectively, passing the 5% significance test, which are the leading factors affecting the spatial pattern of the vulnerability in the urban coupling system.

In 2010, the top six driving factors ranked as follows: plain area ratio (X15) > altitude (X16) > total retail sales of social consumer goods (X7) > actual public steam (electric) vehicles at the end of the year (X13) > newly added fixed assets (X6) > sewage discharge (X5). The plain area ratio is the core driving factor affecting the vulnerability in the urban coupling system, and the maximum explanatory power Q reaches 0.4380 and passes 5%. In addition, the Q value of the water penetration rate and total water supply ranges from 0.3130 to 0.2474.

In 2020, the top six main driving factors of urban coupling system vulnerability are: plain area ratio (X15) > altitude (X16) > total retail sales of social consumer goods (X7) > current assets of industrial enterprises above designated size (X8) > actual public steam (electric) vehicles at the end of the year (X13) > number of students in colleges and universities (X14). Among them, the proportion of the plain area has the greatest influence on the spatial pattern of the vulnerability in the urban coupling system, and the explanatory power Q value is 0.5057 and passes the significance test of 5% (Table 6).

From the comprehensive view of each year, the analysis results are shown in Figure 12. Among the 16 explanatory variables, the proportion of the plain area always ranks first in terms of factor explanatory power, while altitude ranks sixth in terms of influence from 2000 to 2010 and second in terms of influence from 2010 to 2020. Therefore, natural factors have a stable influence on the vulnerability in the urban coupling systems in the three northeastern provinces, and the explanatory power of the natural environment vulnerability index is higher than that of the indicators. Natural factors in the region have an important impact on the vulnerability of the urban coupling systems. From 2000 to 2020, the Q values of the total retail sales of social consumer goods were 0.3567, 0.3802, and 0.2819, respectively. At the end of the year, the actual public bus (electric) vehicles became stronger in 2010–2020, and the Q values were 0.3550 and 0.2746, respectively. At the end of the year, the actual public bus (electric) vehicles showed that human social activities and living standards gradually became important factors affecting the vulnerability of the urban coupling systems in the three northeastern provinces.

From the changing trend of the driving factor action intensity, the Q value of the driving factor fluctuated in 2000, 2010, and 2020. On the whole, the current assets of industrial enterprises above indicate that the size, the number of students in colleges and universities, and the Q value of altitude are on the rise, which has a more and more serious impact on the vulnerability of the urban coupling system. The Q value of domestic garbage removal, industrial sulfur dioxide discharge, water penetration rate, drainage pipe density in built-up areas, and the number of road lighting lamps decreased continuously, which gradually reduced the impact on the vulnerability of the urban coupling system. The other Q values first increased and then decreased, or first decreased and then increased, indicating that the impact on the vulnerability of the urban coupling system is in a fluctuating state.

