

Article

Impact of the Built Environment on Public Sentiment During Winter in Cold-Region Cities: A Case Study of Harbin Based on Social Media

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Abstract

While the influence of the urban built environment on public emotions has garnered extensive attention, existing studies predominantly focus on temperate climates or warmer seasons. As a result, they rarely extend their scope to winter-specific emotions in cold-region cities, thereby overlooking the complex human–environment emotional interactions under extreme climates. To bridge this seasonal research gap, this study develops an innovative analytical framework integrating Large Language Models (LLMs) with Multi-scale Geographically Weighted Regression (MGWR). Drawing on social media data, this framework leverages the powerful zero-shot reasoning capabilities of LLMs to precisely quantify the two-dimensional emotional characteristics of Valence and Arousal. Concurrently, by incorporating the multi-scale spatial modeling strengths of MGWR, it thoroughly investigates the spatial patterns and driving mechanisms of public emotions within the winter context of typical cold-region cities. The results indicate that, first, extreme climates do not lead to urban emotional suppression; instead, frozen rivers transform into vibrant emotional corridors, with the public demonstrating a high degree of thermal-psychological adaptability. Second, by incorporating winter-specific environmental variables, the research reveals a cold-region paradox of emotional valence. Specifically, under snow cover, lower winter Land Surface Temperature (LST) and winter Normalized Difference Vegetation Index (NDVI) paradoxically evoke positive emotions by reconstructing the aesthetic experience of ice-snow landscapes. Furthermore, the impact of urban service facilities on emotional arousal exhibits a significant pattern of diminishing marginal utility. Overall, the LLMs-MGWR framework achieves a closed loop of high-throughput, multi-dimensional semantic decoding and multi-scale spatial interpretation, demonstrating exceptional cross-regional generalizability. Ultimately, this study not only provides a novel paradigm for understanding human–environment interactions in complex environments but also offers transferable planning guidelines for microclimate design, facility decentralization, and the reshaping of winter blue-green infrastructure in global cold-region cities.

Keywords: cold-region city; sentiment analysis; winter context; built environment; social media; MGWR; LLMs



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1. Introduction

While rapidly reshaping environmental spaces, the accelerated process of urbanization has concurrently triggered severe public mental health crises [1]. As a primary space for daily life, the urban built environment exerts a significant influence on public sentiment perception and mental health [2]. Consequently, implementing proactive interventions at the urban design level to enhance residents' well-being has emerged as a core agenda in healthy city research [3]. Existing literature has confirmed that the built environment shapes public sentiment primarily through a multi-dimensional network of spatial elements. Specifically, urban natural and recreational spaces serve as emotional buffers that can significantly improve mental health, induce feelings of pleasure, and alleviate anxiety [4–7]. Moreover, spatial morphological features, such as crowding in public spaces and the quality of streets and neighborhoods, can directly regulate physiological arousal, while dilapidated or high-density environments often induce stress and even increase the risk of depression [8–14]. Furthermore, social support systems, such as transportation modes and travel distances, also indirectly influence sentiment through daily convenience [15]. Alongside these spatial factors, socio-demographic and economic variables are also correlated with public sentiment [16,17]. However, the specific impact mechanisms of the complex stimulus network formed by these interacting elements still require in-depth analysis at a finer spatio-temporal scale.

Research on urban emotional perception can be traced back to classic explorations of human–environment interactions. The introduction of the “mental map” concept established a theoretical framework for the impact of environmental features on human cognition [18]. Building upon this, the “measuring the unmeasurable” framework translated abstract urban design qualities into quantifiable indicators, analyzing how spatial features influence subjective emotional responses, such as a sense of safety and pleasure. This work ultimately became the cornerstone for subsequent empirical research on emotional perception [19]. Methodologically, urban sentiment research has undergone a paradigm shift from micro-level experiments to macro-level digital footprints. Early research primarily relied on “mental maps” [18], questionnaires [16,20], and microscale physiological measurements such as wearable sensors, electroencephalography (EEG) [21], or virtual reality (VR) [22].

Although these traditional methods offer high precision, they are constrained by limited sample sizes and spatiotemporal lags, making it difficult to capture the emotional fluctuations of large populations in real time [4]. However, with the widespread adoption of the mobile internet, geotagged social media data have emerged as “social sensors” for perceiving urban sentiment [23,24]. Concurrently, multisource big data have become the mainstream in current built environment perception research [25]. In practice, researchers utilize social media data to reflect urban sentiment [17,26], construct urban emotion maps [27], investigate the impact of the built environment on public emotions [28], propose a bipolar index to measure urban sentiment [29], and examine the relationship between online popularity and the emotional perception of urban parks [30]. Ultimately, these massive digital footprints provide a bottom-up perspective, making it possible to quantify emotional responses during interactions between individuals and the urban environment [31].

However, at the current stage, sentiment quantification based on social media faces significant technical bottlenecks. When dealing with complex social contexts, traditional text analysis paradigms, such as sentiment dictionaries or early supervised learning models like SVM and basic BERT, prove to be insufficient. Specifically, they struggle to effectively handle unstructured expressions such as code-switching, internet slang, and sarcasm. Furthermore, they cannot directly output continuous emotional dimension values [32–35]. In

recent years, the breakthrough advancements of Large Language Models (LLMs) such as ChatGPT-4o (OpenAI, San Francisco, CA, USA) have provided a revolutionary approach to address this challenge [36,37]. Relying on profound semantic understanding extracted from massive corpora [38,39] and cross-modal zero-shot reasoning capabilities [40], LLMs can accurately identify subtle emotions in complex contexts without requiring extensive training data. Moreover, they can even explore the deep driving factors behind these emotions [41], thereby providing a more solid quantitative foundation for urban sentiment analysis.

Despite continuous advancements in quantification technologies, existing research on the relationship between the built environment and emotions still exhibits a significant seasonal bias. Most literature focuses on warm seasons or annual average conditions [42,43], yet severely neglects the unique context of winter in high-latitude cold cities. Winter in cold regions not only leads to the withering of deciduous vegetation and snow coverage that forms “white spaces” [44–46] with reduced visual salience but also brings dual physiological and psychological challenges under extreme cold climates [47–53]. Numerous thermal comfort studies indicate that in extreme cold climates, outdoor thermal perception is influenced not only by physiological thermal balance but also by psychological adaptation and previous thermal experiences [54,55]. Prolonged exposure to cold environments depletes psychological resources, leading to decreased vitality and the loss of emotional restoration benefits [56,57]. However, psychological adaptation models in thermal comfort research suggest that long-term residents of cold regions may develop higher cold tolerance and even positively reframe cold environments [54,55,58]. This winter context, interwoven with visual deprivation, physiological stress, and psychological adaptation, is highly likely to give rise to interaction patterns between the environment and emotions that are contrary to those observed under normal climates. Currently, there remains a lack of systematic empirical research on how built environment elements drive residents’ emotional valence and arousal under the dual constraints of cold climates and unique winter landscapes.

The impact of the built environment on human sentiment [59] exhibits significant spatial heterogeneity [29]. Drawing on the framework of the “Spatial Variations of the Broken Emotion Conjecture” [60], this study conceptualizes winter emotions in Harbin as a scale-dependent emergent phenomenon, rather than a uniform climatic depression. Traditional global regression models, such as Ordinary Least Squares (OLS), tend to obscure such local variations [61]. Although classical Geographically Weighted Regression (GWR) addresses spatial non-stationarity [62], its assumption that all explanatory variables function at a single spatial scale is at odds with the multiscale complexity of urban systems [63]. Therefore, this study employs the Multiscale Geographically Weighted Regression (MGWR) model to precisely quantify the scale effects and spatial variations in the impact of different built environment indicators on sentiment by searching for the optimal bandwidth for each variable [64].

In summary, cities in cold regions, from Scandinavia to North America, face the challenge of maintaining urban vitality during long winters. To bridge the research gap in emotional perception under winter contexts in cold-region cities, this study takes Harbin as a case study and constructs a novel analytical framework integrating LLMs and MGWR. The specific objectives are to: (1) leverage the zero-shot reasoning capabilities of LLMs to achieve deep semantic parsing of social media data within complex social contexts; (2) construct a dual-dimensional emotion model based on Valence-Arousal (V-A) to precisely quantify public emotions and explore their spatiotemporal evolution characteristics; (3) focus on the specific winter context of cold regions by incorporating winter-specific semantics and constructing a built environment indicator system adaptive to climate characteristics, thereby addressing the gap in seasonal emotional perception research; and (4) apply the MGWR model to accurately analyze the spatial heterogeneity mechanisms through which

urban built environment elements drive V-A dual-dimensional emotions across different spatial scales in the winter context. This study not only provides a novel paradigm for understanding human-place emotional interactions under the winter climate of cold-region cities but also offers empirical support for winter vitality enhancement and spatial planning in similar regions worldwide.

2. Materials and Methods

2.1. Study Area

This study focuses on the central urban area of Harbin, specifically the region enclosed by the Ring Expressway. Characterized by high population density and complex urban functions, this area serves as the primary hub for residents' daily activities. As a representative cold-region city in China, Harbin is distinguished by its long winters and harsh climate [65]. Specifically, Harbin (45.75° N, 126.65° E) belongs to the Dwa climate category in the Köppen climate classification. The study period spans from November 2024 to March 2025, totaling approximately 152 days. During this time, the average daily temperature is -12.4°C , and the cumulative heating degree days are about 4200. Additionally, daylight hours range from 8 h and 26 min to 11 h and 14 min, with an average of 88 snow days annually. This unique environmental context significantly influences residents' emotional perception (Figure 1). To facilitate fine-grained analysis, a grid-based approach was adopted to establish basic analysis units at a scale of $0.5\text{ km} \times 0.5\text{ km}$, resulting in the division of the study area into 2501 grid cells. This approach was designed by referencing existing MGWR-based analytical methods [63], considering the winter walking activity radius in Harbin [66], and balancing the resolutions of various data sources.

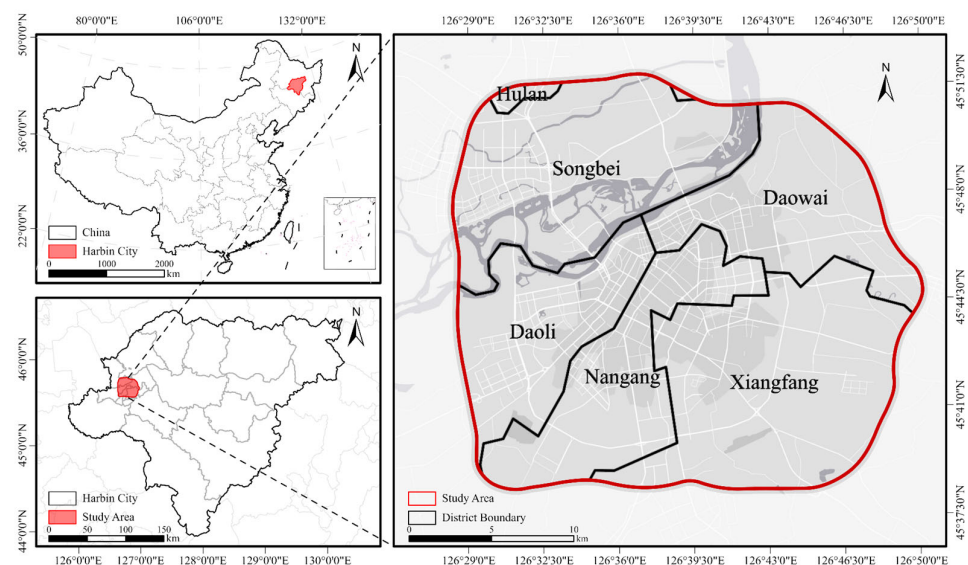


Figure 1. Location of the study area.

