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Precision classification and governance of mining development based on resource endowment and spatial patterns: a case study of Northern Xinjiang, China

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This study examines Northern Xinjiang in the Central Asian Orogenic Belt to systematically reveal the spatial mismatch between the natural clustering of mineral resources and artificially defined administrative boundaries. By constructing a dual-track analytical framework of "administrative units *versus* metallogenic belt units", we apply spatial autocorrelation (Global/Anselin Local Moran's I), Getis-Ord General G/Gi*, kernel density estimation, and centroid migration modeling to mine location data (2011–2021). Results indicate mining distribution is random across administrative units but shows significant, persistent clustering within metallogenic belts (Moran's I = 0.205–0.262, $p < 0.01$). Notably, this clustering remained pronounced even as the total number of mines decreased by approximately 62%, highlighting the enduring control of geological endowment over mining spatial layout—an influence that transcends policy cycles and economic fluctuations. Based on these findings, we further propose a three-tier "endowment-pattern-policy" governance framework, which classifies metallogenic belts into Core Hot Spots, Emerging Potential Zones, and Marginal Scattered Areas, with differentiated management strategies. The study provides a systematic toolkit for spatial governance and supports a shift toward "nature-based precision governance" of mineral resources in China.

KEYWORDS
metallogenic belt, Central Asian Orogenic Belt, spatial analysis, GIS, sustainable mining, spatial governance

1 Introduction

The efficient management and sustainable development of mineral resources are crucial for regional development. For a long time, the formulation and implementation of related policies have largely been based on administrative units. While this approach offers advantages in terms of clear accountability and ease of execution (Reeve and Brunckhorst et al., 2007; Meyer et al., 2015), it may inherently mismatch the natural distribution patterns of mineral resources, which are fundamentally shaped by geological history (Fan et al., 2021). Such spatial disconnection can lead to inefficient resource allocation, regulatory gaps, constraining the achievement of sustainable development goals across various domains, including urban land-use planning (O'Driscoll et al., 2023), regional development coordination (Zeng et al., 2024), and the spatial harmony of sustainability objectives (Liu et al., 2024). Although geology has long established that mineral resources tend to cluster within "metallogenic belts," existing studies still predominantly adopt administrative units as the default analytical framework (Sairinen et al., 2021). There remains a lack of empirical research that systematically compares, within a unified quantitative framework, the explanatory power of "administrative boundaries" versus "metallogenic belt boundaries" on the spatial patterns of mining activities (Jeong, 2023; Benomar et al., 2009; Bai et al., 2023).

This study selects Northern Xinjiang, located in the core of the Central Asian Orogenic Belt, as a representative case area (Figure 1). The region features complex tectonic settings and abundant mineral resources, including significant reserves of energy and strategic minerals in China (Zhao et al., 2009; Li et al., 2013). Its resource endowment pattern—described as "widely distributed yet relatively concentrated"—provides an ideal setting for investigating the dominant controlling factors of mining spatial patterns. To address the core research question—"at a macro-regional scale, are mining development patterns more aligned with human-defined administrative boundaries or with natural metallogenic belt boundaries?"—this study constructs a dual-track analytical framework of "administrative units versus metallogenic belt units." We employ a suite of spatial analysis methods, including global and local spatial autocorrelation (Global/Anselin Local Moran's I), Getis-Ord Gi*hotspot detection, kernel density estimation, and centroid migration modeling. The validity of this methodological suite is anchored in its proven capacity to detect spatial heterogeneity and clustering across disparate phenomena. It has been effectively deployed to quantify administrative boundary effects in regional development, to model the spatial patterns of social systems, and to identify risk hotspots in infrastructure networks (Jeong, 2023; Zeng et al., 2024; Liu et al., 2024). Based on mine location data from 2011 to 2021, this research aims to empirically test the control effects of different boundary units on the spatial patterns of mining development and to reveal the underlying formation mechanisms.

This study seeks not only to deepen the understanding of the fundamental role of natural elements within human-environment system theory but also to provide a scientific basis for optimizing the spatial governance of regional mineral resources. The findings are expected to promote a paradigm shift in mining management from "administrative convenience" toward "scientific precision" (Simoni et al., 2024; Jensen and Greer, 2020). Furthermore, they offer a transferable methodological reference for global discussions on sustainable resource management, contributing to the alignment of governance structures with geological realities.

2 Materials and methods

2.1 Study area

The study area is located in Northern Xinjiang, China (79°–96° E, 41°–49° N), covering approximately 600,000 km^2 (Liang et al., 2008). It spans major tectonic units, including the Altay, Junggar, and Tianshan orogenic belts, which provide superior metallogenic

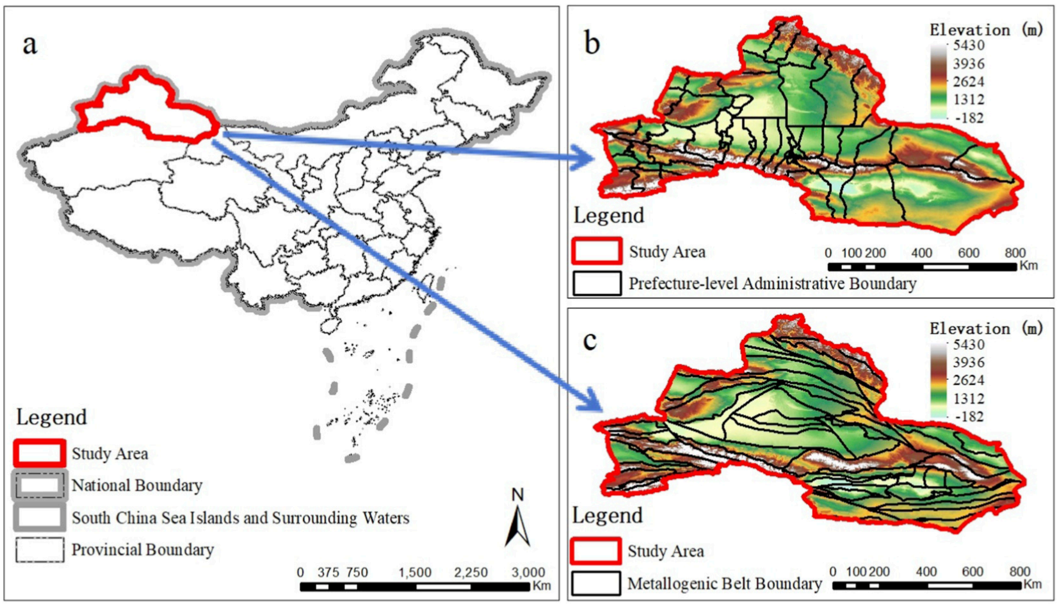

FIGURE 1
Overview of the study area **(a)** simplified map of China(data source: Tianditu); **(b)** prefectural-level administrative boundaries; **(c)** major metallogenic belt boundaries.

conditions and host diverse mineral resources. The region exhibits significant energy resource potential, with estimated reserves of 23 billion tons of petroleum, 16 trillion cubic meters of natural gas, and 2.19 trillion tons of coal, accounting for approximately 30%, 34%, and 40% of China's total onshore resources, respectively (Zhao et al., 2009). It also possesses substantial strategic mineral resources, such as iron, copper, gold, chromium, and nickel, which play a crucial role in the national resource landscape. Furthermore, the area is distinguished by unique mineral resources, including over 70 types of gemstones such as Hetian jade. In total, 142 mineral types have been discovered in the region, 13 of which rank first in China in terms of reserves, making it a key strategic base for energy, metallic, and non - metallic mineral resources in the country (Li et al., 2013).

2.2 Data sources and processing

This study utilized mine location data from six time points (2011, 2013, 2015, 2017, 2019, and 2021), obtained from the "Remote Sensing Geological Survey and Monitoring of National Mine Development Status" project of the China Geological Survey. The dataset, validated through remote sensing interpretation and field surveys, is highly reliable. Key spatial boundary data included administrative divisions (vector boundaries of nine prefectural - level units) and metallogenic belts (compiled based on the National Mineral Resource Potential Assessment and related geological maps, encompassing major belts such as the Southern Junggar, Turpan - Hami Basin, and Altay). All spatial data were uniformly projected into the CGCS2000_3_Degree_GK_Zone_29 coordinate system using the ArcGIS platform and underwent topological validation to ensure analytical accuracy and consistency.