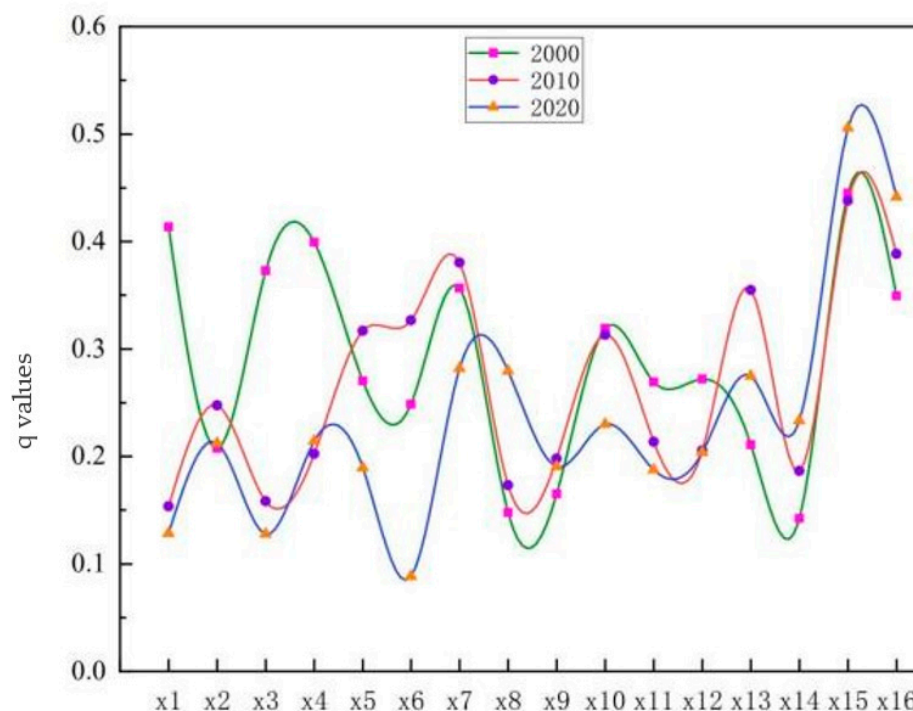


Figure 12. Trend of the Q values of the urban coupling system vulnerability drivers in the three northern provinces from 2000 to 2020. (See Table 3 for indicator definitions.).

4.2. Detection and Analysis of Vulnerability Interaction in Urban Coupling System

Through interactive detection, we can get the interaction of the vulnerability driving factors of the urban coupling systems in northeast China in 2000, 2010, and 2020, and the detection results are shown in Figure 13. Urban vulnerability is a complex system, and it is impossible to accurately analyze the reasons that affect urban vulnerability based on a single factor. Interactive detection mainly identifies the interaction of different influencing factors on the vulnerability change in the urban coupling systems, and the interaction of the driving factors has a stronger explanatory power for the vulnerability in urban coupling systems. From the perspective of interaction types, the types after interaction of different driving factors are mainly single-factor, nonlinear, weakening, double-factor, or nonlinear enhancement.

In 2000, the intensity value of two-factor interaction was mostly higher than that of a single factor in terms of the vulnerability in the urban coupling systems. Among them, the strongest two-factor interaction was the sewage discharge value of the domestic garbage removal amount (0.9389), the total retail sales of social consumer goods value for the road cleaning area (0.8548), the plain area accounting for the value of road cleaning area (0.8569), and the explanatory power for the vulnerability in the urban coupling system was over 85%. The smallest interaction was the current assets of industrial enterprises above a designated size value of industrial sulfur dioxide emission (0.0925). Although the single factor of the number of students in colleges and universities has a weak explanatory power for the vulnerability in the urban coupling system, its explanatory power is enhanced after interacting with other driving factors.

The interactive detection results of the driving factors in 2010 show that the two factors with the strongest interaction are the altitude and sewage discharge (0.7889), followed by the total retail sales of social consumer goods, domestic garbage removal (0.78), the plain area accounting for total retail sales of social consumer goods (0.778), which can explain the vulnerability in the urban system by more than 77%, and the smallest interaction are the local general public budget revenue and the road cleaning area (0.2094). Although the

single factor of domestic garbage removal has weak explanatory power for the vulnerability in the urban coupling system, the explanatory power is as high as 70% after interacting with the total retail sales of social consumer goods and the proportion of the plain area.