2.2. Data Sources and Processing

This study utilizes Sina Weibo data as the source of residents' emotions [29,67] and incorporates eight major categories of data, including population, economy, road traffic, vegetation, temperature, wind speed, POI, and snow cover, to construct a built environment indicator system suitable for emotional observation in the winter context. Furthermore, $0.5\text{ km} \times 0.5\text{ km}$ grids were uniformly constructed as the basic analysis units using the ArcGIS Pro 3.0 platform (Esri, Redlands, CA, USA) (Table 1).

- (1) Public sentiment data were acquired from Sina Weibo posts within the study area, spanning the period from November 2024 to March 2025. The raw dataset comprised

85,622 records, containing attributes such as posting location, user ID, timestamp, and textual content. To ensure data quality, a rigorous cleaning process was implemented to eliminate invalid entries, including advertisements, bot-generated content, hyperlinks, illicit information, and duplicate posts. Consequently, a total of 77,136 valid posts were retained for subsequent analysis.

- (2) Both the Normalized Difference Vegetation Index (NDVI) and Land Surface Temperature (LST) data were retrieved from 30 m remote sensing imagery acquired by the Landsat 8/9 satellites. The temporal window was aligned with the study period, spanning from November 2024 to March 2025. Following preprocessing steps that included cloud removal and atmospheric correction, NDVI data were synthesized using the Maximum Value Composite (MVC) method, while LST data were obtained through thermal infrared band inversion. Subsequently, bilinear interpolation was employed for resampling, and the mean value of valid pixels within each grid cell was calculated.
- (3) In terms of population, this study utilized the LandScan HD 2020 global population dataset with a resolution of approximately 100 m. For this type of count data, an area-weighted aggregation method was adopted to uniformly aggregate the data into 0.5 km grids to represent the regional population concentration.
- (4) For GDP, the 2020 GDP kilometer grid data from the Chinese Academy of Sciences was adopted, with a resolution of 1 km. Similarly, for continuous raster data, bilinear interpolation was employed for spatial resampling to uniformly allocate the data into 0.5 km grids to represent regional economic vitality.
- (5) In terms of urban built facilities, the data were primarily sourced from Amap in 2025. Specifically, the road network data underwent topological cleaning before calculating the line density within the grids. For the POI dataset, density metrics (points per area) were applied to evaluate five types of facilities, namely catering, shopping, accommodation, medical services, and enterprises. For parks, squares, and scenic spots, following the same method used for bus and subway stations, proximity analysis was utilized to compute the Euclidean distance from the center of the grid to the closest facility, characterizing landscape accessibility and transportation convenience, respectively.
- (6) For snow cover data, the MOD10A1 daily product provided by NASA was adopted, with a spatial resolution of 500 m. Based on the Normalized Difference Snow Index (NDSI), these data intuitively represent the snow cover percentage within a pixel using values from 0 to 100. During data preprocessing, the Quality Assessment (QA) band was utilized to filter high-quality observations, and cloud removal algorithms along with time-series synthesis techniques were applied to enhance data reliability. To maintain consistency with the analytical scale of this study, spatial resampling was performed on the continuous raster data using bilinear interpolation to uniformly extract the data into 0.5 km grids, thereby calculating the average snow cover during the study period.
- (7) Wind speed data were sourced from the ERA5-Land reanalysis dataset released by the European Centre for Medium-Range Weather Forecasts (ECMWF), with an original spatial resolution of approximately 9 km. During data preprocessing, the 10 m u-component (u10) and v-component (v10) of wind were first extracted to calculate the resultant scalar wind speed. To overcome the limitation of the coarse original resolution and maintain consistency with the analytical scale of this study, spatial downscaling and resampling were performed on the continuous raster data using bilinear interpolation to uniformly extract the data into 0.5 km grids.

Table 1. Data sources and processing methods.

Data Source	Data Category	Processing Method
Sina Weibo	Sentiment text	Data cleaning
Landsat8/9	NDVI, LST	Cloud removal and atmospheric correction preprocessing; NDVI used Maximum Value Composite (MVC), LST used thermal infrared band retrieval; finally, bilinear interpolation was used for resampling to calculate the grid mean
LandScan HD	Population density	For count data, area-weighted aggregation was used to uniformly aggregate to 0.5 km grids
CAS	GDP	Bilinear Interpolation was used for spatial resampling to 0.5 km grids
Gaode Map	Road networks, Catering, Shopping, Accommodation, Medical services, Enterprises, Parks and Squares, Scenic spots, Bus, Subways	• Road networks: Calculate line density after topology cleaning • Catering, shopping, accommodation, medical services, enterprises: Calculate point density (number of points per area) • Parks and squares, scenic spots, public transit, subways: Use proximity analysis to calculate the Euclidean distance to the nearest facility point
NASA MOD10A1	Snow cover	QA band filtering, cloud removal algorithms, and time series synthesis; bilinear interpolation was used for spatial resampling to 0.5 km grids and calculating the mean
ERA5-Land	Wind speed	Extract u10 and v10 components to synthesize scalar wind speed; bilinear interpolation was used for spatial downscaling and resampling to 0.5 km grids

2.3. Research Framework

The research framework consists of three main stages. First, raw Weibo data were pre-processed using a keyword-based filtering method. Subsequently, prompts were designed based on a zero-shot learning strategy, employing the GPT-4o model to classify the text into specific sentiment dimensions. Sentiment was operationalized into two dimensions: Valence and Arousal. The Valence dimension, encompassing positive, neutral, and negative categories, was assigned intensity values ranging from -5 to 5 . The Arousal dimension was quantified on a scale of 1 to 10 , reflecting the level of emotional activation. Second, a built environment indicator system suitable for emotion observation in winter contexts was constructed. This system is divided into three dimensions: winter-specific variables, winter-context moderating variables, and basic structural variables, serving as the set of independent variables for subsequent analysis. Third, regression analyses were conducted to examine the determinants of emotional Valence and Arousal. Initially, OLS regression was applied to screen for multicollinearity and insignificant variables, thereby establishing a global regression baseline. Building upon this, GWR and MGWR were introduced to capture local spatial variations. By comparing the goodness-of-fit and parameter distributions across these models, the optimal model was identified to investigate the spatial heterogeneity of the built environment's impact on public sentiment (Figure 2).

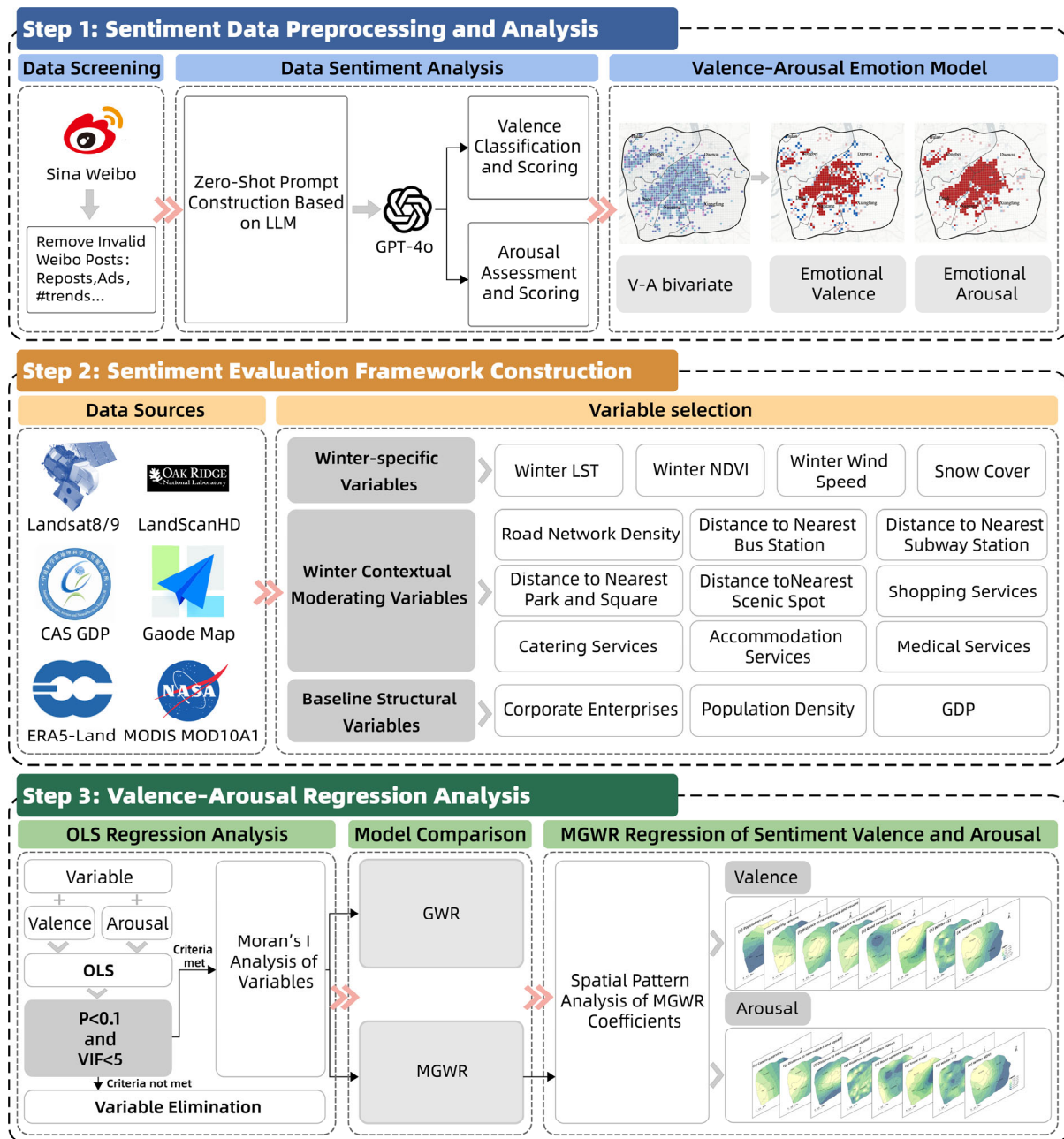


Figure 2. Research frame.

2.4. Construction of Evaluation Indicators for Winter Built Environment

Traditional built environment measurements are mostly based on 3D or 5D frameworks for static evaluation [68,69], often ignoring the dynamic impacts of seasonal climate on environmental perception. Drawing on previous research findings regarding the interaction mechanisms between the built environment and emotions [28,70], the indicator system of this study specifically refers to the built environment observed in winter contexts. Based on the unique characteristics of cold-region cities and considering data availability, this evaluation system is primarily divided into three dimensions: winter-specific variables, winter-context moderating variables, and basic structural variables, encompassing a total of 16 specific indicators (Table 2).

Table 2. Variable selection.