2.3 Analytical framework and methods

To systematically compare the controlling effects of administrative boundaries and metallogenic belt boundaries on mining spatial patterns, this study constructed a dual-track analytical framework, following the logical progression of "administrative unit → metallogenic belt unit → evolutionary trend".

The spatial analysis employed a comprehensive technical chain that progresses from global to local scales and from static to dynamic analysis:

Global Moran's I identifies the overall spatial distribution pattern by calculating the spatial autocorrelation index (Zhang et al., 2024; Zhang et al., 2023; Thioulouse et al., 1995).

Getis-Ord General G distinguishes the dominant type of clustering (high-value or low-value) by comparing observed and expected values (Liang et al., 2020; Yoon et al., 2019).

Anselin Local Moran's I detects spatial heterogeneity and identifies specific clustering areas by computing local spatial autocorrelation (Zhang et al., 2023; Porat et al., 2011; Anselin et al., 1997).

Getis-Ord Gi*identifies statistically significant hot spots and cold spots and their confidence levels through significance testing (Ahmad et al., 2023; Shams, 2021; Liu et al., 2019). A tiered confidence level system (90%, 95%, 99%) was used for hotspot classification. This approach is justified because it maintains graded statistical rigor and directly informs the subsequent three-tiered governance framework (e.g., Core Hot Spots), translating statistical confidence into actionable policy categories.

Kernel density estimation visualizes spatial distribution characteristics and agglomeration intensity by generating continuous density surfaces (Zheng et al., 2021). In this analysis, a fixed bandwidth method was employed. The bandwidth (search radius) was set to 26,631 m (approximately 26.6 km). This value was determined by the spatial characteristics of the input data using the ArcGIS software's default algorithm and validated through sensitivity testing to ensure it effectively revealed regional-scale clustering patterns without excessive smoothing.

The centroid model characterizes spatiotemporal evolution patterns and directions by tracking the movement trajectory of the distribution center (Kang et al., 2017; Kandeepan et al., 2019). To assess its spatial constraint, a 15 km buffer was applied. This threshold was determined through sensitivity testing as the minimum distance that fully contained all annual centroids within the core Shihezi-Santai metallogenic belt, ensuring a robust measure of spatial confinement. This methodological system provides multi-layered evidence to test the research hypotheses (Figure 2).

The specific analytical procedure consisted of three steps:

1. Pattern analysis based on administrative units. Using prefectural-level administrative regions as the analysis unit, the complete spatial statistics method sequence was applied to assess the spatial characteristics of mine distribution within the administrative framework, thereby revealing the detailed spatial structure within administrative units.

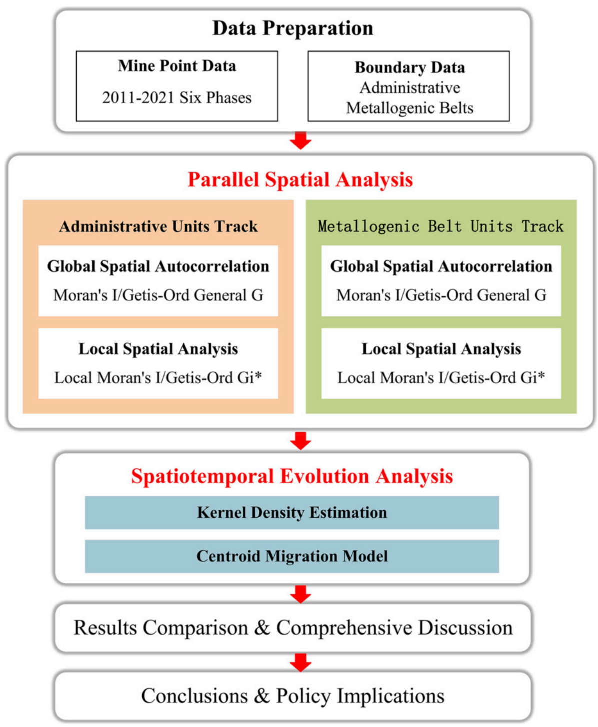

FIGURE 2
Technical workflow of the dual-track analytical framework.

2. Pattern analysis based on metallogenic belt units. The analysis unit was switched to metallogenic belts, applying the identical methodological workflow used for administrative units to compute the spatial patterns within the metallogenic belt framework.
3. Spatiotemporal evolution trend analysis. To reveal dynamic changes in the spatial pattern of mines, kernel density estimation was used to generate continuous density surfaces, visually displaying the spatiotemporal evolution of mine aggregation centers and extents. Simultaneously, the centroid model was utilized to track the movement trajectory of the average annual center of mine distribution, providing a dynamic perspective to corroborate the stability of the spatial pattern and its dominant controlling factors.

All spatial autocorrelation analyses for areal data were performed on the ArcGIS platform, using the "CONTIGUITY_EDGES_CORNERS" spatial relationship definition and "ROW" standardization, ensuring the rigor of the analytical process and the comparability of the results. For the Moran's I and Getis-Ord indices, the input variable was the count of mines within each spatial unit. We deliberately used the raw count rather than density to focus on detecting the absolute spatial association of mining occurrences themselves, which is directly relevant for evaluating the alignment of mining patterns with pre-existing geological boundaries.

This complete dual-track framework and methodological chain ensures a comprehensive demonstration, progressing from global to local scales and from static comparison to dynamic verification.

This study compares mining spatial patterns using two spatial unit systems within a dual-track analytical framework: 55 administrative units and 62 metallogenic belt units. We recognize that spatial autocorrelation analysis is sensitive to the definition of the spatial weight matrix and that differences in the number, size, and shape of units may affect the comparability of results. To ensure a fair comparison, this study adopts three strategies: First, within each system, the same spatial weight matrix (first-order Queen contiguity with row-standardization) and the same statistical methodological workflow are strictly applied, ensuring that any sensitivity arising from matrix specification or boundary effects is equally present in both analytical tracks, thereby avoiding bias in the comparative conclusions. Second, the analytical focus is on testing whether statistically significant spatial clustering patterns exist within each system, rather than directly comparing the absolute values of statistics between the two systems. Third, supplementary analyses based on point data methods, such as kernel density estimation and centroid migration modeling, are employed; the results from these methods, which are independent of zonal demarcations, align with and are strengthened by the conclusions derived from areal unit analyses. In summary, despite differences between the unit systems, through the consistent analytical setup and the convergence of evidence from multiple sources, this study effectively evaluates and compares the explanatory power of the two systems regarding the spatial patterns of mining development.

3 Results

3.1 Ambiguous and random patterns under the administrative boundary framework

Global spatial analysis based on prefectural-level administrative units revealed a distinct pattern. As shown in Tables 1, 2, the Global Moran's I index did not pass the significance test at the 5% level across all six time periods (p-value >0.05 for all years), indicating no significant spatial autocorrelation in mine distribution under the administrative unit framework, with the overall pattern approximating a random distribution. Although the Getis-Ord General G index indicated statistically significant clustering in some years (e.g., 2011, 2015, 2017, 2019, 2021; p-value <0.05), the magnitude of this clustering was weak. The absolute differences between observed and expected values were small (ranging from 0.003 to 0.005), and the z-scores, while statistically significant,

TABLE 1 Global Moran's I index based on administrative units.

Year	2011	2013	2015	2017	2019	2021	Pooled data 2011–2021
Moran's I index	−0.050028	−0.080729	−0.006737	−0.008161	−0.075014	0.013672	−0.051521
Expected index	−0.018519	−0.018519	−0.018519	−0.018519	−0.018519	−0.018519	−0.018519
Variance	0.006385	0.006274	0.006002	0.006018	0.007014	0.006124	0.006050
z-score	−0.394315	−0.785386	0.152077	0.133520	−0.674577	0.411363	−0.424293
p-value	0.693349	0.432227	0.879126	0.893782	0.499945	0.680806	0.671352

TABLE 2 Global Getis-Ord General G index based on administrative units.