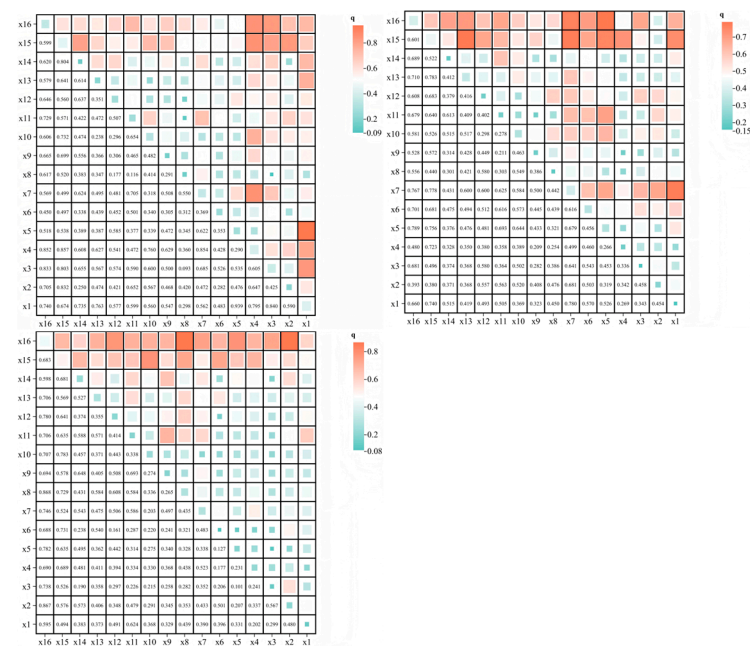


Figure 13. Heat map of vulnerability driver interaction of urban coupling system in three northeastern provinces. (See Table 3 for indicator definitions).

The interactive detection results of driving factors in 2020 show that the two factors with the strongest interaction are the current assets of the industrial enterprises above and the designated size (0.8676), followed by the total water supply at altitude (0.8671), which can explain the vulnerability in the urban coupling system by more than 86%, and the smallest interaction is sewage discharge (0.1014). Although the single factor of newly added fixed assets has weak explanatory power for the vulnerability in the urban coupling system, its explanatory power is over 68% after interacting with the plain area and altitude.

To sum up, the explanatory power of most driving factors with insignificant single-factor detection results in interactive detection and tends to increase, which indicates that the interaction between different driving factors has a better explanatory power for the vulnerability in the urban coupling systems. In 2000, compared with the interaction between altitude and other driving factors, the original single factor was in a state of enhanced explanatory power, and most of them were above 60%. In 2010, compared with the interaction between altitude and other driving factors, the original single factor is in a state of enhanced explanatory power, and the explanatory power, except for newly added fixed assets, is above 50%. In 2020, compared with the interaction between altitude and other driving factors, the original single factor is in a state of enhanced explanatory power. From 2000 to 2020, new fixed assets, local general public budget revenue, and altitude are the key factors affecting the spatial pattern of the vulnerability in the urban coupling systems in the three northeastern provinces. These driving factors interact with other indicators to form the difference in spatial pattern distribution of the vulnerability in the urban coupling systems. At the same time, the factors with a strong single-factor drive generally have a strong explanatory power after the interaction of two factors.

4.3. Detection and Analysis of Vulnerability Leading Driving Factors of Each Subsystem

4.3.1. Detection and Analysis of Vulnerability Leading Driving Factors of Resource and Environment Subsystem

The vulnerability of resources and environment subsystems in the three northeastern provinces from 2000 to 2020 is analyzed by factor detection, and the results are shown in Figure 14. From 2000 to 2010, the amount of domestic garbage removal was the primary driving factor, and from 2010 to 2020, the total amount of water supply was the primary driving factor, which reflects the use efficiency and adequacy of water resources. However, during the study period, the influence of the domestic garbage removal factor continued to decline.

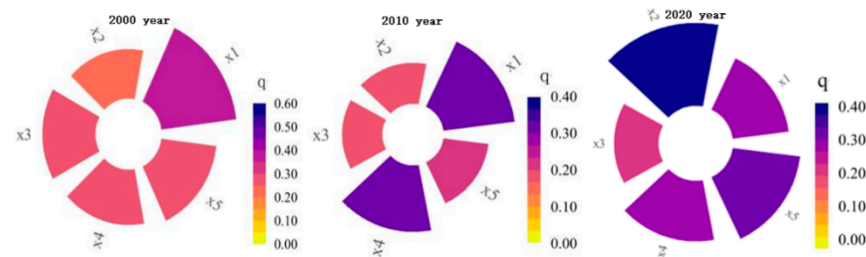


Figure 14. Results diagram of the vulnerability of the resource environment subsystems in 2000–2020. (See Table 3 for indicator definitions).