Dimension	Variable	Description
Winter-specific Variables	Winter NDVI	The maximum value of the normalized difference vegetation index within the study unit
	Winter LST	Land surface temperature within the study unit
	Winter Wind Speed	Mean wind speed within the study unit during winter
	Snow Cover	Average snow coverage within the study unit.
Winter contextual moderating variables	Road network density	Total length of roads within the study unit
	Distance to nearest bus station	Distance from the centroid of the study unit to the nearest bus station
	Distance to nearest subway station	Distance from the centroid of the study unit to the nearest subway station
	Distance to nearest park and square	Distance from the centroid of the study unit to the nearest park or square
	Distance to nearest scenic spot	Distance from the centroid of the study unit to the nearest scenic spot
	Shopping services	Number of shopping facilities within the study unit
	Catering services	Number of catering service points within the study unit
	Accommodation services	Number of accommodation facilities within the study unit
Baseline structural variables	Medical services	Number of medical facilities within the study unit.
	GDP	Gross domestic product within the study unit
	Population density	Population count within the study unit
	Corporate enterprises	number of corporate enterprises within the study unit

2.5. The Valence-Arousal (V-A) Model of Sentiment

The V-A model conceptualizes sentiment along two orthogonal dimensions [71]. Valence denotes the hedonic tone of an emotion, ranging from positive (pleasant) to negative (unpleasant), while Arousal indicates the level of physiological activation or energy elicited by external stimuli [72]. By establishing a two-dimensional coordinate system, this model maps sentiments into four distinct quadrants (Figure 3). Given that human emotional experiences are inherently complex, this dimensional approach facilitates a more nuanced interpretation of the actual state of ambiguous or mixed sentiments.

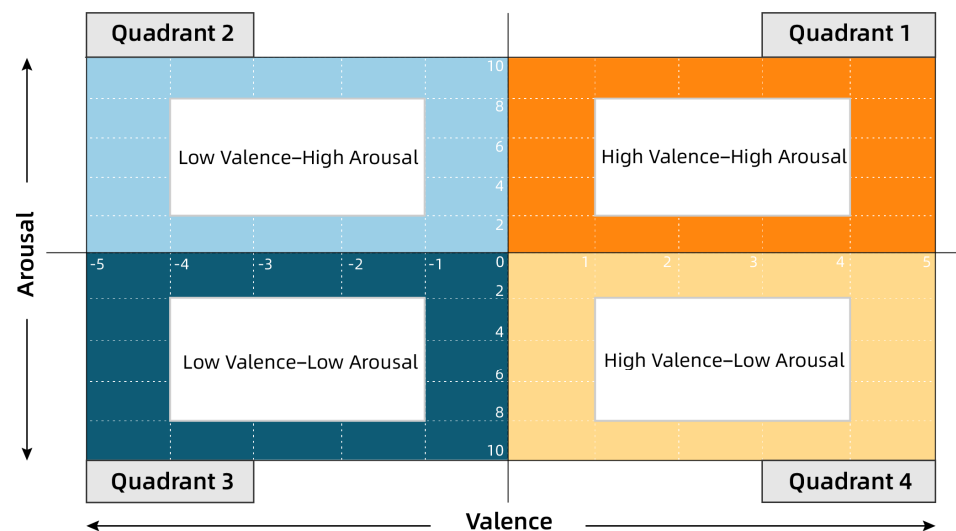


Figure 3. Sentiment quadrants based on the circumplex model of affect.

2.6. LLMs Analysis and Validation

LLMs exhibit robust semantic understanding and logical reasoning capabilities, offering novel approaches for processing complex social media texts. Unlike traditional analytical methods, which often struggle to capture subtle emotional nuances, LLMs excel at performing in-depth sentiment classification by leveraging contextual information [41]. Consequently, this study employs LLMs for the analysis of Weibo sentiment.

A zero-shot learning strategy was adopted, wherein the model was guided through a structured prompt framework designed to address the specific context of “Harbin in winter.” The prompt explicitly defined the model’s role as an “expert in urban sociology and sentiment analysis.” Crucially, the instructions included contextual constraints to correct potential biases; for instance, the model was instructed that keywords typically associated with physical discomfort (e.g., “freezing,” “minus 20 degrees”) should not be automatically classified as negative, as they often express excitement or a unique aesthetic experience in the context of ice-and-snow tourism. The model was tasked with outputting sentiment scores for Valence (ranging from -5 to $+5$) and Arousal (ranging from 1 to 10) based on these nuanced criteria. To ensure reproducibility and minimize randomness in the output, the model’s temperature parameter was fixed at 0.

To ensure the rigor of data processing and to address the necessity of human–machine validation before the large-scale application of large language models, this study implemented a strict expert scoring process to establish a reliable ground truth. Specifically, 500 Weibo texts were randomly extracted from the dataset, and three experts in the fields of environmental psychology and urban sociology were invited to independently annotate these texts. The experts strictly followed the standardized scoring criteria based on the V-A model: they rated Valence (-5 to $+5$) and Arousal (1 to 10) with full consideration of the aforementioned “Harbin winter” context. The inter-rater reliability among the three experts was high, with the intraclass correlation coefficient (ICC) reaching 0.88. For a small number of scoring discrepancies, the experts reached a consensus through discussion, ultimately finalizing the ground truth dataset. Subsequently, the zero-shot prediction results of the LLM were benchmarked against this expert-annotated dataset. The results showed that the LLM achieved an accuracy of 88.2% and a weighted F1 score of 0.86, significantly outperforming traditional lexicon-based baseline models. This human–machine calibration process confirmed that the LLM approach adopted in this study possesses sufficient robustness and reliability for large-scale urban sentiment quantification.

Error analysis on the misclassified cases ($n \approx 59$) revealed three predominant patterns: sarcasm and counter-factual expressions ($\sim 45\%$), code-switching between Mandarin and Northeastern Chinese dialect ($\sim 30\%$), and ambiguous neutral statements containing weather descriptors ($\sim 25\%$). These error types align with known limitations of zero-shot LLM sentiment inference in dialectal urban contexts.

2.7. MGWR Analysis

MGWR enables the selection of optimal bandwidths for each specific variable during regression, thereby capturing spatial processes at varying scales. This study utilizes the variable-specific bandwidths of MGWR as a key diagnostic tool. We hypothesize that the three dimensions in the evaluation system constructed in this study—namely, winter-specific variables, winter-context moderating variables, and basic structural variables—influence urban sentiment across different spatial scales. Therefore, bandwidth estimation can directly test this multiscale theoretical structure of winter urban sentiment geography. This overcomes the limitation of the classic GWR model, which is constrained to a single, fixed bandwidth for all variables [64]. The model is expressed as follows:

$$y_i = \sum_{j=1}^k \beta_{bwj}(u_i, v_i) x_{ij} + \varepsilon_i$$

where y_i represents the specific sentiment dimension for the i -th spatial grid cell in Harbin; β_{bwj} denotes the local regression coefficient associated with the optimal bandwidth for the j -th variable, reflecting the scale-dependent impact of the built environment on winter sentiment; (u_i, v_i) represents the centroid coordinates of grid cell i ; x_{ij} is the observed value of the j -th built environment indicator under the winter context; and ε_i denotes the random error term. In this study, MGWR 2.2 software (School of Geographical Sciences and Urban Planning, Arizona State University, Tempe, AZ, USA) was employed for model estimation to capture these multiscale spatial variations, and ArcGIS Pro 3.0 was utilized to map and visualize the spatial heterogeneity of the emotional responses.

3. Results

3.1. Bivariate Analysis of Sentiment V-A

3.1.1. Bivariate Spatial Distribution Analysis of Sentiment V-A

The bivariate spatial map (Figure 4) reveals a pronounced spatial correlation between valence and arousal within the study area, characterized by marked spatial heterogeneity across the banks of the Songhua River. Specifically, clusters of high valence and high arousal (HH) exhibit a distinct dual-center pattern. These clusters are predominantly concentrated on the south bank of the Songhua River (Jiangnan)—particularly within the Daoli, Nangang, and Xiangfang districts—accounting for approximately 85% of the total HH area. Conversely, the north bank (Jiangbei) comprises only about 15%, exhibiting a notably lower density. This dual-center structure is further reinforced by areas of positive valence and moderate arousal, which maintain a strong spatial correlation and mirror the distribution of the HH clusters. Surrounding these active cores, areas of neutral valence and low arousal are distributed in a ring-like pattern. In contrast, areas characterized by negative valence and moderate-to-high arousal display weaker spatial correlation, presenting a fragmented and sparse distribution; notably, no significant clusters of negative valence and low arousal (LL) were observed.

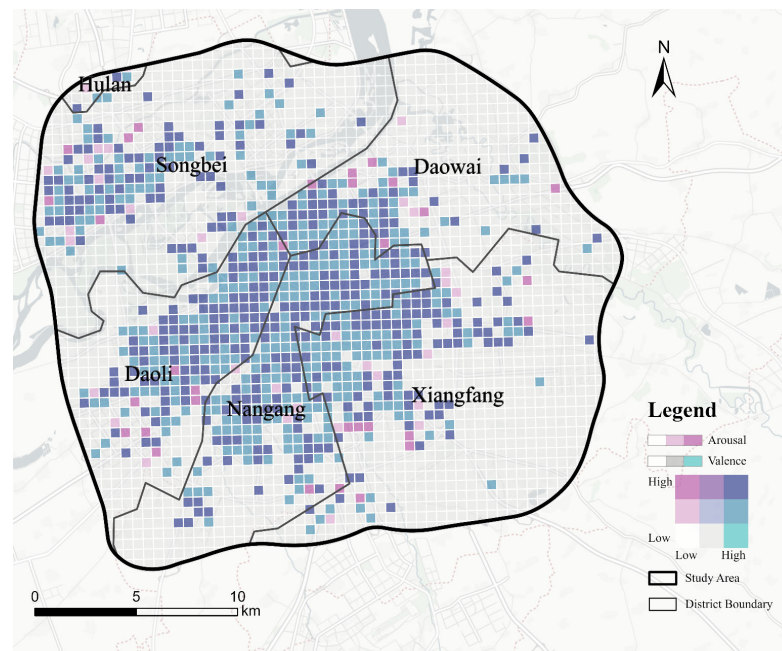


Figure 4. Bivariate spatial distribution of sentiment V-A in Harbin.

3.1.2. Spatial Clustering Patterns of Sentiment Valence

The cluster and outlier analysis of sentiment valence (Figure 5) reveals significant positive spatial autocorrelation and distinct spatial heterogeneity within the study area. Specifically, HH clusters are predominantly concentrated in the central riverside zone of the Jiangnan region and the western periphery of the Jiangbei region, forming contiguous hotspots of positive sentiment. Conversely, LL clusters are scattered throughout the study area, exhibiting a fragmented and patchy distribution. This spatial configuration suggests that high-valence areas are spatially continuous and distributed along the river, whereas low-valence areas are characterized by a more localized and dispersed distribution pattern.

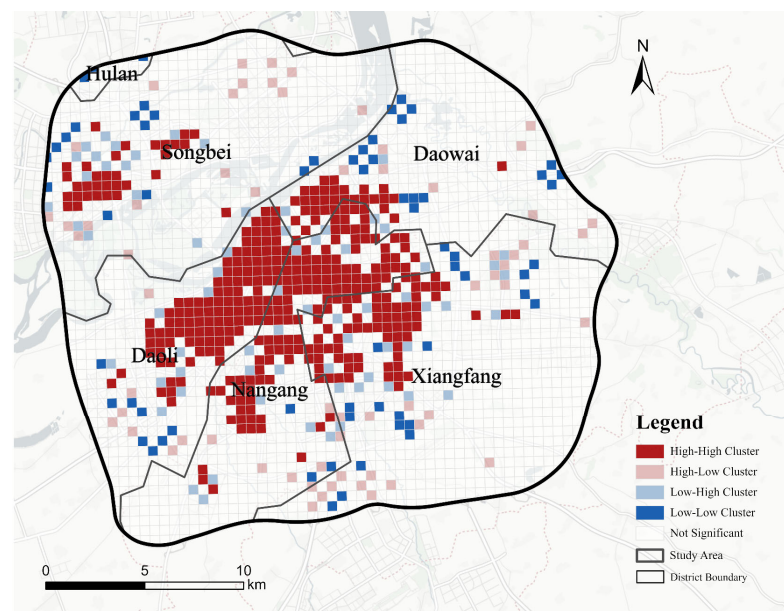


Figure 5. Cluster and outlier analysis of sentiment valence.