Year	2011	2013	2015	2017	2019	2021	Pooled data 2011–2021
General G observed	0.022517	0.020971	0.022004	0.021988	0.021530	0.023462	0.021847
General G expected	0.018519	0.018519	0.018519	0.018519	0.018519	0.018519	0.018519
Variance	0.000004	0.000002	0.000002	0.000002	0.000002	0.000004	0.000002
z-score	2.128989	1.745307	2.342152	2.327529	2.096626	2.439067	2.238788
p-value	0.033255	0.080931	0.019173	0.019937	0.036027	0.014725	0.025170

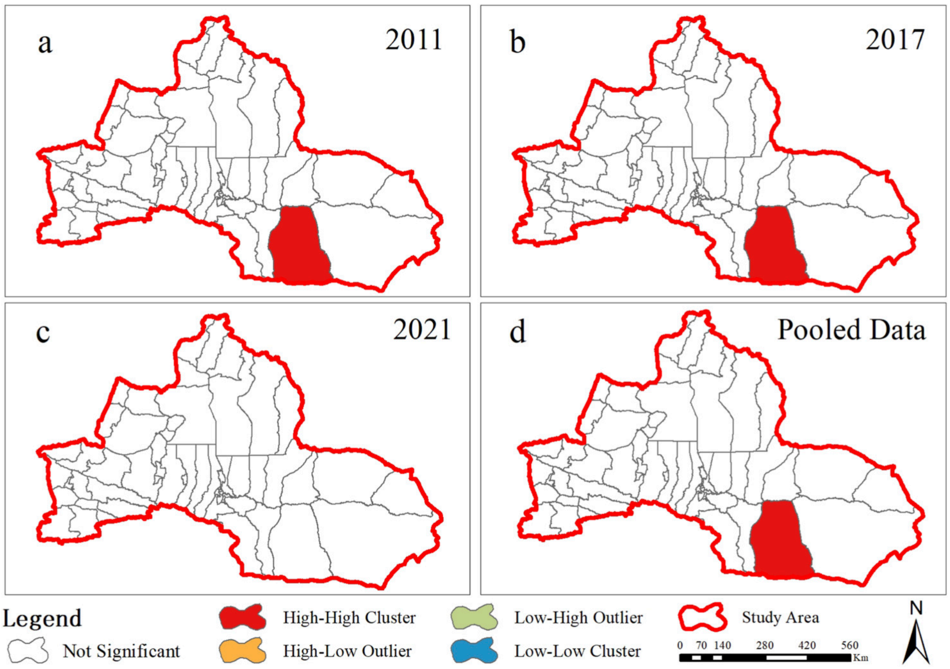

FIGURE 3
Spatial pattern comparison of Anselin Local Moran's I results based on administrative units **(a)** 2011; **(b)** 2017; **(c)** 2021; **(d)** pooled data 2011–2021.

were modest (1.75–2.44). This indicates that any local clustering within the administrative framework lacked a strong, cohesive structure at the macro-regional scale, and the overall spatial pattern remained predominantly random. These results statistically refute the effectiveness of administrative units in characterizing the spatial pattern of mining development, setting a baseline against which the explanatory power of natural geological units can be contrasted.

Local spatial analysis provided finer evidence for this random pattern. As shown in Figure 3 and Table 3, the Anselin Local Moran's I analysis identified only Shanshan County as showing "H-H" clustering in some years (2011, 2015, 2017, and the pooled data 2011–2021 data), without forming persistent, contiguous high-value agglomeration areas. Similarly, Getis-Ord Gi*hot spot analysis (Figure 4; Table 4) revealed that hot spots were scattered and unstable in spatiotemporal distribution. Although Shanshan County, Mulei County, and Yiwu County were identified as hot spots with varying confidence levels (90%–95%) in different years, they failed to form a geographically coherent pattern.

TABLE 3 **Local High-High Clusters based on administrative units (Anselin Local Moran's I).**

Year	High-high clusters
2011	Shanshan county
2013	Not significant
2015	Shanshan county
2017	Shanshan county
2019	Not significant
2021	Not significant
Pooled data 2011–2021	Shanshan county

3.2 Significant and aggregated patterns under the metallogenic belt framework

In fundamental contrast to the ambiguous and random patterns observed under administrative boundaries, analysis based on metallogenic belt units reveals a highly significant, stable, and strongly aggregated spatial configuration of mining activity.

The analysis shows strong spatial autocorrelation in mining distribution under the metallogenic belt framework. As seen in Table 5, the Global Moran's I indices for metallogenic belts are consistently and significantly positive across all years ($p < 0.01$ for 2011–2021), with values ranging from 0.205 to 0.262. These are markedly higher than the results under the administrative framework. This confirms that geological structural units exert fundamental control over the spatial configuration of mining development. The Getis-Ord General G index provides stronger evidence (Table 6). The observed values (approx. 0.028–0.032) are nearly double the expected value (0.016) annually, with p-values reaching extreme significance ($p < 0.001$). This finding confirms not only the presence of clustering but, more critically, reveals that it is predominantly driven by high-density mining areas. This empirically aligns with the known distribution patterns of ore deposit clusters.

At the local scale, the spatial location of core aggregation zones is identified. The Anselin Local Moran's I results (Figure 5) show that mining development forms persistent and stable "High-High" clustering areas in space (Table 7). The Ili Basin, Urumqi-Dushanzi,

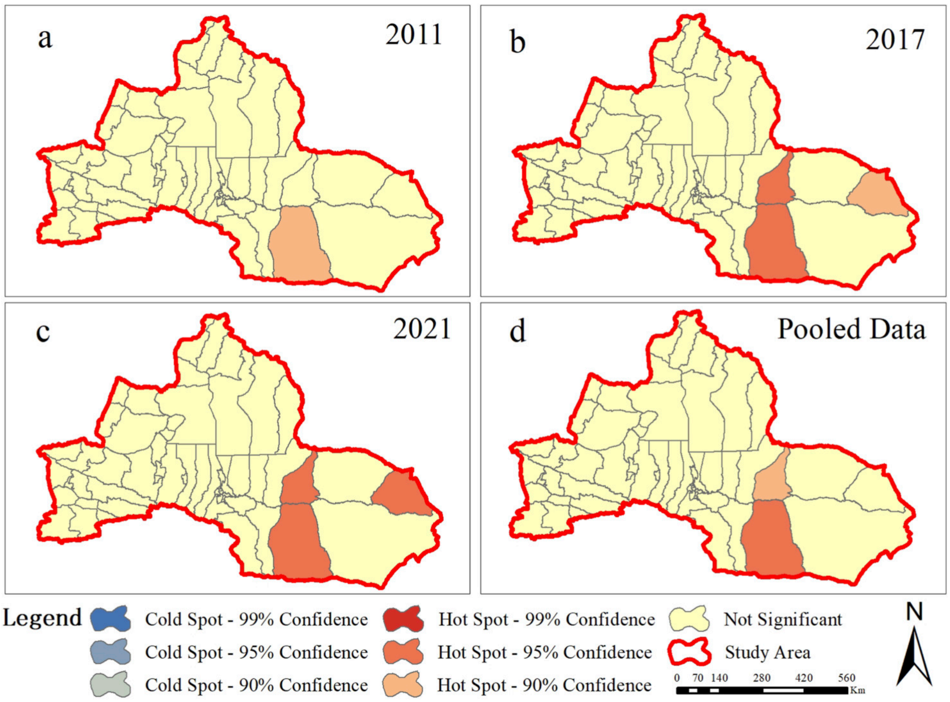

FIGURE 4
Spatial pattern comparison of Getis-Ord Gi*hot spot analysis results based on administrative units **(a)** 2011; **(b)** 2017; **(c)** 2021; **(d)** pooled data 2011–2021.

TABLE 4 **Local hot spots based on administrative units (Getis-Ord Gi*).**

Year	Hot spots (by confidence level)
2011	Shanshan county (90% confidence)
2013	Not significant
2015	Shanshan county, Mulei county (95% confidence); Yiwu county (90% confidence)
2017	Shanshan county, Mulei county (95% confidence); Yiwu county (90% confidence)
2019	Shanshan county (90% confidence)
2021	Shanshan county, Mulei county, Yiwu county (95% confidence)
Pooled data 2011–2021	Shanshan county (95% confidence); Mulei county (90% confidence)

Bogda, and Shihezi-Santai metallogenic belts constitute the core high-value agglomeration zones. They exhibit significant spatial positive correlation in the vast majority of years.