4.3.2. The Detection and Analysis of the Leading Driving Factors of the Vulnerability in the Economic Subsystem

The vulnerability of economic subsystems in the three northeastern provinces from 2000 to 2020 is analyzed by factor detection, and the results are shown in Figure 15. The explanatory power of new fixed assets, total retail sales of social consumer goods, and local general public budget revenue to economic vulnerability is increasing continuously, and the explanatory power of the driving factors of the economic vulnerability subsystem is higher than the other three subsystems, which has an important impact on economic vulnerability.

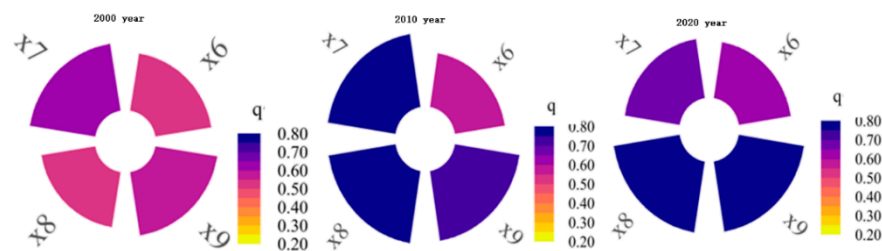


Figure 15. The result chart of the leading driving factors of the economic subsystem vulnerability from 2000–2020. (See Table 3 for indicator definitions).

4.3.3. The Detection and Analysis of the Leading Driving Factors of the Vulnerability in Social Subsystems

The vulnerability of social subsystems in the three northeastern provinces from 2000 to 2020 is analyzed by factor detection, and the results are shown in Figure 16. In the social vulnerability index, the explanatory power of the water supply pipeline density in built-up areas, the actual public steam (electric) vehicles at the end of the year, and the number of students in colleges and universities gradually weakened the vulnerability of the social subsystems. Although the explanatory power of the actual public steam (electric) vehicles at the end of the year declined seriously, they were still the main driving factors in the study period, and the explanatory power of the water penetration rate dropped sharply from 2010 to 2020, ranking last in 2020.

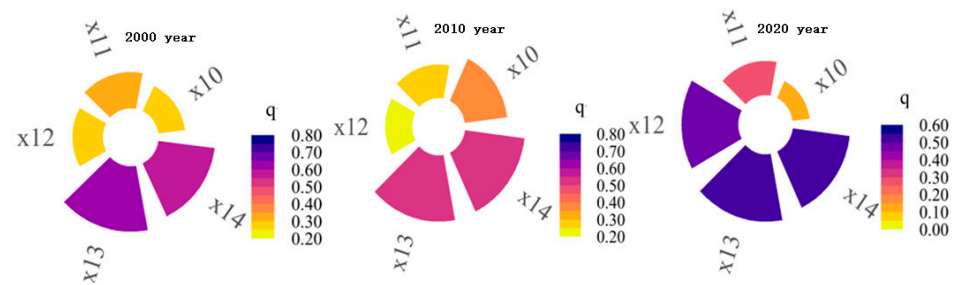


Figure 16. Leading driver results diagram of social subsystem vulnerability in 2000–2020. (See Table 3 for indicator definitions).

4.3.4. Detection and Analysis of Dominant Driving Factors of Vulnerability of Natural Subsystems

The vulnerability of natural subsystems in the three northeastern provinces from 2000 to 2020 is analyzed by factor detection, and the results are shown in Figure 17. The explanatory power of the plain area ratio and altitude to the vulnerability of the natural subsystem gradually weakens, but they are still the main driving factors.

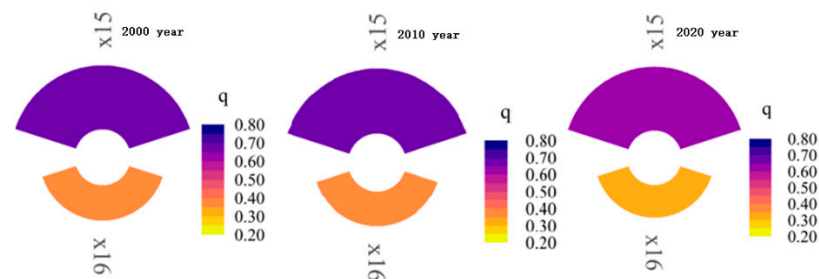


Figure 17. Results plot of natural subsystem vulnerability dominant driver in 2000–2020. (See Table 3 for indicator definitions).