3.1.3. Spatial Clustering Patterns of Sentiment Arousal

The cluster and outlier analysis of sentiment arousal (Figure 6) reveals that sentiment arousal within the study area exhibits significant positive spatial autocorrelation, characterized by a distinct heterogeneous distribution. Specifically, HH clusters constitute the dominant clustering type, displaying a dual-core pattern separated by the Songhua River. In the Jiangbei region, high-arousal grids are primarily concentrated along the western periphery, whereas in the Jiangnan region, they form a contiguous distribution along the central section of the Songhua River. This suggests that these locales not only possess high sentiment arousal but are also enveloped by neighbors with similarly elevated levels. Furthermore, no significant LL clusters were detected, suggesting that low-arousal areas are spatially dispersed and do not form large-scale cold spots.

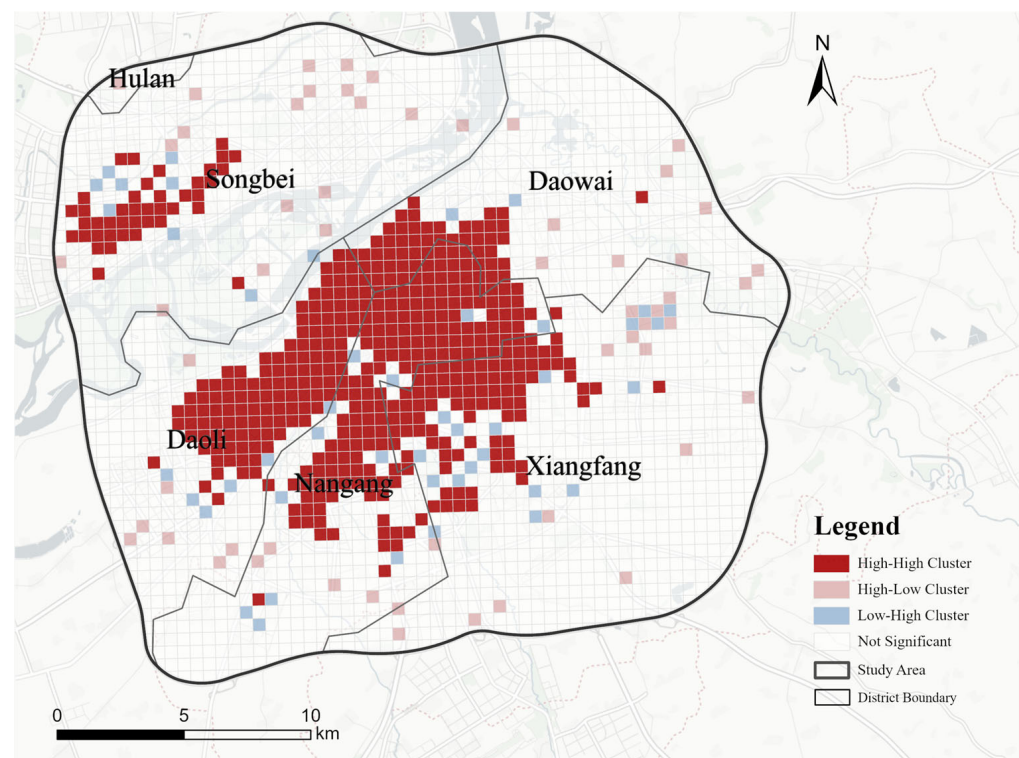


Figure 6. Cluster and outlier analysis of sentiment arousal.

3.2. Variable Analysis

3.2.1. OLS Regression Results

An OLS regression model was constructed with sentiment Valence as the dependent variable and the metrics listed in Table 2 as independent variables. As shown in Table 3, Variance Inflation Factor (VIF) values for all variables remained below 5.000, confirming the absence of severe multicollinearity and ensuring model reliability. Notably, sentiment Valence was positively associated with winter NDVI, snow cover, road network density, catering services, and population density, but negatively correlated with winter LST, distance to the nearest bus station, and distance to the nearest park and square. The remaining variables were not statistically significant.

Table 3. The results of OLS regression on sentiment valence.

Variable	Coef.	Standard Error	t-Value	p-Value	Robust_SE	Robust_t	Robust_Pr ^b	VIF ^c
Intercept	0.089	0.165	0.537	0.591	0.131	0.677	0.498	-----
Winter NDVI	0.526	0.191	2.757	0.006 *	0.172	3.055	0.002 *	1.918
Winter LST	−0.139	0.015	−9.320	0.000 *	0.018	−7.873	0.000 *	2.092
Winter Wind Speed	−0.077	0.076	−1.011	0.312	0.045	−1.718	0.086	1.425
Snow Cover	0.013	0.003	4.020	0.000 *	0.003	4.944	0.000 *	1.494
Road network density	29.425	3.101	9.490	0.000 *	3.827	7.689	0.000 *	2.914
Distance to nearest bus station	−0.180	0.045	−3.991	0.000 *	0.0350	−5.149	0.000 *	1.552
Distance to nearest subway station	−0.025	0.017	−1.427	0.154	0.018	−1.364	0.173	4.394
Distance to nearest park and square	−0.042	0.016	−2.711	0.007 *	0.015	−2.723	0.007 *	3.757
Distance to nearest scenic spot	0.014	0.015	0.959	0.338	0.014	0.973	0.330	1.670
Shopping services	0.004	0.003	1.479	0.139	0.004	1.012	0.312	2.130
Catering services	0.030	0.008	3.791	0.000 *	0.009	3.526	0.000 *	3.355
Accommodation services	−0.010	0.010	−1.006	0.314	0.008	−1.193	0.233	2.111
Medical services	−0.007	0.009	−0.816	0.414	0.008	−0.903	0.367	1.573
GDP	0.000	0.000	1.178	0.239	0.000	1.035	0.301	1.613
Population density	0.000	0.000	2.053	0.040 *	0.000	1.703	0.089	1.318
Corporate enterprises	0.004	0.009	0.427	0.669	0.007	0.526	0.599	1.315

Notes: ^b Robust probabilities; ^c Variance Inflation Factor (VIF); * $p < 0.05$.

Correspondingly, a parallel regression analysis was performed with sentiment arousal as the dependent variable and the indicators listed in Table 1 as independent variables. The statistical outcomes (Table 4) confirm that the VIF values for all predictors remained below 5.000, verifying the absence of severe multicollinearity. Notably, sentiment arousal was significantly and positively associated with winter NDVI, snow cover, road network density, and catering services, but negatively correlated with winter LST, distance to the nearest bus station, distance to the nearest subway station, and distance to the nearest park and square. The remaining variables were not statistically significant.

Table 4. The results of OLS regression on sentiment arousal.

Variable	Coef.	Standard Error	t-Value	p-Value	Robust_SE	Robust_t	Robust_Pr ^b	VIF ^c
Intercept	0.462	0.260	1.774	0.0762	0.223	2.066	0.039 *	-----
Winter NDVI	0.880	0.300	2.929	0.003 *	0.293	3.006	0.003 *	1.918
Winter LST	−0.288	0.023	−12.262	0.000 *	0.029	−10.017	0.000 *	2.092
Winter Wind Speed	−0.122	0.120	−1.013	0.311	0.085	−1.437	0.151	1.425
Snow Cover	0.024	0.005	4.544	0.000 *	0.005	5.194	0.000 *	1.494
Road network density	68.486	4.886	14.018	0.000 *	6.407	10.690	0.000 *	2.914
Distance to nearest bus station	−0.408	0.071	−5.730	0.000 *	0.064	−6.393	0.000 *	1.552
Distance to nearest subway station	−0.105	0.027	−3.840	0.000 *	0.030	−3.506	0.000 *	4.394
Distance to nearest park and square	−0.065	0.024	−2.666	0.008 *	0.025	−2.632	0.009 *	3.757
Distance to nearest scenic spot	0.041	0.023	1.811	0.070	0.023	1.825	0.068	1.670
Shopping services	0.001	0.004	0.237	0.813	0.007	0.152	0.880	2.130
Catering services	0.036	0.013	2.848	0.004 *	0.013	2.714	0.007 *	3.355
Accommodation services	0.005	0.015	0.306	0.760	0.013	0.369	0.712	2.111
Medical services	−0.001	0.014	−0.062	0.951	0.015	−0.056	0.955	1.573
GDP	0.000	0.000	1.682	0.093	0.000	1.568	0.117	1.613
Population density	0.000	0.000	0.242	0.809	0.000	0.235	0.814	1.318
Corporate enterprises	0.012	0.013	0.872	0.384	0.009	1.377	0.169	1.315

Notes: ^b Robust probabilities; ^c Variance Inflation Factor (VIF); * $p < 0.05$.

Following the OLS screening, 8 variables were retained for Valence MGWR and 8 for Arousal MGWR. Note that Wind Speed, although a winter-specific variable of theoretical interest, did not reach significance and was excluded from final modeling.

3.2.2. Spatial Autocorrelation Analysis

Global models based on OLS estimation presuppose that the influence of explanatory variables is spatially homogeneous. However, variations in the spatial distribution patterns

of variables may lead to spatial non-stationarity. Spatial autocorrelation assesses the similarity between a variable and its values at neighboring locations [73]. To examine the spatial autocorrelation of the selected variables, the Global Moran's I statistic was calculated for each. The results (Table 5) demonstrate that all variables exhibit statistically significant positive spatial clustering patterns.

Table 5. The Moran's I of variables.

Variable	Moran'I	Z-Score	p-Value
Winter NDVI	0.667	46.606	0.000
Winter LST	0.715	49.970	0.000
Snow Cover	0.554	38.603	0.000
Road network density	0.744	52.009	0.000
Distance to nearest bus station	0.876	61.243	0.000
Distance to nearest subway station	0.989	69.121	0.000
Distance to nearest park and square	0.988	69.064	0.000
Catering services	0.614	43.090	0.000
Population density	0.790	55.620	0.000

3.3. Model Comparison and Comparison of Variable Bandwidths

Building upon the significant variables identified in the preceding OLS regression analysis, MGWR models were constructed for sentiment Valence and sentiment Arousal, respectively. The comparative results (Table 6) indicate that the MGWR model demonstrated superior performance over the classical GWR model in capturing the spatial heterogeneity of sentiment Valence.

Table 6. Regression results of GWR and MGWR models for sentiment valence.

Model Statistics	GWR	MGWR
R^2	0.445	0.475
Adjusted R^2	0.423	0.446
AICc	6724.591	5759.025
Effective Number of Parameters	95.773	127.228
Residual Sum of Squares	2028.561	1314.276

Specifically, the MGWR model achieved an R^2 of 0.475, surpassing the 0.445 observed in the classical GWR model, which indicates that MGWR possesses stronger explanatory power regarding spatial variation. Furthermore, the MGWR model yielded a lower Residual Sum of Squares (RSS) and a significantly reduced AICc value compared to the classical GWR model. Although the MGWR model incorporated a larger number of effective parameters, the substantial reduction in AICc confirms that the improvement in model fit is sufficient to offset the increase in complexity, thereby validating MGWR as the more accurate modeling choice.