Hotspot analysis further delineates the detailed spatial extent and statistical confidence of these clusters. Getis-Ord Gi*analysis (Figure 6) identifies specific hotspot regions. As shown in Table 8, the Urumqi-Dushanzi and Shihezi-Santai metallogenic belts consistently function as core hotspots with 99% confidence throughout the entire study period. Multiple other belts, including Bogda and Alatau, also achieve high confidence levels (above 95%) in most years. Together, they form an extensive "mining cluster" with broader spatial coverage and higher statistical significance.

In conclusion, evidence from global to local analysis, and from confirming aggregation to locating core areas, demonstrates that mining development under the metallogenic belt framework is characterized by spatially contiguous distribution and temporally persistent stability. This stands in fundamental opposition to the random and unstable patterns identified under the administrative framework. It forcefully underscores the superior explanatory power of natural geological units in interpreting the spatial patterns of mining development.3.3 Spatiotemporal Evolution as Evidence of Dominant Controlling Factors.

The dominant control of metallogenic belts, established through the static comparative analysis above, is further corroborated by the dynamic spatiotemporal evolution of mining patterns. To analyze these evolution characteristics of mineral resource distribution, this study employed kernel density estimation for quantitative analysis. The results were classified into three tiers (high, medium, and low) based on the percentile distribution of the kernel density values themselves: the low-value tier encompassed the lowest 20% of density values, representing sparse areas with limited practical significance; the medium-value tier included values between the 20 th and 60 th percentiles, indicating zones of moderate resource aggregation; and the high-value tier comprised the top 40% of density values, corresponding to areas of relative resource enrichment within the distribution for each time point. This quantile-based classification scheme provides an objective, data-driven framework, minimizing the subjective bias inherent in

TABLE 5 Global Moran's I index based on metallogenic belt boundaries.

Year	2011	2013	2015	2017	2019	2021	Pooled data 2011–2021
Moran's I index	0.205134	0.261751	0.261478	0.261490	0.227795	0.234270	0.239200
Expected index	−0.01639	−0.01639	−0.01639	−0.01639	−0.01639	−0.01639	−0.01639
Variance	0.005459	0.007276	0.007270	0.007270	0.005878	0.006738	0.006469
z-score	2.998175	3.260736	3.259283	3.259172	3.184899	3.053617	3.177866
p-value	0.002716	0.001111	0.001138	0.001117	0.001448	0.002261	0.001484

TABLE 6 Global Getis-Ord General G index based on metallogenic belt boundaries.

Year	2011	2013	2015	2017	2019	2021	Pooled data 2011–2021
General G observed	0.032046	0.030357	0.028627	0.028645	0.030603	0.027987	0.030010
General G expected	0.016393	0.016393	0.016393	0.016393	0.016393	0.016393	0.016393
Variance	0.000018	0.000017	0.000012	0.000012	0.000015	0.000010	0.000014
z-score	3.719956	3.418768	3.575878	3.571651	3.703460	3.612778	3.680857
p-value	0.000199	0.000629	0.000349	0.000355	0.000213	0.000303	0.000232

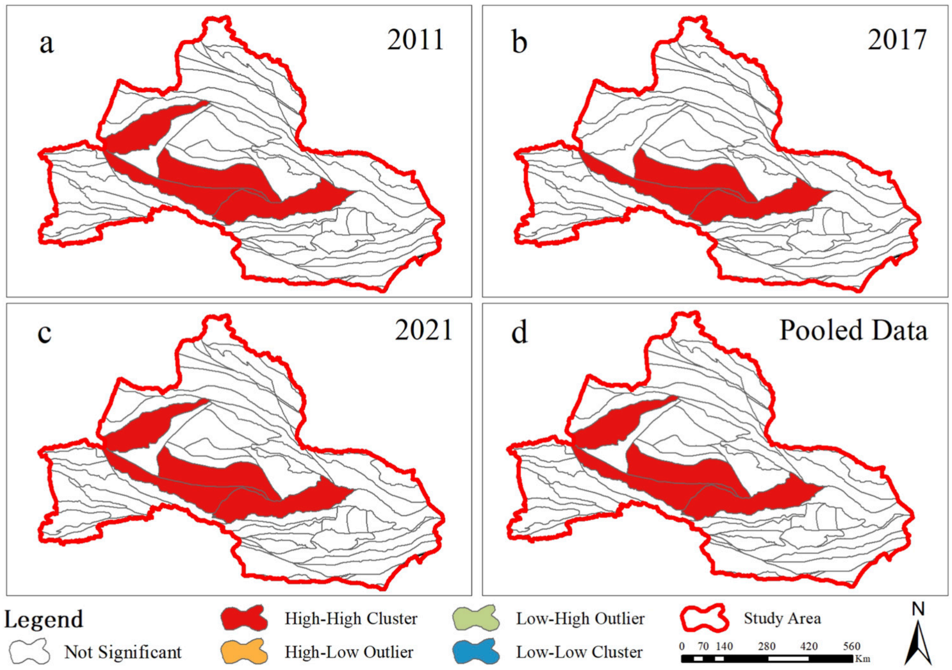

FIGURE 5
Spatial pattern comparison of Anselin Local Moran's I results based on metallogenic belt units **(a)** 2011; **(b)** 2017; **(c)** 2021; **(d)** pooled data 2011–2021.

alternative methods (e.g., natural breaks). More importantly, it ensures consistent interpretability across time—the 'high-tier' consistently represents the top 40% of density values in any given year—enabling robust temporal comparison of relative spatial enrichment.

The kernel density estimation results revealed a continuous dispersion trend in the spatial distribution of mines from 2011 to 2021. The threshold for high-density areas decreased from 0.128 to 0.213 in 2011 to 0.021–0.035 in 2021. This trend corresponds with the decline in the total number of mines from 3,464 to 1,304. The decrease in thresholds quantitatively reflects the overall convergence of regional resource development intensity and, furthermore, reveals the evolutionary trajectory of the spatial pattern: a transition from the initial high-intensity core agglomeration to a multi-center, low-intensity diffusion model within the context of metallogenic belts.

TABLE 7 Local High-High Clusters based on metallogenic belt units (Anselin Local Moran's I).

Year	High-high clusters
2011	Ili Basin, Urumqi-Dushanzi, Bogda, Shihezi-Santai
2013	Urumqi-Dushanzi, Bogda, Shihezi-Santai, Tangbale-Hatu
2015	Urumqi-Dushanzi, Bogda, Shihezi-Santai
2017	Urumqi-Dushanzi, Bogda, Shihezi-Santai
2019	Ili Basin, Urumqi-Dushanzi, Bogda, Shihezi-Santai
2021	Ili Basin, Urumqi-Dushanzi, Bogda, Shihezi-Santai
Pooled data 2011–2021	Ili Basin, Urumqi-Dushanzi, Bogda, Shihezi-Santai

This shift likely results from the combined effects of resource endowment conditions, market regulation policies (such as capacity reduction and stricter environmental regulations), and environmental constraints, marking a transition in regional mining development from extensive expansion to intensive and refined stages.

Spatially, the extent of high-density areas began to contract between 2011 and 2013, remained stable from 2015 to 2017 (with high-value ranges consistently between 0.038 and 0.064), showed a slight rebound in 2019, and became further dispersed by 2021, forming several scattered high-density patches. This reflects an evolutionary pattern where mineral resource development gradually shifted from initial relative concentration to multi-polar diffusion.

The migration trajectory of the distribution centroid further corroborates the ongoing adjustment of the spatial pattern. Although the centroid of mineral resource distribution shifted between Changji, Hutubi, and Wujiaqu from 2011 to 2021, buffer analysis showed that the maximum distance from the centroid to the boundary of the Shihezi-Santai metallogenic belt never exceeded 15 km. The centroid consistently remained within this metallogenic belt without cross-boundary migration, indicating that resource development activities are spatially constrained by the distribution of resource endowment. The metallogenic belt acts as a "gravitational center" for development activities.