4.4. Vulnerability Interaction Detection and Analysis of Various Systems

4.4.1. Detection and Analysis of Vulnerability Interaction of Resource and Environment Subsystem

The interaction results of the vulnerability driving factors of resource and environment subsystems from 2000 to 2020 are shown in Figure 18. In 2000, the strongest interaction was between the road cleaning area and domestic garbage removal amount (0.6849), and the weakest interaction was between industrial sulfur dioxide emission and total water supply amount (0.1349). In 2010, the strongest interaction was sewage discharge in the air (0.8155), and the weakest interaction was sewage discharge (0.2739). In 2020, the strongest interaction was the industrial sulfur dioxide discharge value of domestic garbage removal (0.6452), and the weakest interaction was the sewage discharge value of domestic garbage removal (0.3389).

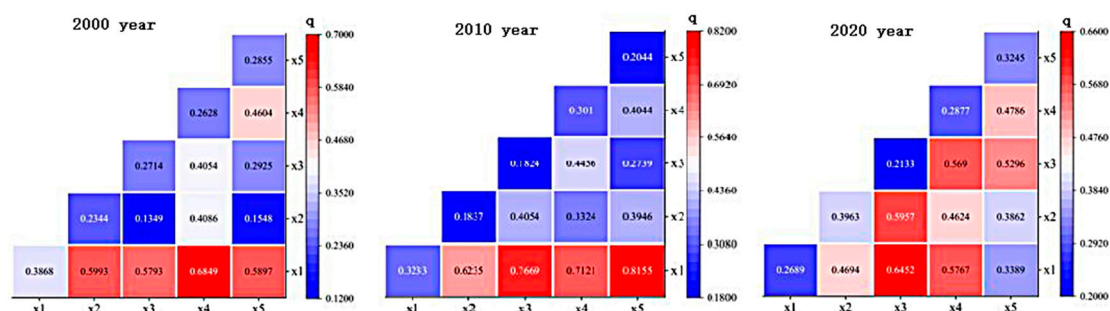


Figure 18. 2000–2020 resource and environment subsystem vulnerability driver interaction thermodynamic diagram. (See Table 3 for indicator definitions).

4.4.2. Detection and Analysis of Vulnerability Interaction of Economic Subsystem

The interaction results of the vulnerability driving factors of the economic subsystem from 2000 to 2020 are shown in Figure 19. In 2000, the strongest interaction was between the local general public budget revenue and total retail sales of social consumer goods (0.7451), and the weakest interaction was between the local general public budget revenue and new fixed assets (0.6268). In 2010, the strongest interaction was the total retail sales of social consumer goods (0.9325), and the weakest interaction was the local general public budget income (0.5525). In 2020, the strongest interaction was the local general public budget revenue (0.9074), and the weakest interaction was the current assets of industrial enterprises above the designated size (0.7847).

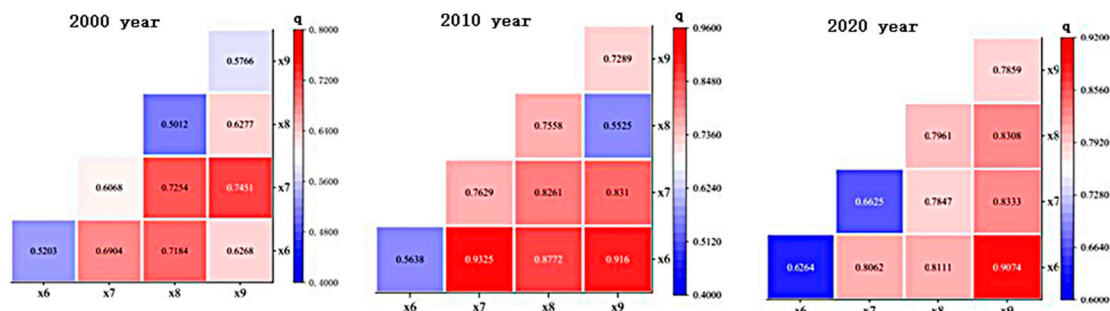


Figure 19. 2000–2020 thermodynamic diagram of the interaction of the vulnerability drivers in the economic subsystem. (See Table 3 for indicator definitions).