Furthermore, the bandwidth comparison (Table 7) highlights a key methodological advantage of the MGWR model. Unlike the classical GWR, which imposed a uniform bandwidth of 642 across all variables, MGWR successfully captured the varying spatial scales of different predictors. Specifically, the narrower bandwidths for road network density (666) and winter LST (1059) reveal highly localized spatial processes. In contrast, the maximum bandwidths (2501) observed for variables such as population density and distance to the nearest bus station indicate regional or global spatial stationarity. By effectively distinguishing between local and global dynamics, MGWR minimizes overfitting and bias, offering a more rigorous framework for interpreting the spatial drivers of sentiment Valence.

Table 7. Bandwidths of variables in GWR and MGWR models for sentiment valence.

Variable	GWR	MGWR
Winter NDVI	642	2278
Winter LST	642	1059
Snow Cover	642	2501
Road network density	642	666
Distance to nearest bus station	642	2501
Distance to nearest park and square	642	2501
Catering services	642	2501
Population density	642	2501

Mirroring the comparative analysis for sentiment Valence, the diagnostic statistics in Table 8 confirm the overall superiority of the MGWR framework for modeling sentiment Arousal. While the classical GWR model produced a marginally higher R^2 , this apparent advantage comes at the cost of increased model complexity and potential over-fitting, as evidenced by its higher effective number of parameters. Conversely, MGWR achieved a dramatic reduction in the RSS alongside a substantially lower AICc value. Collectively, these diagnostics indicate that MGWR successfully optimizes the trade-off between model complexity and goodness-of-fit, delivering a more parsimonious and rigorous analytical solution.

Table 8. Regression results of GWR and MGWR models for sentiment arousal.

Model Statistics	GWR	MGWR
R^2	0.634	0.603
Adjusted R^2	0.596	0.587
AICc	8896.715	4994.429
Effective Number of Parameters	122.104	98.527
Residual Sum of Squares	4399.196	992.888

Consistent with the multi-scale characteristics previously observed in sentiment Valence, the spatial processes of sentiment Arousal exhibit a similarly pronounced scalar variation, as detailed in Table 9. While the GWR model applied a restricted, uniform bandwidth of 233 across all predictors, MGWR successfully differentiated its operating scales. For instance, the bandwidth for road network density was notably constrained at 423, indicating a highly localized influence on Arousal. Conversely, variables such as winter LST, distance to the nearest subway station, distance to the nearest park and square, and catering services reached the maximum global bandwidth of 2501. These results further reinforce the capacity of MGWR to uncover nuanced, multi-scale spatial relationships that remain completely obscured under the fixed-bandwidth assumption of classical GWR.

Table 9. Bandwidths of variables in GWR and MGWR models for sentiment arousal.

Variable	GWR	MGWR
Winter NDVI	233	2140
Winter LST	233	2501
Snow Cover	233	974
Road network density	233	423
Distance to nearest bus station	233	1918
Distance to nearest subway station	233	2501
Distance to nearest park and square	233	2501
Catering services	233	2501

3.4. Analysis of Spatial Patterns of Coefficient

3.4.1. Analysis of Spatial Patterns of Coefficients for Variables Influencing Valence

Figure 7a illustrates the distribution of influence coefficients for winter NDVI on sentiment valence. The spatial structure exhibits a stepped pattern, with coefficient values decreasing from the southeast to the northwest. Notably, the majority of the region demonstrates a negative correlation with sentiment valence. The areas with the lowest coefficient values (indicating the strongest negative association) are traversed by the Songhua River and feature a dense distribution of wetlands and park green spaces. In the context of Harbin's severe winter, the low vegetation index in these areas is indicative of open terrain, which is conducive to creating large-scale, expansive snowscapes. This visual characteristic aligns perfectly with visitors' expectations for a winter destination. Consequently, a lower winter NDVI is associated with more positive sentiment valence.

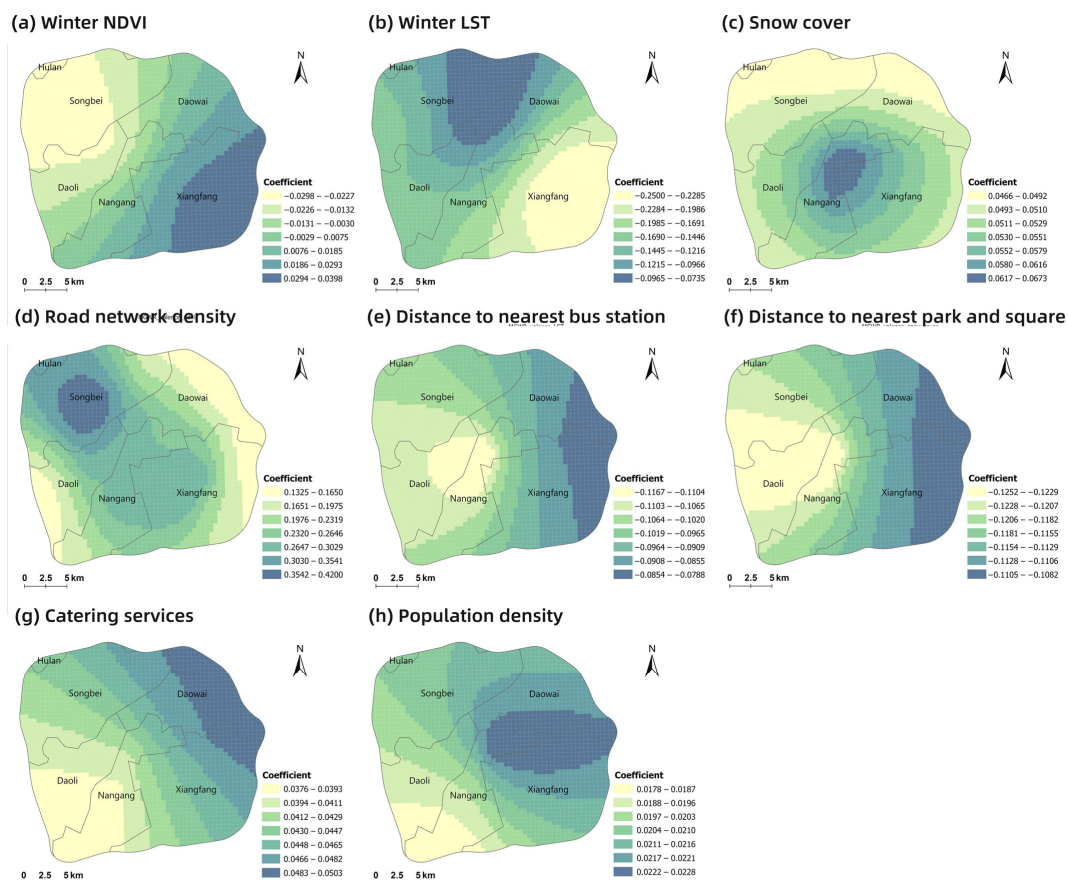


Figure 7. Spatial distribution of MGWR coefficients for variables affecting sentiment valence.

There is a general negative correlation between winter LST and sentiment Valence (Figure 7b), and its spatial distribution exhibits significant spatial heterogeneity—specifically, the lower the winter LST, the more positive the public sentiment tends to be. This phenomenon is closely related to the urban characteristics of cold regions. In these regions, sustained low temperatures are crucial for maintaining high-quality ice and snow landscapes, thereby enhancing winter recreational experiences. Specifically, the high-value areas are predominantly located in the primary urban built-up areas. In these densely populated urban environments, microclimate shelters can mitigate the wind chill effect [48], allowing the psychological benefits derived from cold-dependent winter ice and snow activities to dominate. Conversely, in the northern open areas and the riparian zones of the Songhua River, the negative correlation diminishes significantly. In these expansive regions, extremely low temperatures coupled with higher wind exposure are

likely to result in severe cold stress, thereby partially offsetting the positive emotions derived from the winter landscape [74].

Snow cover is positively correlated with sentiment Valence (Figure 7c), meaning that the higher the snow cover, the more positive the sentiment. Specifically, the high-value areas are primarily concentrated in the core urban built-up areas. In these areas, snow cover combined with Harbin's historical architecture creates a unique winter ice and snow landscape atmosphere. Furthermore, the findings regarding winter LST also indicate that urban microclimate cold-relief facilities can mitigate the severe cold, while the well-developed infrastructure and efficient snow removal services in the city center effectively alleviate the traffic inconvenience and cold stress caused by snow accumulation. Together, these factors enable people to maximize their enjoyment of the snowscape while minimizing physical discomfort. Conversely, the low-value areas are primarily distributed in the open northern peripheral regions, where the daily inconveniences caused by persistent snow accumulation slightly diminish this generally positive effect. Overall, however, this variable is a global variable (Table 7) with minimal spatial variation, indicating that the enhancement of positive sentiment by snow cover is highly stable across the study area.

Road network density exhibited a positive correlation with sentiment valence (Figure 7d), indicating that higher density is associated with more positive sentiment. The spatial distribution of the coefficients displays a concentric pattern, characterized by a gradual decrease in the magnitude of influence from the center outwards. Specifically, the areas with the highest coefficient values encompass key tourist attractions, including the Harbin Ice and Snow World, Sun Island Scenic Area, Harbin Polar Park, and the Siberian Tiger Park. High road network density signifies convenient transportation and high accessibility to scenic spots, as well as strong regional landscape continuity. These conditions facilitate easier access to pleasant landscape experiences for both residents and tourists [75], thereby contributing to more positive sentiment valence. Conversely, the low-value zones are primarily distributed along the periphery of the study area, which is dominated by cultivated land, logistics, and warehousing districts. The road infrastructure in these regions comprises primarily wide arterial roads and freight corridors, resulting in a characteristically low road network density. Activities in this region are predominantly utilitarian, consisting mainly of commuting or work-related tasks. This functional focus limits engagement with environmental aesthetics and spatial experiences. Consequently, emotional valence exhibits lower sensitivity to road network density, a pattern reflected by the lower magnitude of the influence coefficients.

The Distance to nearest bus station exhibited a negative correlation with sentiment valence (Figure 7e), indicating that shorter distances correspond to more positive sentiment. The spatial distribution of the coefficients presents a stepped pattern, with the magnitude of influence decreasing from the west towards the east. The areas exhibiting the strongest influence are primarily situated in the old urban core of Harbin, characterized by dense residential districts where residents rely heavily on the public bus system for daily commuting. Proximity to bus stops effectively reduces travel time and enhances transport convenience, thereby fostering more positive sentiment valence. In contrast, areas with weaker influence are mainly located in the urban suburbs, where residential zones, while clustered, are of lower density. Given that residents in these areas rely more heavily on private transportation, the distance to bus stops exerts a less significant impact on sentiment valence. Overall, this predictor operates as a global variable with minimal spatial heterogeneity. Regarding the absolute values of the coefficients, the magnitude of its impact is relatively weak. This suggests a relatively equitable distribution of bus stops across the study area, which consequently exerts a limited influence on residents' sentiment valence.

The Distance to nearest park or square exhibited a significant negative correlation with sentiment valence (Figure 7f), indicating that closer proximity corresponds to more positive

sentiment. The spatial distribution of the coefficients presents a stepped pattern, with the magnitude of influence decreasing from the west towards the east. The areas exhibiting the strongest influence are primarily situated in the western and central districts of Harbin, characterized by high residential density and elevated levels of daily life stress. As parks and squares serve as vital spaces for leisure and emotional regulation, high accessibility to these amenities can effectively mitigate the pressures of urban living [76]. Conversely, the areas displaying weaker influence mainly comprise the eastern districts. Although large-scale parks and squares are relatively scarce in these regions (Figure 8g), internal green coverage within communities is generally high, allowing residents to derive recreation and relaxation directly from their immediate residential environment. Furthermore, consistent with earlier observations, residents in these areas rely heavily on private transportation. Consequently, their sensitivity to the distance to public parks is lower, which manifests as reduced influence coefficients (in absolute terms).