In summary, against the backdrop of a declining number of mines, the spatial distribution exhibits dynamic adjustments characterized by dispersion and multi-polarization. However, the distribution centroid remains strictly confined within the spatial extent of core metallogenic belts, such as Shihezi-Santai. This spatiotemporal trajectory strongly demonstrates that the resource base provided by geological endowment functions as an "attractor" in the spatial evolution of the mining system, exhibiting control that is long-term and stable, transcending policy cycles and economic fluctuations. This spatiotemporal evolutionary process not only reinforces the conclusion that resource endowment is the dominant spatial attractor but also provides a dynamic foundation for understanding the mechanisms behind the pattern differences, which we will further disentangle in the Discussion. It offers a scientific basis for integrated regional resource management and planning layout.

3.3 Robustness of the spatial pattern amidst industry contraction

A critical consideration is the robustness of the identified spatial clustering pattern given the substantial contraction in mining activity, with the total number of mines declining by approximately 62% from 2011 to 2021. To assess whether this dramatic change in sample size affected our core finding, we examined the relationship between the annual scale of activity (total mine count) and the intensity of spatial agglomeration measured by the Global Moran's I for metallogenic belt units.

As shown in Figure 7, the scatter plot reveals that Moran's I values remained consistently high and statistically significant (ranging from 0.205 to 0.262) across the entire period, despite the precipitous drop in mine numbers. Statistical analysis indicates a moderate negative correlation (Pearson's $r = -0.625$, $p = 0.183$; $R^2 = 0.391$, $n = 6$). While this correlation does not meet the conventional threshold of statistical significance ($p < 0.05$), likely due to the limited number of temporal observations, the consistent direction and magnitude of the relationship are noteworthy. It suggests a tendency for spatial clustering within metallogenic belts to become slightly more pronounced as the total number of mines decreases.

This observation aligns with the concept of "selective survival" or "rationalization to the core" during industry consolidation. It is plausible that mines closed during this period were disproportionately located in geologically marginal areas or outside the core metallogenic zones, while operations within the resource-rich heart of the belts demonstrated greater resilience. Consequently, the spatial signal—the stark contrast between clustered development within belts and scattered activities outside—was not diluted but potentially sharpened despite the overall industry contraction.

Therefore, this sensitivity analysis provides strong, quasi-experimental support for our central thesis. It demonstrates that the fundamental control exerted by geological endowment is not only stable across time but may even be accentuated under conditions of external pressure and sectoral downsizing, acting as a durable spatial anchor that guides the evolution of the mining landscape.

4 Discussion

4.1 The foundational control of resource endowment: a mechanistic interpretation

The findings from Chapter 3 establish a clear empirical contrast: mining development exhibits no statistically significant spatial pattern under administrative units, yet demonstrates strong, persistent, and significant clustering within metallogenic belts. This systematic divergence originates from a deeper, synergistic control mechanism, conceptualized in this study as the "resource-economy-technology triangular constraint." This framework elucidates the causal logic behind the observed spatial patterns.

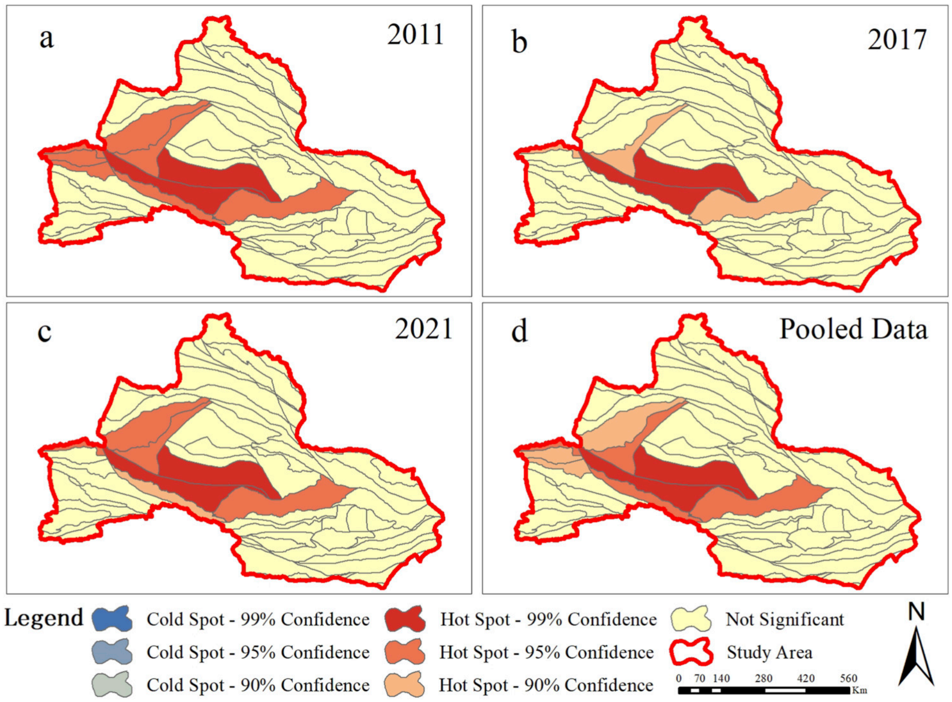

FIGURE 6
Spatial pattern comparison of Getis-Ord Gi*hot spot analysis results based on metallogenic belt units **(a)** 2011; **(b)** 2017; **(c)** 2027; **(d)** pooled data 2011–2021.

Geological endowment is the primary constraint. The consistently high Moran's I values (0.205–0.262, $p < 0.01$, Table 5) reflect how tectonic history preconfigures mineral distribution. This geological foundation establishes the essential, non-negotiable template for all subsequent activity. Economic rationality operates within this template. The Getis-Ord General G index results (Table 6), indicating clustering driven by high values, encapsulate the market's efficiency logic: investment and operational resources converge preferentially on areas where superior geological endowment promises higher economic returns. Economics thus activates and intensifies the pre-existing spatial pattern dictated by geology.

Over time, this pattern is stabilized through technological and infrastructural lock-in, creating path dependency. The spatiotemporal evolution analysis (Section 3.3, Figures 8, 9) confirms that while mining intensity may vary, its spatial anchors remain firmly within core metallogenic belts. This stability arises from substantial, location-specific investments in specialized extraction and processing technologies, tailings management systems, and dedicated transport networks. These sunk costs and localized expertise render the initial geography highly resistant to change.

This mechanism explains why clustering persisted during industry contraction (Section 3.4) (Cainelli et al., 2020). The persistence—and even strengthening—of spatial aggregation amidst a 62% reduction in mine numbers suggests a process of spatial rationalization: under pressure, operations in geologically and economically marginal areas are selectively discontinued, while those best aligned with the core "resource-economy-technology" logic endure. This confirms resource endowment as a durable spatial anchor, whose control is clarified, not diluted, during systemic stress. The failure of the administrative framework stems from its misalignment with this synergistic reality, revealing a critical disconnect between conventional governance structures and the actual drivers of mining geography.

4.2 The imperative for a governance paradigm shift

The mechanistic understanding developed in Section 4.1 reveals a profound governance misalignment. The prevailing paradigm, which relies on static administrative boundaries as the primary spatial unit for policy, is fundamentally disconnected from the dynamic "resource-economy-technology" system that actually governs mining location and evolution. This disconnect generates systemic inefficiencies that hinder sustainable resource management.

In regions of intense mining activity, administrative boundaries fragment integrated geological systems. This fragmentation impedes coordinated environmental management of cross-jurisdictional issues like cumulative water pollution, complicates planning for shared infrastructure, and frustrates the development of unified strategies for industrial synergy or post-mining transition. Governance efforts become diluted and potentially contradictory across jurisdictions managing parts of the same resource system.

Conversely, in areas of sparse or dispersed activity, the administrative model leads to inefficient allocation of regulatory resources. Oversight is spread thinly over vast areas for minimal

TABLE 8 Local hot spots based on metallogenic belt units (Getis-Ord Gi*).