4.4.3. Detection and Analysis of Vulnerability Interaction of Social Subsystems

The interaction results of vulnerability drivers in social subsystems from 2000 to 2020 are shown in Figure 20. In 2000, the strongest interaction was the number of students in colleges and universities (0.8758). In 2010, the strongest interaction was between the number of students in colleges and universities and the density of drainage pipes in built-up areas (0.7287). In 2020, the strongest interaction was the number of road lighting lamps of public steam (electric) vehicles at the end of the year (0.7973) and the number of students in colleges and universities (0.7973). From 2000 to 2020, the weakest interaction is the density of drainage pipes in built-up areas (0.2857).

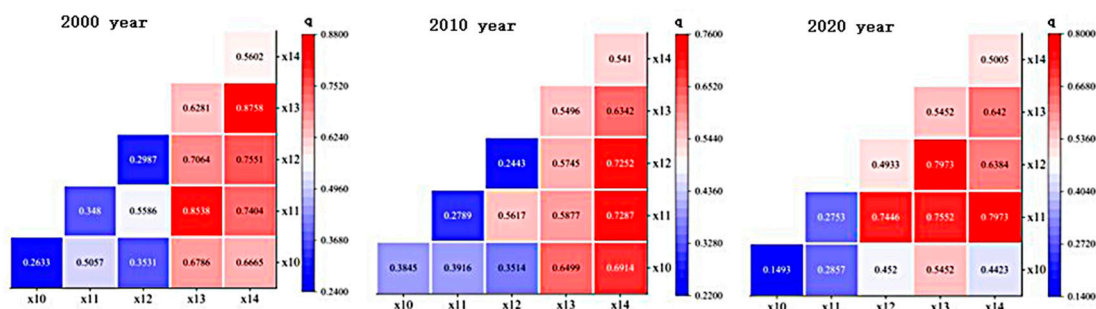


Figure 20. 2000–2020 thermodynamic diagram of the interaction of the vulnerability drivers of the social subsystems. (See Table 3 for indicator definitions).

4.4.4. Detection and Analysis of Vulnerability Interaction of Natural Subsystems

The interaction results of the vulnerability drivers of the natural subsystems from 2000 to 2020 are shown in Figure 21. The type of vulnerability driving factors of the urban coupling systems in northeast China is a two-factor nonlinear enhancement. The interaction influence between two factors is greater than that of a single factor on the vulnerability in the urban coupling system.

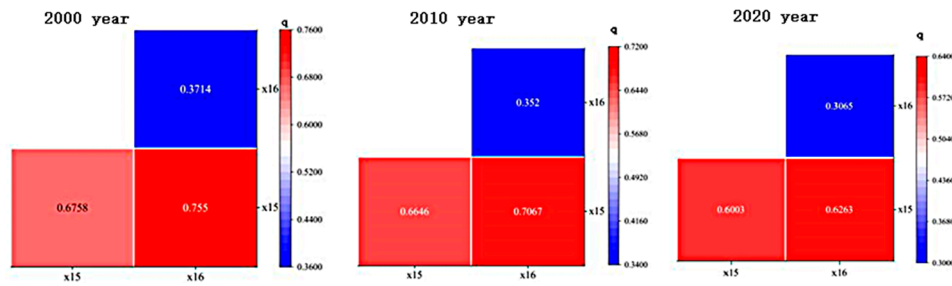


Figure 21. 2000–2020 natural subsystem vulnerability driver interaction heat map. (See Table 3 for indicator definitions).