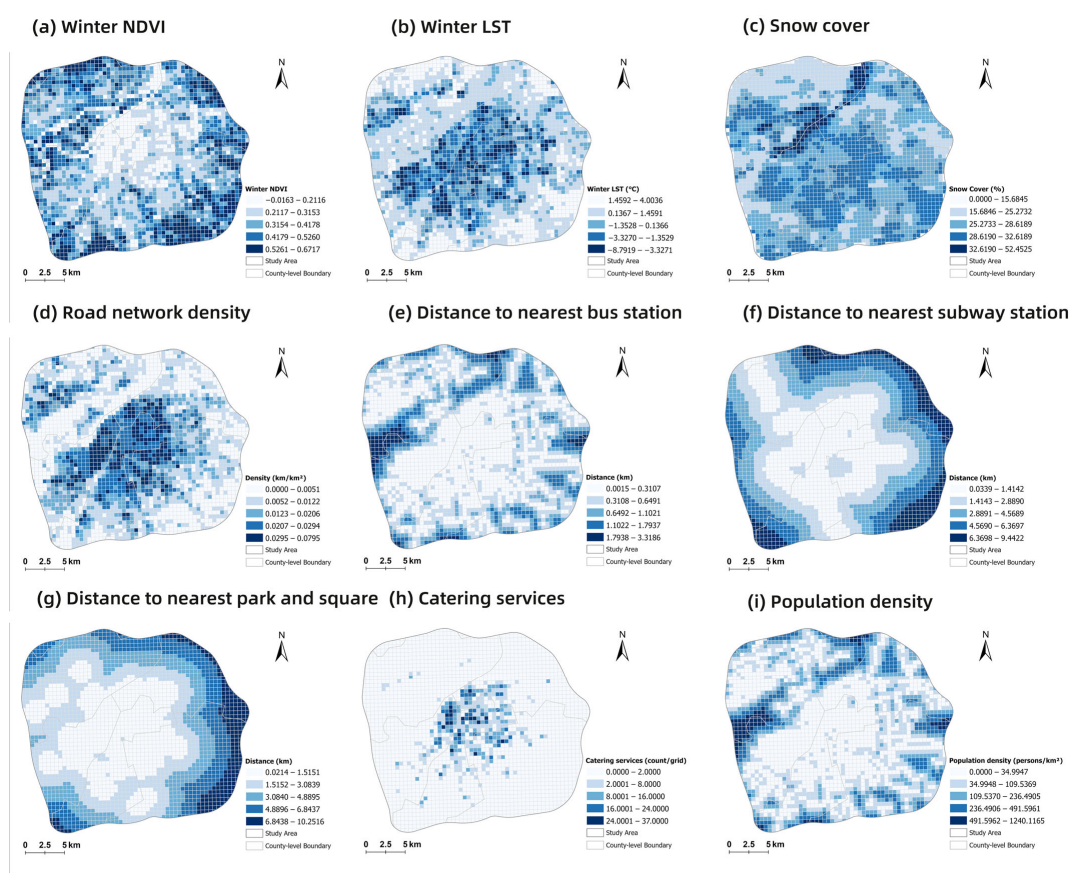


Figure 8. Spatial distribution of variables.

The density of catering services exhibited a positive correlation with sentiment valence (Figure 7g), indicating that a higher concentration of catering facilities is associated with more positive sentiment. The magnitude of this influence displays a spatial gradient, increasing from the southwest towards the northeast. The areas exhibiting the strongest influence are primarily concentrated in the northeastern sectors of Xiangfang District and Daowai District. In contrast to the old urban core, these regions have historically been underserved regarding commercial amenities. Consequently, improvements in the commercial environment, specifically in catering, are likely to yield a stronger marginal utility. Such enhancements elevate residents' satisfaction and fulfill unmet needs, thereby fostering positive sentiment valence. Conversely, areas showing weaker influence primarily comprise the old urban core and its immediate periphery. These areas are characterized by

a saturated supply of catering services and a mature consumer base. As a result, sentiment valence in these regions is less sensitive to the quantity of catering facilities, manifesting in lower influence coefficients. Overall, however, this predictor operates as a global variable, characterized by minimal spatial heterogeneity and a relatively weak magnitude of impact.

Population density exhibits a positive correlation with sentiment Valence (Figure 7h), indicating that higher population density corresponds to more positive sentiment. The spatial distribution of the coefficients displays a wave-like pattern, with values gradually increasing from the southwest to the east/northeast. The areas with the highest influence coefficients are primarily located in the eastern and northeastern sectors, which are characterized by relatively lower population density. In these less crowded areas, an increase in population density may bring more urban vitality and social interaction, thus exerting a stronger marginal positive effect on sentiment. Conversely, the areas with lower coefficients correspond to the southwestern regions, which represent the traditional old town and core residential zones with inherently high population density. In these already densely populated areas, further increases in density might lead to crowding effects, rendering sentiment Valence less sensitive to population growth, hence the smaller influence. However, given the minimal spatial variation in the coefficients, population density functions similarly to a global variable, and its overall intensity of influence—when judged by the absolute values of the coefficients—is considered weak.

3.4.2. Analysis of Spatial Patterns of Coefficients for Variables Influencing Arousal

Figure 9a illustrates the spatial distribution of the influence coefficients of winter NDVI on sentiment arousal. The distribution is characterized by significant spatial heterogeneity. Areas exhibiting a negative correlation are primarily concentrated in built-up regions, where elevated winter NDVI typically corresponds to localized, small-scale evergreen belts or snow-covered zones. Such landscapes are defined by monotonous color palettes and limited sensory stimulation, reinforcing perceptions of “tranquility” and “cold solitude,” thereby suppressing sentiment arousal. In contrast, the southeastern urban-rural transition zone exhibits a positive correlation. Attributable to winter snow and ice coverage, the brightness, reflectivity, and spatial openness of the landscape in this region are significantly higher than in the central urban area [77], generating intense visual stimulation. Research in environmental psychology indicates that natural landscapes characterized by high brightness and contrast can trigger physiological activation and psychological excitement, thereby elevating sentiment arousal [78].

Winter LST is negatively correlated with sentiment Arousal (Figure 9b), indicating that the lower the winter temperature, the higher the sentiment Arousal. Overall, this variable is a global variable (Table 9) with minimal spatial variation. Influenced by the lifestyle characteristics of cold regions, local residents exhibit strong adaptability and tolerance to low winter temperatures [54]. This adaptability leads to a reduced subjective sensitivity to LST variations, thereby resulting in weaker psychological responses to temperature fluctuations. Specifically, the low-value areas encompass large outdoor open spaces where human activities primarily consist of prolonged outdoor ice and snow recreation, exhibiting an extremely high functional dependence on the low-temperature physical environment. Consequently, minor fluctuations in winter LST directly affect the quality of the ice and snow landscape and the recreational experience, making sentiment Arousal in these areas more sensitive to temperature changes.

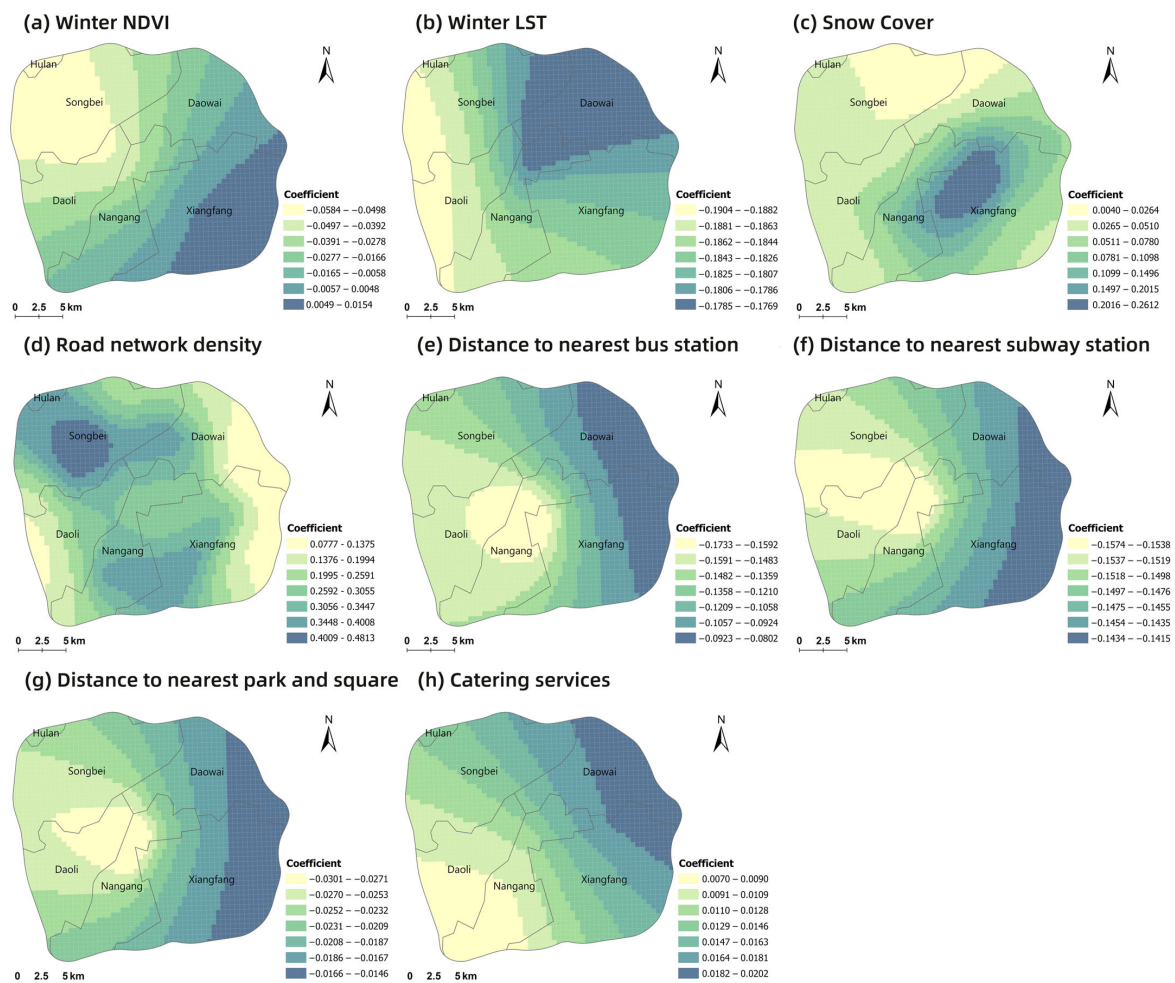


Figure 9. Spatial distribution of MGWR coefficients for variables affecting sentiment arousal.

Snow cover is positively correlated with sentiment Arousal (Figure 9c), indicating that the higher the snow cover, the higher the sentiment Arousal. Specifically, the high-value areas are primarily concentrated in urban built-up areas. Similar to its impact on sentiment Valence, the widely distributed recreational and commercial facilities in these built-up areas interact with the snowscape, providing outdoor activities with unique winter characteristics. This synergistic effect effectively enhances sensory stimulation, causing snow cover to exert a strong positive marginal effect on sentiment Arousal. Conversely, in the surrounding low-value areas, the lack of such interactive facilities makes the snowscape appear relatively monotonous, resulting in a relatively lower impact on sentiment Arousal.