Year	Hot spots (by confidence level)
2011	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 95% confidence: Alatau, Hanjiga, Sailimu, Yilianhabier, Tangbale-Hatu, Karamay-Urho, Bogda
2013	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 90% confidence: Ili Basin, Awulale, Alatau, Yilianhabier, Bogda, Karamay-Urho
2015	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 90% confidence: Bogda, Karamay-Urho
2017	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 90% confidence: Bogda, Karamay-Urho
2019	99% confidence: Urumqi-Dushanzi, Shihezi-Santai, Bogda 95% confidence: Alatau, Hanjiga, Yilianhabier, Tangbale-Hatu, Karamay-Urho 90% confidence: Sailimu
2021	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 95% confidence: Bogda, Alatau, Tangbale-Hatu, Karamay-Urho 90% confidence: Yilianhabier
Pooled data 2011–2021	99% confidence: Urumqi-Dushanzi, Shihezi-Santai 95% confidence: Bogda, Alatau, Yilianhabier, Karamay-Urho 90% confidence: Sailimu, Hanjiga, Tangbale-Hatu

aggregate impact, diverting capacity from zones where it is more critically needed. This uniform approach fails to distinguish between areas of inherently high and low developmental pressure or risk.

The empirical evidence, particularly the stark explanatory contrast between administrative and metallogenic belt units detailed in Chapter 3, provides a compelling scientific rationale for change. It demonstrates that governance effectiveness depends on congruence between the unit of management and the unit of the underlying process. Therefore, a deliberate shift from a paradigm of "administrative convenience" to one of "scientific precision" is a necessary precondition for coherent, efficient, and sustainable mineral resource governance (Simoni et al., 2024; Murguía and Bastida, 2024; Dycá et al., 2024).

4.3 Developing a precision classification and governance framework

To translate spatial diagnostics into actionable policy, this study proposes a precise "endowment-pattern-policy" framework. It classifies metallogenic belts into distinct governance types using transparent, quantitative criteria derived from Chapter 3's results, ensuring objectivity and reproducibility. The classification synthesizes two key analytical outputs: local hotspot confidence (Getis-Ord Gi*) and activity intensity (kernel density percentiles). Three governance types are defined.

1. Core Hot Spots: This type includes belts identified as 99% confidence hotspots in the Getis-Ord Gi*analysis for at least 75% of the study years (Figure 6, Table 8) and with annual kernel density values persistently within the top 40 th percentile (i.e., ≥60 th percentile) (Section 3.3, Figure 7). Examples include the Urumqi-Dushanzi and Shihezi-Santai metallogenic belts. For these zones, governance must prioritize intensive management and optimization. Core objectives and instruments, detailed in Table 9, focus on mining rights consolidation, the implementation of the most stringent life-cycle environmental standards coupled with mandatory remediation plans, and the proactive development of post-mining economic transition strategies.
2. Emerging Potential Zones: This category encompasses belts with 90%–95% confidence hotspot status in the Getis-Ord Gi*analysis and kernel density values primarily fluctuating within the 20 th to 60 th percentile. Governance for these areas should focus on preventive guidance and structured development. As outlined in Table 9, key strategies include legally mandated environmental and social carrying capacity assessments prior to any new development and the formalization of community co-construction mechanisms from the outset.
3. Marginal Scattered Areas: This type is defined by belts showing no significant clustering in hotspot analysis and with kernel density values persistently below the 20 th percentile. The governance priority, summarized in Table 9, is strict control and rationalization. This involves rigorous socio-environmental screening for access, encouragement for the aggregation of scattered operations, and the designation of areas for conservation.

This structured classification framework, along with its targeted governance strategies, is visually synthesized in Table 9. The spatial application of this framework across the study area is presented in Figure 10, which maps the resultant precision governance zoning. This approach enables a fundamental shift from uniform regulation to differentiated governance, ensuring policy interventions are aligned with the inherent spatial logic diagnosed through the "resource-economy-technology" constraint.

4.4 Policy implementation feasibility and transitional pathways

Implementing a geology-aligned governance framework necessitates navigating the tension between cross-boundary resource logic and entrenched administrative systems. A pragmatic, transitional approach is essential, favoring incremental adaptation over immediate institutional overhaul (Woiwode et al., 2024; Foxon et al., 2009; Termeer et al., 2024).

Strategic pilots should begin in Core Hot Spots, where the need for integration is most acute. This could involve establishing inter-administrative coordination bodies with mandates for belt-wide environmental and infrastructure planning. Crucially, performance metrics for involved jurisdictions should be redesigned to reward collaborative, belt-scale outcomes.

For Emerging Potential Zones, integration can occur through planning instruments. Major metallogenic belts should be

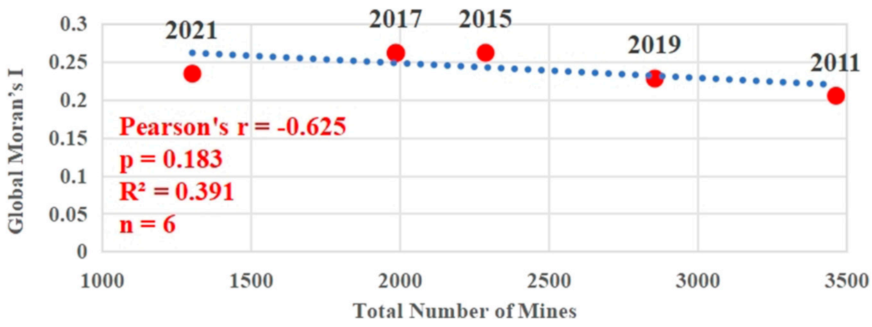

FIGURE 7
Relationship between the annual total number of mines and the Global Moran's I for metallogenic belt units (2011–2021; the dashed line indicates the linear regression trend).

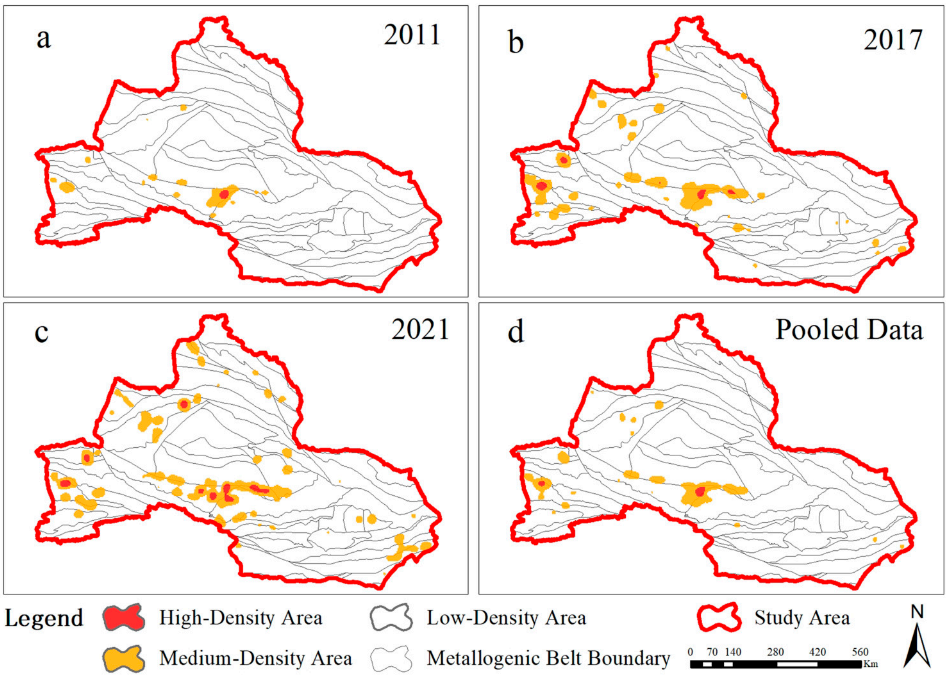

FIGURE 8
Comparison of spatial evolution of mine kernel density results **(a)** 2011; **(b)** 2017; **(c)** 2021; **(d)** pooled data 2011–2021.

recognized as a key layer in regional land-use and Strategic Environmental Assessments. Project permitting should require analysis of cross-jurisdictional, belt-scale impacts.

Governance of Marginal Scattered Areas can be streamlined by delegating primary regulatory oversight to a higher administrative level (e.g., provincial), ensuring consistent policy application and freeing local capacity for more complex zones.

The goal is not to redraw administrative maps but to superimpose a science-informed functional governance layer onto the existing structure. This hybrid model incentivizes cross-jurisdictional collaboration, aligns policies with natural systems, and builds the institutional experience needed for more effective and sustainable outcomes.