5. Conclusions and Countermeasures

5.1. Conclusions

Based on the concept, connotation, and related theories of urban vulnerability, this paper constructs an evaluation index system of four dimensions: resource and environment vulnerability, economic vulnerability, social vulnerability, and natural vulnerability, selects the index data of 34 prefecture-level cities in three northeastern provinces from 2000 to 2020, calculates the vulnerability index and comprehensive vulnerability index of each subsystem in the urban coupling system by using weighted summation model, explores the spatial differences of the urban coupling system vulnerability, and finally finds out the core driving factors of fragility from the comprehensive and subsystem perspectives, according to the factor detection and interactive detection of geographical detectors, putting forward scientific and effective suggestions for urban existing problems. This provides a basis for the healthy and sustainable development of cities. The main conclusions of the study are as follows:

(1) The spatial and temporal pattern analysis of each dimension of the vulnerability in the urban coupling system in the three northeastern provinces.

From 2000 to 2020, the vulnerability subsystem of resources and environment shows a trend of first declining and then rising, while the vulnerability subsystem of the economy shows a trend of first declining and then rising, while the vulnerability subsystem of society shows a continuous upward trend and the vulnerability subsystem of nature shows a continuous downward trend. But overall, the vulnerability index of the social vulnerability subsystem is higher than the other three subsystems.

From the perspective of space, the area of hot spots of resource and environment vulnerability first increases and then decreases, the area of sub-hot spots gradually increases, and the area of cold spots gradually decreases. The cold spot area of economic vulnerability first decreases and then increases into a contiguous agglomeration in the central area of the central axis, while the sub-hot spot area gradually decreases. The hot spots and cold spots of social vulnerability gathered in a large area by 2020, while the areas of sub-hot spots and warm spots decreased obviously, and the sub-cold spots changed from a contiguous gathering to a discrete state by 2020, with a small decreasing trend. The hot spots and temperature spots of natural vulnerability obviously decrease; the temperature spots and sub-cold spots change dramatically in space, and the cold spots change little in area.

(2) Spatial and temporal pattern analysis of the comprehensive vulnerability in the urban coupling system in three northeastern provinces.

From the analysis of time evolution, from 2000 to 2020, the comprehensive vulnerability index of the urban coupling systems in the three northeastern provinces showed a state of continuous fluctuation. In the past 20 years, the comprehensive vulnerability index value was between 0.3652 and 0.7468, and most of the cities were in moderate vulnerability, among which Liaoyang and Qitaihe were always ranked first, while Benxi and Daqing

were always ranked lower. There are obvious sequential changes in the vulnerability in the coupling systems in the 34 prefecture-level cities in the three northeastern provinces, which can be divided into three types according to the changing trend: vulnerability fluctuation type, vulnerability rising type, and vulnerability declining type.

From the perspective of spatial evolution, in 2000, 2010, and 2020, the spatial distribution of the comprehensive vulnerability index of the urban coupling systems in northeast China showed a weak agglomeration phenomenon, and the spatial dispersion phenomenon of urban vulnerability became more and more obvious. In 2000, the fragile cold spots of the urban coupling system in the three northeastern provinces continuously gathered in the central and southeastern regions, with a large area of cold spots and hot spots concentrated in Liaoning and Heilongjiang provinces. Sub-hot spots, warm spots, and sub-cold spots are scattered in space. In 2010, the area of vulnerability, the cold spot area of the urban coupling system in the three northeastern provinces, decreased sharply and concentrated in the western region, and the sub-hot spot area increased in the central region. In 2020, the number of vulnerable sub-cold spots in the urban coupling system in the three northeastern provinces could increase, and they could be concentrated in the marginal areas of Jilin Province, Liaoning Province, and Heilongjiang Province.

(3) Analysis of driving forces of spatial and temporal evolution of vulnerability in three northeastern provinces.

Through the driving force analysis results of 16 indicators, the single factor driving force detection shows that from 2000 to 2020, the proportion of the plain area, altitude, and total retail sales of social consumer goods are the main driving factors affecting the vulnerability in the urban coupling system in the three northeastern provinces. During the study period, the driving factors for the continuous increase of the Q value are the current assets of enterprises above the designated size, the number of students in colleges and universities, and the altitude. The Q value decreased continuously in domestic garbage removal, industrial sulfur dioxide discharge, water penetration rate, drainage pipeline density in built-up areas, and the number of road lighting lamps. The interactive detection results show that from 2000 to 2020, the proportion of the plain area and altitude are the key factors affecting the spatial pattern of the vulnerability in the urban coupling systems in the three northeastern provinces.