Road network density is positively correlated with sentiment Arousal (Figure 9d) and exhibits significant spatial heterogeneity in its distribution, indicating that the higher the road network density, the higher the sentiment Arousal. Specifically, the high-value areas are primarily urban core areas characterized by a dense concentration of commercial, cultural, and landscape spaces. In these areas, high road network density translates to greater accessibility and abundant opportunities for urban experiences. The high-frequency external stimuli inherent in these accessible areas readily trigger higher levels of Arousal. Conversely, areas with lower impact coefficients are primarily distributed in the eastern and western peripheral regions, which are characterized by a relatively tranquil environment. In these areas, transportation planning prioritizes utilitarian traffic functions over crowd-gathering activities. This functional orientation implies that even with an increase in road network density, the resulting external environmental stimuli remain highly limited. Consequently, its enhancing effect on sentiment Arousal is relatively weak.

Distance to nearest bus station is negatively correlated with sentiment Arousal (Figure 9e) and exhibits significant spatial heterogeneity in its distribution, indicating that the greater the distance, the lower the sentiment Arousal. Similar to its impact pattern on sentiment Valence, the high-value areas are concentrated in the old urban areas. As indicated by Figure 7e, these areas feature highly dense bus networks, and bus hubs are frequently closely integrated with highly vibrant commercial or public activities. Consequently, a reduction in distance exerts a strong arousing effect on sentiment. Conversely, urban peripheral areas typically correspond to monotonous residential zones, undeveloped vacant land, or fringe areas lacking vitality. Given that the baseline environmental stimuli in these areas are inherently low and the spatial environment exhibits strong homogeneity, the marginal inhibitory effect of further increasing the distance to bus stations on sentiment Arousal is no longer significant.

Distance to nearest subway station is negatively correlated with sentiment Arousal (Figure 9f), indicating that the shorter the distance, the higher the sentiment Arousal. In terms of spatial distribution, the impact of this variable exhibits a distinct radial gradient, demonstrating significant spatial heterogeneity. Specifically, the high-value areas are concentrated in the city center, which is characterized by a high intensity of environmental stimuli. Subway stations are densely distributed in the central areas (Figure 8f), typically serving as highly integrated transit hubs that combine transportation, commerce, and pedestrian flow. Therefore, people in close proximity to these central stations are exposed to high levels of sensory and social stimuli. Continuous exposure to such a stimulating environment activates the sympathetic nervous system, thereby significantly elevating sentiment Arousal levels [79]. Conversely, moving away from these central stations leads to a sharp decline in environmental stimuli, thereby weakening the impact on sentiment Arousal.

Distance to nearest park or square is significantly negatively correlated with sentiment Arousal (Figure 9g), indicating that the shorter the distance, the higher the residents' sentiment Arousal. In terms of spatial layout, it exhibits a gradually diminishing gradient from west to east. Specifically, the high-value areas are primarily concentrated in the central core region, which features a high density of parks and squares (Figure 8g). In high-density urban built environments, parks and squares often serve as vibrant hubs for intensive social interactions, physical exercise, and leisure activities. This generates abundant sensory stimulation and urban vitality, thereby elevating the physiological and psychological Arousal levels of nearby residents [80]. Therefore, sentiment Arousal levels in this region are highly sensitive to spatial accessibility. Conversely, the low-value areas are primarily located in the urban periphery, which features a relative scarcity of parks and squares (Figure 8g). Due to reduced activity frequencies and a decline in overall spatial vitality, changes in the distance to these areas consequently have a diminished impact on sentiment Arousal.

Catering services are significantly positively correlated with sentiment Arousal (Figure 9h), indicating that the higher the density of catering services, the more they generally elevate sentiment Arousal levels. In terms of spatial layout, it exhibits a gradually increasing gradient from southwest to northeast. Specifically, the high-value areas are primarily located in the eastern and peripheral regions. These regions feature a relatively sparse distribution of catering services (Figure 8h). Due to the relative scarcity of commercial and social amenities in these urban-rural transition zones or industrial areas, the mere presence or addition of catering services can significantly enrich activity diversity and provide social spaces. Therefore, sentiment Arousal is highly sensitive to catering services [81]. Conversely, the low-value areas are primarily located in the older urban areas, where catering services are already highly saturated and densely clustered (Figure 8h). Due to environmental saturation and potential sensory fatigue, the marginal stimulatory effect of additional catering facilities is diminished.

4. Discussion

4.1. Spatial Patterns of Urban Sentiment Valence and Arousal

In this study, the spatial patterns of sentiment valence and arousal exhibit a dual-core distribution along the Songhua River. The HH clusters are concentrated in the Daoli and Nangang districts of the southern bank (Jiangnan) and the core of the Jiangbei New Area to the north. This alignment with Harbin's historical and commercial centers corroborates the theory of polycentric urban vitality, suggesting that areas characterized by a high degree of functional mix and profound historical context often serve as catalysts for urban vitality. Notably, the Songhua River does not act as a geographical barrier fragmenting sentiment; instead, it has formed a corridor of affective connectivity, facilitated by ice and snow tourism activities across both banks. This finding extends the theory regarding the health benefits of blue spaces: in a frozen winter state, rivers transform from passive visual amenities into accessible activity spaces, thereby enhancing their function in promoting social interaction and winter health [82]. Furthermore, no significant LL arousal clusters were identified within the study area, indicating that Harbin has not become an “emotional desert” despite the severe cold climate. This reflects the unique climatic adaptability of residents in cold-region cities. By engaging in specific winter outdoor activities and modes of social interaction, they mitigate environmental stress and maintain a high level of urban vitality [83].

4.2. Factors Influencing Sentiment Valence

The MGWR results indicate that sentiment Valence is synergistically driven by spatial accessibility, service facility convenience, and unique microclimate factors. The significant spatial heterogeneity exhibited by this impact underscores the unique human–environment interactions in cold-region cities during winter.

The study reveals that the impact of Harbin's built environment on public sentiment during winter is profoundly moderated by the severe cold climate and ice-and-snow culture. Traditional urban studies generally posit that higher NDVI and higher LST contribute to enhancing positive public sentiment [59]. However, this study identifies a “cold-region paradox” during winter: winter NDVI and winter LST are negatively correlated with sentiment Valence, whereas snow coverage exhibits a positive correlation. This counterintuitive phenomenon can be explained by the mechanism of thermal psychological adaptation [54]. This theory posits that when the public possesses explicit psychological expectations regarding extreme climates and can derive specific cultural and aesthetic value from them, their tolerance to cold is significantly enhanced, even transforming climatic disadvantages into positive emotional experiences. Specifically, given Harbin's urban identity as a winter tourism destination, areas exhibiting the lowest winter NDVI—such as the banks of the Songhua River—provide open terrain that forms vast snowscapes, perfectly aligning with tourists' aesthetic expectations. Meanwhile, a lower winter LST is a prerequisite for maintaining high-quality ice-and-snow architecture; in this context, the cold ceases to be merely a physiological stimulus and is instead reframed as an aesthetic asset.

Notably, the positive public sentiment toward severe cold and ice-and-snow is highly contingent upon the buffering effects of urban microclimates and municipal support [47]. In the core built-up areas, the integration of historic architecture and snowscapes fosters a distinctive landscape ambiance, while dense building clusters serve as microclimatic shields, effectively mitigating the impact of cold winds. Coupled with highly efficient municipal snow removal services, this allows the public to appreciate the winter aesthetics without encountering mobility challenges induced by road snow accumulation. Conversely, in the exposed northern areas, the absence of wind barriers compounded by extremely low temperatures results in severe cold stress, exceeding the regulatory limits of psychological

adaptation and thereby partially offsetting the psychological benefits derived from the winter landscape [74]. This suggests that the psychological benefits of the winter landscape can only be maximized when physiological cold stress is effectively mitigated through microclimatic design and infrastructure.

Concurrently, the emotional impact of transportation infrastructure also varies significantly depending on spatial functional attributes. Road network density is positively correlated with sentiment Valence, with its most pronounced impact primarily concentrated around winter tourist attractions. In these areas, high road network density ensures the accessibility and continuity of the landscapes, alleviating mobility challenges for tourists and thereby effectively enhancing the recreational experience [69]. In contrast, in peripheral logistics and warehousing zones, the road network primarily serves utilitarian purposes such as freight transport and commuting. Consequently, the lack of spatial functions for aesthetic engagement renders public emotion less sensitive to road network density. Similarly, the distance to the nearest bus station primarily affects the old urban areas, where high population density leads to a heightened reliance on public transportation. In sub-zero environments, proximity to bus stations effectively reduces outdoor waiting times and walking distances, which is crucial for mitigating the risk of cold exposure and maintaining positive travel emotions [84]. However, this variable manifests overall as a global variable with a relatively weak impact, suggesting that the current distribution of bus stations in Harbin is relatively balanced and largely satisfies the commuting demands across most of the study area.

The spatial distribution of urban facilities and social vitality exhibits a pattern consistent with the concept of marginal utility in economics. In the densely populated central and western districts characterized by high living pressure, proximity to parks and squares significantly enhances positive emotions, playing a crucial role in emotional regulation [85]. Conversely, in the eastern districts, a higher rate of intra-community green space compensates for the lack of large public parks, thereby reducing residents' sensitivity to park accessibility. Both catering services and population density exhibit a positive correlation with emotions; however, their strongest impacts are concentrated in the eastern and north-eastern districts, areas historically characterized by insufficient commercial facilities or lower population densities. In these areas, the addition of catering services or population growth fosters urban vitality and social interaction, yielding a highly positive marginal effect on public emotions [86]. Conversely, in the traditional southwestern old districts where commercial services are already saturated and population density is inherently high, further densification is prone to trigger crowding effects and resource competition [87]. Consequently, in these core areas, the addition of facilities or population growth yields significantly diminishing emotional returns. This spatial heterogeneity suggests that future urban renewal in cold-climate cities should prioritize the equitable distribution of facilities in peripheral or underserved areas, rather than over-concentrating resources in already-saturated urban cores.

4.3. Driving Mechanisms of Sentiment Arousal

The MGWR results indicate that public sentiment Arousal is primarily driven by the synergistic effects of the visual stimulation intensity of natural landscapes, sensory exposure to transport hubs, and the marginal effects of urban vitality. Unlike sentiment Valence, which reflects the positive or negative polarity of emotions, Arousal primarily reveals the impact of the urban spatial environment on the physiological activation and psychological excitement levels of individuals.

First, winter natural landscapes and microclimatic features significantly modulate sentiment Arousal through visual stimulation and the mechanisms of Attention Restoration

Theory (ART). The study reveals that the impact of winter NDVI on Arousal exhibits a high degree of spatial heterogeneity. In urban built-up areas, higher NDVI values typically correspond to small-scale evergreen vegetation belts. According to ART, these natural landscapes interspersed within the bustling urban environment can provide soft fascination and a sense of being away [80]. Such environmental characteristics help alleviate directed attention fatigue induced by high-density urban living, lowering sentiment Arousal by inhibiting the overactivity of the sympathetic nervous system, thereby enhancing the public's psychological perception of tranquility. Furthermore, Harbin residents demonstrate remarkable climate adaptability to low winter temperatures [54], but in large outdoor open spaces, the public's functional dependence on the low-temperature physical environment is extremely high. Minor fluctuations in Winter LST can directly affect the quality of ice and snow landscapes, thereby making the Arousal of people in these areas exceptionally sensitive to temperature changes. Simultaneously, Snow Cover demonstrates the strongest positive Arousal effect in built-up areas, owing to the synergy between snowscapes and dense recreational and commercial facilities, where abundant interactive ice and snow activities significantly enhance sensory stimulation. Conversely, in peripheral areas lacking interactive facilities, the enhancing effect of monotonous snowscapes on Arousal diminishes significantly.