4.5 Data characteristics, limitations, and future directions

This study is based on mine location data from 2011 to 2021, revealing the macro-scale spatial configuration of mining activity in Northern Xinjiang. A 62% decline in the total number of mines during this period aligns with nationwide, policy-driven industrial restructuring, including the consolidation of mining rights, enhanced safety production, and the advancement of ecological civilization. This context further reinforces the core finding: despite sector-wide adjustment, mining activity remains significantly and increasingly concentrated within major metallogenic belts, confirming the persistent role of geological

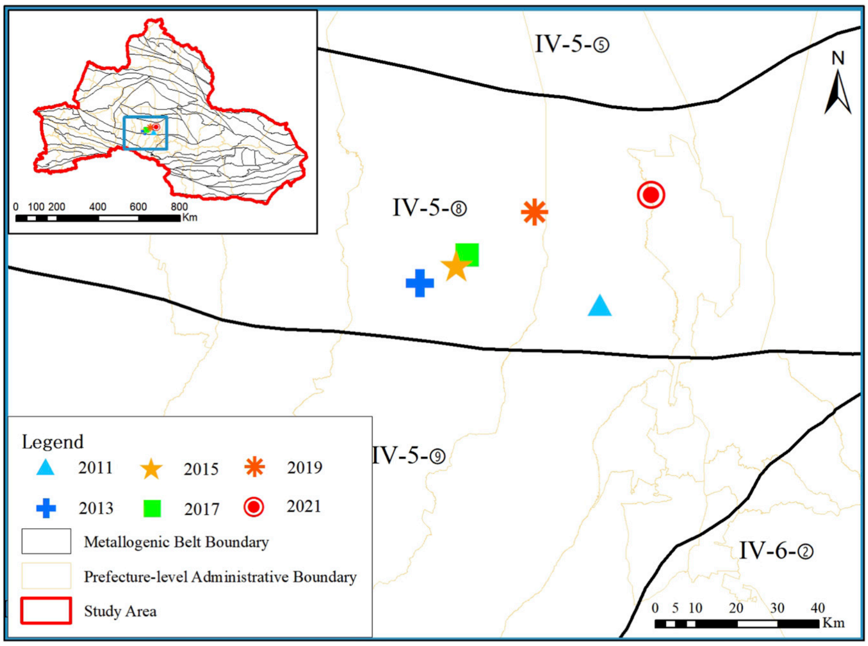

FIGURE 9
Evolutionary trajectory of mine distribution centroid migration.

TABLE 9 **Classification and governance framework for mining development.**

Governance type	Spatial identification indicators	Core objectives
Core hot spot (Urumqi-Dushanzi, Shihezi-Santai)	99% confidence hot spots Kernel density values persistently within the top 40 th percentile (i.e., ≥60 th percentile) Persistence and stability for over 6 years	Quality and efficiency improvement Green transition
Emerging potential zones (Ili Basin, Alatau, etc.)	90%–95% confidence hot spots Kernel density values primarily within the 20th–60 th percentile Significant spatiotemporal fluctuations	Standardized guidance Preventive protection
Marginal scattered areas	Low-density/Cold spot areas Kernel density values persistently below the 20th percentile Dispersed distribution	Strict access control Orderly exit

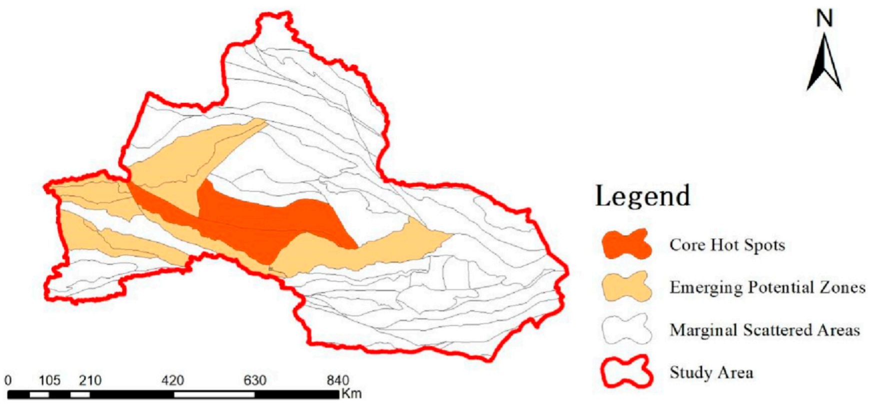

FIGURE 10
Map of precision classification and governance zoning for mining development.

endowment as a fundamental spatial constraint. However, this study has the following limitations.

1. The mine-count indicator effectively identifies the spatial clustering of mining activities and provides the basis for the three-tier governance zoning proposed in this study (Core Hot Spots, Emerging Potential Zones, and Marginal Scattered Areas). Nevertheless, this indicator has inherent limitations: it cannot reflect variations in mine scale, production level, or environmental impact, and thus fails to capture the multi-dimensional intensity and comprehensive effects of mining development.
2. As a spatially explicit case study, the specific spatial patterns and policy thresholds identified here are strongly conditioned by the unique resource endowment and developmental context of the study area. While the analytical logic—emphasizing geological over administrative units—is transferable in principle, extending this framework to other major metallogenic belts (e.g., the Andean or Tethyan belts) would require further explicit testing and calibration in future research to formally delineate its scope conditions.
3. The proposed governance framework incorporates key environmental and social governance instruments (such as carrying-capacity assessments). However, it does not yet fully integrate more complex dimensions, including cumulative environmental impact assessment across multiple projects within a belt, or systematic environmental-justice analysis based on the spatial equity of benefits and burdens. Deepening these aspects is essential to evolve the framework from a spatial-diagnostic tool into an integrated sustainable-management approach.

Therefore, future research should aim to develop a multi-dimensional mining-intensity indicator system that integrates multi-source data from production-economic (e.g., output value, production volume), environmental-pressure (e.g., land use, emissions), and social dimensions. By coupling spatial patterns with intensity attributes, secondary classification within the existing governance zones can be achieved—for instance, distinguishing high-intensity development sub-zones from ecological-restoration units—thereby providing a scientific basis for designing differentiated policy instruments such as tiered environmental access standards and ecological compensation mechanisms.

In summary, this study establishes a foundation for spatial diagnostics. Subsequent integration of intensity-based information and in-depth socio-environmental assessments will further advance mining spatial governance toward more precise, adaptive, and sustainable pathways.

5 Conclusion

This study demonstrates that resource endowment, through a "resource-economy-technology" triangular constraint, fundamentally controls the spatial patterns of mining development. We accordingly propose a three-tier "endowment-pattern-policy" precision governance framework, classifying metallogenic belts into Core Hot Spots, Emerging Potential Zones, and Marginal Scattered Areas to enable differentiated management. These findings and the resulting framework together provide a systematic toolkit for achieving nature-based precision governance, offering a scientifically grounded pathway towards more sustainable mineral resource management and spatial governance.

Data availability statement

The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Author contributions

TL: Conceptualization, Funding acquisition, Methodology, Project administration, Software, Validation, Writing – original draft, Writing – review and editing. GT: Data curation, Software, Validation, Writing – original draft. YS: Formal Analysis, Validation, Visualization, Writing – original draft, Writing – review and editing. FZ: Formal Analysis, Project administration, Supervision, Writing – review and editing. WW: Formal Analysis, Investigation, Validation, Writing – review and editing. WC: Resources, Software, Writing – review and editing.

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Conflict of interest

Author YS was employed by Extra-High Voltage Branch Company, State Grid Xinjiang Electric Power Co., Ltd.