From the results of the four subsystems, the single-factor driving force detection results show that from 2000 to 2010, the amount of domestic garbage removal always ranks first, and the total amount of water supply in the later period is the main driving force. In the economic vulnerability subsystem, the total retail sales of social consumer goods from 2000 to 2010 are the main driving factor, and the current assets of enterprises above a designated size are the main driving force in the later period. In the subsystem of social vulnerability, the primary driving factor is that there are public buses (electric vehicles) operating at the end of the year. The proportion of the plain area in the natural vulnerability subsystem is the primary driving factor. The explanatory power of the economic vulnerability driving factors is higher than that of the other subsystem driving factors.

5.2. Countermeasures and Suggestions

By analyzing the fragility and brittle factors of the urban coupling system in the three northeastern provinces from 2000 to 2020, it can be seen that there are some problems, such as the uncoordinated and unbalanced development among the 34 prefecture-level cities in the three northeastern provinces, and there are great differences in urban development process among regions. Among them, the average value of the vulnerability index of the resource and environment vulnerability subsystem shows a downward trend first and then an upward trend, while that of the economic vulnerability subsystem shows a downward

trend first and then an upward trend, that of the social vulnerability subsystem shows a continuous upward trend, and that of natural vulnerability subsystem shows a continuous downward trend. Therefore, given the problems existing in urbanization, this paper starts with the factors that affect the vulnerability in urban coupling systems and provides development countermeasures for urban sustainable development. Vulnerability regulation needs to combine the vulnerability degree and the coordination of each subsystem in the city.

(1) Improve the level of economic development and strengthen the ability of innovation.

From the results of the vulnerability index, it can be seen that economic vulnerability has risen rapidly in the past 20 years, which is an important factor affecting urban vulnerability. We should increase efforts to attract foreign investment and adjust the economic and industrial structure. The economic and industrial structure reform in the three northeastern provinces is slow, and most of them are traditional industries, lacking new industries, which leads to a serious brain drain. In recent years, the natural population growth rate in the three northeastern provinces has dropped significantly. By 2020, only Harbin and Daqing had a growth rate of 5.13% and 1.24%, and other prefecture-level cities had negative growth. The city's GDP growth rate began to decline seriously in 2020, most obviously in Siping and Mudanjiang. The city's GDP growth rates were -33.85% and -35.55% . Less investment in education and scientific research is the main reason for the obstruction of innovation and the lack of high-quality talent. It is necessary to increase investment in education and scientific research, and attract high-level talents to enter campuses and industrial enterprises to help the region. At the same time, it is necessary to increase investment in R&D projects and provide technical support for traditional enterprises and enterprises that are slow to upgrade and transform, and cannot find a breakthrough.

(2) Improve the infrastructure of social life and reduce environmental pollution.

An increase in infrastructure construction, such as domestic water and electricity consumption, updating basic medical equipment, increasing tourist attractions and entertainment places, such as cinemas and parks, improving people's daily living standards, and enhancing cities' ability to cope with vulnerabilities, is needed. Because of the problem of high industrial carbon emissions, enterprises should promote the use of clean energy instead of fossil fuels to effectively reduce excessive carbon emissions. More afforestation should be planted in appropriate areas to purify the air, motor vehicle restriction measures should be taken in pollution source areas, and early warning and emergency management measures for severe air pollution should be improved.

(3) Improve the status of urban resources and the environment.

With the acceleration of urbanization, we should fully consider the per capita road area, per capita park green area, and per capita land resources when using land for construction, and pay attention to avoiding affecting the urban ecological environment while utilizing and developing urban resources. The government should formulate policies to rationally use resources, strengthen the level of urban greening, establish green space in urban areas to improve vegetation coverage, and promote the sustainable development of the urban ecological environment.

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