Secondly, the impact mechanism of transportation infrastructure on Arousal aligns with the spatial distribution logic of Valence, as transportation hubs in urban cores and old city districts feature a high concentration of commercial activities and pedestrian traffic. Proximity to these areas implies individual exposure to high-frequency external environmental stimuli, significantly elevating psychological Arousal and alertness levels [88]. Conversely, transportation facilities in peripheral areas primarily serve utilitarian functions, featuring high spatial homogeneity and extremely low baseline environmental stimuli; consequently, altering the density of transportation facilities in these regions no longer exerts a significant marginal stimulatory effect on sentiment Arousal.

Finally, the spatial distribution of urban recreational and commercial facilities further corroborates the aforementioned principle of diminishing marginal effects, profoundly manifesting the sensory fatigue mechanism in relation to Arousal. In the central core area, high-density parks and squares, serving as hubs of vitality, provide abundant sensory stimuli, decisively elevating residents' Arousal levels [89]. The scarcity of commercial services such as dining in the eastern regions and urban-rural transition zones enables newly added facilities to rapidly disrupt environmental monotony, thereby eliciting extremely high Arousal sensitivity. However, in the highly facility-saturated southwestern old city districts, environmental stimuli have already reached a state of overload. Integrating the ART framework and environmental psychology perspectives, additional facilities in this context not only fail to further enhance excitement but instead accelerate the depletion of directed attention, ultimately triggering sensory fatigue [90]. This indicates that the rational dispersion of urban facilities is not only a matter of spatial equity but also the key to preventing localized stimulus overload and maintaining a healthy and moderate urban sentiment environment.

4.4. Methodological Advantages of the LLMs-MGWR Framework

By integrating LLMs with MGWR, this study overcomes limitations inherent in two key stages of previous research. First, regarding semantic understanding, unlike traditional approaches relying on sentiment dictionaries or deep learning models, LLMs possess human-like zero-shot reasoning and contextual alignment capabilities [91]. This enables the identification of not only explicit emotional vocabulary but also the decoding of complex sentiments implicit in social media texts, including cultural metaphors and irony. Such

deep semantic parsing significantly enhances the accuracy of sentiment quantification, thereby more authentically capturing residents' subjective experiences within complex urban environments [92].

Second, regarding spatial analysis, traditional GWR models enforce a uniform bandwidth across all variables, which often leads to the oversmoothing of local variations or the overfitting of global trends. In contrast, MGWR allows different variables to operate at their distinct optimal spatial scales, thereby precisely disentangling the hierarchical structure of environmental influences [64]. For example, in this study, distance to nearest park and square and catering services were identified as global variables, constituting a relatively stable urban sentiment baseline across the entire region. Conversely, road network density emerged as a local variable, indicating that the marginal effects of micro-scale traffic on sentiment exhibit strong spatial heterogeneity. This capacity for multi-scale interpretation offers robust empirical support for precision planning [93].

4.5. Generalizability and Cross-Regional Implications

The core sentiment-environment interaction mechanisms identified in this study are rooted in universally applicable theoretical frameworks, rather than being isolated phenomena confined to specific cultural contexts. First, based on ART [80], the psychological restorative functions of natural landscapes in cold environments exhibit cross-cultural universality. Secondly, the law of diminishing marginal utility demonstrated by commercial space agglomeration [94] reflects the universal human psychological trait of developing sensory fatigue when exposed to high-density stimuli. Finally, the mechanism of thermal psychological adaptation enables coldness to be reframed from a climatic disadvantage into an aesthetic asset [54]. These universal mechanisms indicate that the fundamental sentiment-environment relationships revealed in this study are highly transferable to other cities facing similar winter challenges. Furthermore, the LLMs-MGWR methodological framework proposed in this study is itself highly transferable. The zero-shot reasoning capability of large language models enables them to directly process social media texts in other languages without requiring domain-specific retraining. Meanwhile, the MGWR model can be widely applied to any region with geo-referenced data.

While the underlying mechanisms are universal, specific contextual factors in different cities may exert a significant moderating effect on these relationships. The first factor is the difference in cultural attitudes. For example, the cultural tradition of "friluftsliv" (outdoor living) embraced in Scandinavia may further amplify the facilitative effect of cold natural landscapes on positive sentiment [58]. The second factor is the influence of tourism intensity. Harbin's tourism-driven context, centered around the Ice and Snow Festival, may evoke positive sentiment associated with low temperatures more intensely than the everyday contexts of typical cold-climate cities. Finally, the inherent differences across different cities in urban morphology and transportation infrastructure will also reshape the spatial distribution patterns of sentiment responses.

Based on the aforementioned universal mechanisms and contextual differences, future research should establish a broader cross-regional comparative agenda. It is recommended that the LLMs-MGWR framework proposed in this study be applied to other typical cold-climate cities worldwide, such as Helsinki (Finland), Sapporo (Japan), and Edmonton (Canada) [83,95]. Conducting parallel comparative studies in cities across different continents and cultural backgrounds will help to further distinguish between universal principles and contingent effects constrained by local contexts, thereby providing more comprehensive theoretical support for the evidence-based planning of cold-climate cities globally.

4.6. Limitations and Future Research

First, given that social media user demographics are skewed towards a younger, urban, and educated digital population, this study may not adequately represent other age groups, particularly older adults, who are more sensitive to the adverse effects of winter climates. While the LandScan population and GDP data serve as objective demographic anchors that partially mitigate self-selection bias, future research should be supplemented with household surveys or multi-platform data triangulation. Second, although winter LST was incorporated as a thermal indicator, the study did not include a comprehensive outdoor thermal comfort assessment. Key microclimatic parameters such as mean radiant temperature and solar radiation are well-established determinants of thermal comfort in cold climates [54,55]. Future studies should integrate microclimate simulations or field measurements to derive composite thermal comfort indices (e.g., UTCI or PET), combined with multi-source demographic data, to enhance the granularity and holism of the analysis. Furthermore, the selection of urban built environment indicators remains limited; future research should progressively expand the breadth and depth of these metrics. Finally, subsequent studies could further explore the potential of LLMs in interpreting visual content to construct a multimodal framework integrating text and imagery for urban perception.

5. Conclusions

This study proposes an innovative analytical framework integrating LLMs and MGWR to investigate the spatial patterns and driving mechanisms of winter sentiment Valence and Arousal in typical cold-climate cities. By decoding complex semantic details in social media data and capturing multi-scale spatial heterogeneity, this framework provides a novel perspective on human–environment interactions under cold-climate winter conditions. The key findings are as follows:

- (1) The spatial distribution of sentiment Valence and Arousal exhibits a dual-core pattern along the Songhua River. Rather than acting as a geographical barrier that fragments sentiment connections, the frozen river serves as a vibrant corridor of sentiment connectivity, facilitated by winter ice and snow activities along both banks. Furthermore, the absence of significant low-low (LL) Arousal clusters within the study area suggests that Harbin is not reduced to a sentiment desert during the severe winter. On the contrary, residents demonstrate remarkable thermal-psychological adaptability, effectively mitigating environmental stress and maintaining high urban vitality through participation in specific winter outdoor activities. This implies that the spatial pattern of sentiment exhibits a high degree of climatic adaptability.
- (2) In terms of sentiment Valence, this study reveals a cold-climate paradox: under conditions of high snow coverage, a lower winter Normalized Difference Vegetation Index (NDVI) and a lower winter Land Surface Temperature (LST) are unexpectedly associated with positive sentiment. The harsh climate is reframed from a physiological stimulus into a landscape aesthetic experience, and extremely low temperatures become a prerequisite for maintaining high-quality snowscapes and ice and snow architecture. However, this positive sentiment also depends on the buffering effect of urban microclimates and efficient municipal snow removal services.
- (3) The spatial heterogeneity of sentiment Arousal is primarily driven by the visual stimulus intensity of natural landscapes and the sensory exposure at transportation hubs. Small-scale urban greenery within built-up areas provides soft fascination and fosters a sense of tranquility, whereas expansive snowscapes in the urban-rural transition zone trigger intense physiological activation. Furthermore, urban recreational and commercial facilities demonstrate a pronounced pattern of diminishing marginal

utility. In underserved peripheral areas, additional facilities can significantly elevate sentiment Arousal; conversely, in highly saturated older urban cores, further densification instead leads to sensory fatigue and crowding effects, significantly diminishing sentiment returns.

- (4) The LLMs-MGWR framework proposed in this study demonstrates significant advantages over traditional methods. In terms of semantic decoding, LLMs overcome the binary classification limitations of traditional sentiment lexicons, enabling the precise extraction of multidimensional sentiment features of Valence and Arousal based on psychological models. Leveraging their zero-shot reasoning capabilities, they can accurately identify complex sentiment in social media texts without requiring domain-specific retraining. In terms of spatial analysis, the MGWR model successfully distinguishes the spatial scales of influence of environmental variables. More importantly, the deep integration of the two establishes a closed-loop system featuring high-throughput semantic processing and multi-scale spatial interpretation, which not only overcomes the overfitting issues of traditional GWR models but also endows the framework with robust cross-regional generalization capabilities, providing a more rigorous methodological paradigm for urban sensing research.

Based on the aforementioned findings, this study proposes a set of spatial optimization strategies tailored for winter use in cold-climate cities. First, emphasis should be placed on microclimate creation. Considering that positive sentiment is highly dependent on microclimate buffering, it is recommended to introduce temporary wind barriers in open ice and snow landscapes or utilize architectural setback designs to mitigate wind velocity, thereby extending users' outdoor dwell time in extreme cold environments and maximizing the psychological benefits derived from the cold-climate paradox. Second, the decentralization of service facilities should be considered during the design process. In light of the diminishing marginal utility of facilities, future urban regeneration should avoid the over-concentration of resources in already saturated urban cores. Planning priorities should shift towards urban-rural transition zones or underserved peripheral areas, where embedding small-scale, multi-functional winter activity nodes can yield the maximum enhancement of social vitality with minimal investment. Furthermore, the winter revitalization of blue-green infrastructure should be considered. By breaking away from the conventional notion of viewing frozen waterways as geographical barriers, winter rivers and lakes should be planned as seasonal linear parks. Enhancing barrier-free accessibility and temporary heating amenities along both banks will reinforce their role as urban sentiment connection corridors.

Ultimately, this study demonstrates that under the extreme winter climate conditions of cold-region cities, cities do not inevitably succumb to sentiment depression and declining vitality. By effectively leveraging thermal psychological adaptation mechanisms and winter-specific ice and snow landscapes, cold-region cities can equally stimulate high levels of positive public sentiment and spatial vitality. The LLMs-MGWR framework developed in this study has successfully achieved the leap from large-scale semantic decoding to fine-grained spatial mechanisms, providing a novel methodology for understanding human–environment interactions in complex environments. This not only provides transferable empirical evidence for cities worldwide with similar winter scenarios but also offers design guidelines for winter space utilization in cold-region cities. These guidelines clarify how to alleviate environmental stress through fine-grained spatial interventions and microclimate regulation, thereby comprehensively enhancing residents' psychological well-being and winter outdoor vitality.

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