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Supplementary material

The Supplementary Material for this article can be found online at: https://www.frontiersin.org/articles/10.3389/feart.2026.1766224/full#supplementary-material

References

Ahmad, I., Zelenakova, M., Fenta, A., Dar, M. A., Teka, A. H., Berhan, M., et al. (2023). Configuring the groundwater potential zone spatially using optimized hotspot analysis. *Environ. Earth Sci.* 82 (20), 467. doi:10.1007/s12665-023-11160-2

Anselin, L., and Kelejian, H. H. (1997). Testing for spatial error autocorrelation in the presence of endogenous regressors. *Int. Regional Sci. Rev.* 20, 153–182. doi:10.1177/016001769702000109

Bai, L., Dai, J., and Wu, C. (2023). Predictive prospecting using remote sensing in a mountainous terrestrial volcanic area, in Western Bangongco-Nujiang mineralization Belt, Tibet. *Remote Sens.* doi:10.3390/rs15194851

Benomar, T. B., Hu, G., and Bian, F. (2009). A predictive GIS model for potential mapping of copper, lead, and zinc in Langping area, China. *Geo-Spatial Inf. Sci.* 12 (4), 243–250. doi:10.1007/s11806-009-0089-0

Cainelli, G., Ganau, R., and Jiang, Y. (2020). Detecting space–time agglomeration processes over the great recession using firm-level micro-geographic data. *J. Geogr. Syst.* 22 (4), 419–445. doi:10.1007/s10109-020-00332-4

Dycá, B., Carsjens, G. J., Endl, A., and Gugerell, K. (2024). Beyond the surface: an analysis of the institutional regime in the extractive industries in Sweden and Spain. *Ecol. Econ.* 226, 108321. doi:10.1016/j.ecolecon.2024.108321

Fan, J., Wang, Y., Lian, Y., Zhou, K., and Liu, W. (2021). Spatial distribution and geographical mechanism of natural resources in China under the orientation of the new economic demands. *Sustainability* 13 (14), 7956. doi:10.3390/su13147956

Foxon, T. J., Reed, M. S., and Stringer, L. C. (2009). Governing long-term social–ecological change: what can the adaptive management and transition management approaches learn from each other? *Environ. Policy Gov.* 19 (1), 3–20. doi:10.1002/eet.496

Jensen, M., and Greer, L. (2020). The drive towards consensual perspectives for enhancing sustainable mining. *Resources* 9 (12), 147. doi:10.3390/resources9120147

Jeong, J. (2023). Discontinuities in regional economic development due to administrative boundaries: examining the mechanisms of the boundary effect. *Environ. Plan. B-Urban Anal. City Sci.* 51, 1227–1247. doi:10.1177/23998083231217013

Kandeepan, Xinghuo, and Yu, M. G. K. (2019). Accurate analysis of weighted centroid localization. *IEEE Trans. Cognitive Commun. Netw.* doi:10.1109/tccn.2018.2874452

Kang, Y. J., Noh, Y., and Lim, O. K. (2017). Kernel density estimation with bounded data. *Struct. Multidiscip. Optim.* 57 (1), 95–113. doi:10.1007/s00158-017-1873-3

Li, C., Wang, A., Chen, X., Chen, Q., Zhang, Y., and Li, Y. (2013). Regional distribution and sustainable development strategy of mineral resources in China. *Chin. Geogr. Sci.* 23 (4), 470–481. doi:10.1007/s11769-013-0611-z

Liang, T., Huang, X., Ren, J., Liu, X., Li, W., Guo, Z., et al. (2008). An application of MODIS data to snow cover monitoring in a pastoral area: a case study in Northern Xinjiang, China. *Remote Sens. Environ.* 112 (4), 1514–1526. doi:10.1016/j.rse.2007.06.001

Liang, S., Han, D., and Yang, Y. (2020). Cluster validity index for irregular clustering results. *Appl. Soft Comput.* 95, 106583. doi:10.1016/j.asoc.2020.106583

Liu, Z., and Gu, H. (2019). Evolution characteristics of spatial concentration patterns of interprovincial population migration in China from 1985 to 2015. *Appl. Spatial Analysis Policy* 13 (2), 375–391. doi:10.1007/s12061-019-09308-4

Liu, Q., Li, F., Dong, S., Cheng, H., Liang, L., and Xia, B. (2024). Spatial-temporal heterogeneity of sustainable development goals and their interactions and linkages in the Eurasian continent. *Sustain. Prod. Consum.* 52, 151–165. doi:10.1016/j.spc.2024.06.007

Meyer, W. S., Bryan, B. A., Summers, D. M., Lyle, G., Wells, S., McLean, J., et al. (2015). Regional engagement and spatial modelling for natural resource management planning. *Sustain. Sci.* 11 (5), 733–747. doi:10.1007/s11625-015-0341-5

Murguía, D. I., and Bastida, A. E. (2024). The elephant in the mine: why voluntary sustainability standards are insufficient to ensure responsible mining. *Extr. Industries Soc.* 19, 101485. doi:10.1016/j.exis.2024.101485

O'Driscoll, C., Crowley, F., Doran, J., and Mccarthy, N. (2023). Land-use mixing in Irish cities: implications for sustainable development. *Land Use Policy* 128, 106615. doi:10.1016/j.landusepol.2023.106615

Porat, I., Shoshany, M., and Frenkel, A. (2011). Two phase temporal-spatial autocorrelation of urban patterns: revealing focal areas of Re-Urbanization in Tel Aviv-Yafo. *Appl. Spatial Analysis Policy* 5 (2), 137–155. doi:10.1007/s12061-011-9065-9

Reeve, I., and Brunckhorst, D. (2007). Spatially bounded regions for resource governance. *Australas. J. Environ. Manag.* 14, 142–154. doi:10.1080/14486563.2007.10648712

Sairinen, R., Sidorenko, O., and Tiainen, H. (2021). A research framework for studying social impacts: application to the field of mining. *Environ. Impact Assess. Rev.* 86, 106490. doi:10.1016/j.eiar.2020.106490

Shams, A. N. K. A. (2021). GIS-based crash hotspot identification: a comparison among mapping clusters and spatial analysis techniques. *Int. J. Inj. Control Saf. Promot.* doi:10.1080/17457300.2021.1925924

Simoni, M. U., Drielsma, J. A., Ericsson, M., Gunn, A. G., Heiberg, S., Heldal, T. A., et al. (2024). Mass-balance-consistent geological stock accounting: a new approach toward sustainable management of mineral resources. *Environ. Sci. and Technol.* 58, 971–990. doi:10.1021/acs.est.3c03088

Termeer, K., Dewulf, A., and Biesbroek, R. (2024). Three archetypical governance pathways for transformative change toward sustainability. *Curr. Opin. Environ. Sustain.* 71, 101479. doi:10.1016/j.cosust.2024.101479

Thioulouse, J., Chessel, D., and Champely, S. (1995). Multivariate analysis of spatial patterns: a unified approach to local and global structures. *Environ. Ecol. Statistics* 2 (1), 1–14. doi:10.1007/bf00452928

Woiwode, C., Ramachandran, A., Philip, T., Rishika, D., and Rajan, S. C. (2024). Identifying entry points for adaptive governance in peri-urban Chennai (India): a multi-dimensional, multi-level, and multi-scalar approach. *Front. Sustain. Cities* 6, 1368240. doi:10.3389/frsc.2024.1368240

Yoon, S., Kim, J., Kim, S. K., Baik, B., Chi, S. M., Kim, S. Y., et al. (2019). GScluster: network-weighted gene-set clustering analysis. *BMC Genomics* 20 (1), 352. doi:10.1186/s12864-019-5738-6

Zeng, C., Yin, Y., Guo, L., Liu, C., Zhang, Y., and Huang, Z. (2024). Integrating the administrative spillover effect into the spatial governance system to revisit land development: a study in urban-rural fringe areas of Wuhan and neighboring cities, China. *Land Use Policy* 139, 107060. doi:10.1016/j.landusepol.2024.107060

Zhang, C., Lv, W., Zhang, P., and Song, J. (2023). Multidimensional spatial autocorrelation analysis and it's application based on improved Moran's I. *Earth Sci. Inf.* 16 (4), 3355–3368. doi:10.1007/s12145-023-01090-9

Zhang, C., Lv, W., Liu, G., and Wang, Y. (2024). Multidimensional spatiotemporal autocorrelation analysis theory based on multi-observation spatiotemporal Moran's I and its application in resource allocation. *Earth Sci. Inf.* 18 (1), 36. doi:10.1007/s12145-024-01598-8

Zhao, C., Liu, Q., and Wang, J. (2009). Subdivisions of the central-east Asia multi-energy minerals metallogenetic domain and types of those basins. *Energy Explor. and Exploitation* 27 (5), 305–330. doi:10.1260/014459809789618830

Zheng, Y., Ou, Y., Lex, A., and Phillips, J. M. (2021). Visualization of big spatial data using coresets for kernel density estimates. *IEEE Trans. Big Data* 7, 524–534. doi:10.1109/tbdata.2019.2913655