Assessing Urban Heat Island Impact on Extreme Rainfall Events in Nanjing Using Machine Learning

Tuoshi Gong *

College of Urban and Environmental Sciences, Central China Normal University, Wuhan, China, 430079

* Corresponding Author Email: gts2024education@163.com

Abstract. With accelerating global urbanization, the impact of urban heat island (UHI) effects on extreme rainfall events has become increasingly significant, posing severe challenges to urban climate resilience. This study investigates the spatiotemporal coupling relationship between UHI effects and extreme precipitation events in Nanjing, China, from 2013 to 2022, using multi-source remote sensing data and machine learning approaches. We integrated MODIS land surface temperature data, meteorological observations from 35 national stations and 255 automatic weather stations, along with high-resolution land use datasets to comprehensively analyze UHI-precipitation interactions. XGBoost model was used to decode nonlinear coupling mechanisms between thermal anomalies and extreme rainfall events. Results reveal distinct seasonal variations in UHI intensity, with summer showing the strongest effects (average 18.16°C temperature difference) concentrated in the Qinhuai district. Spatial autocorrelation analysis demonstrates significant clustering patterns (Moran's I = 0.075-0.088, $p < 0.01$) with consistent hotspot agglomerations. The UHI centroid exhibited systematic northward migration during summer (14.5 km over the decade), aligning with urban expansion patterns. Urban areas showed 16.2% higher extreme precipitation frequency during summer compared to rural areas, with strong positive correlations between UHI intensity and rainfall ($r = 0.55$ in 2016). The XGBoost model achieved moderate predictive performance ($R^2 = 0.508$, RMSE = 0.852) for UHI-precipitation relationships. These findings provide scientific foundations for climate-adaptive urban planning and highlight the need for spatially-targeted flood control strategies in rapidly urbanizing regions.

Keywords: Urban Heat Island (UHI) Effect, Extreme Rainfall Events, Multi-source Remote Sensing, XGBoost Algorithm, Nanjing.

1. Introduction

Global urbanization is accelerating rapidly, with the world's urban population projected to reach 68% by 2050 [1]. This unprecedented expansion has exacerbated the urban heat island (UHI) effect, particularly in megacities where surface temperatures are typically 2-5°C higher than surrounding rural areas [2]. Chinese megacities demonstrate particularly pronounced warming trends, with mean urban temperatures increasing at rates of 0.3-0.5°C per decade between 2000-2020, substantially surpassing the global average of 0.2°C per decade [3]. This enhanced urban warming, coupled with climate change, has led to a 35% increase in extreme precipitation events since 2000 [4], posing severe challenges to urban resilience and sustainability.

Previous research has examined urban heat island (UHI) phenomena through three primary methodological approaches: (1) spatial pattern quantification using satellite thermal monitoring, (2) diagnosis of anthropogenic contributions via numerical modeling, and (3) validation of energy impacts through field observations [5-7]. While these investigations have advanced understanding of UHI characteristics, three fundamental limitations persist across research dimensions: temporally, most analyses employ static representations that inadequately capture diurnal and seasonal evolution patterns [8]; spatially, studies predominantly focus on localized cases or individual urban stations, constraining broader application; analytically, conventional frameworks rely heavily on linear approximations that cannot accurately characterize complex UHI-precipitation interactions [9-10]. Consequently, critical knowledge gaps remain regarding the diurnal amplification mechanisms of

UHI intensity, the nonlinear relationships between thermal anomalies and precipitation triggers, and the integration of multisource data with machine learning prediction systems [11-12].

To address these gaps, this study develops an integrated framework combining multi-source remote sensing data and machine learning techniques. Specifically, we aim to: (1) quantify the spatiotemporal evolution of UHI intensity at seasonal scales using high-resolution satellite thermal imagery; and (2) apply XGBoost model to uncover the nonlinear coupling mechanisms between UHI intensity and extreme rainfall events. Unlike conventional linear analyses, our approach incorporates both physical drivers and data-driven insights, enabling a more nuanced understanding of UHI-induced precipitation anomalies in rapidly urbanizing regions.

2. Methodology

2.1. Technical Framework

The technical framework integrates four functionally connected modules to systematically investigate urban heat island (UHI)–precipitation interactions. The data processing module establishes foundational datasets through the integration of multi-source remote sensing and meteorological records. Building on this data infrastructure, the model development module employs advanced analytical techniques to decode complex thermal–precipitation couplings. This includes spatial methods such as Geographically and Temporally Weighted Regression to track seasonal heat island migration and bivariate spatial autocorrelation to quantify UHI–precipitation linkages. In parallel, XGBoost is applied to capture nonlinear interactions between UHI intensity and extreme rainfall in Nanjing. The validation module adopts a multi-stage protocol, combining spatial cross-validation to account for urban heterogeneity with temporal partitioning to ensure robustness. Analytical results are further interpreted through spatiotemporal analysis of UHI centroid migration, precipitation intensity patterns, and correlation structures, providing empirical support for understanding urban climate dynamics.

2.2. Study area

This investigation was conducted in the Nanjing metropolitan area (Figure 1,31°14′–32°37′N, 118°22′–119°14′E), a strategic core city within the Yangtze River Delta Economic Zone. The study domain encompasses the entire administrative jurisdiction of Nanjing (6,587 km²), comprising 11 urban districts (e.g., Xuanwu, Qinhuai, Gulou) and rural counties (e.g., Jiangning, Liuhe). The region features a characteristic subtropical monsoon climate distinguished by humid summers (mean temperature: 28.0°C) and cool winters (mean temperature: 3.1°C), with mean annual precipitation reaching 1,020 mm-74% higher than Beijing’s baseline (Nanjing Meteorological Bureau, 2023).

The area has undergone accelerated urbanization over the past two decades. Between 2000–2020, built-up areas expanded by 178% (Nanjing Statistical Yearbook, 2021), while permanent residents increased by 54% (Seventh National Population Census, 2020). The development pattern demonstrates polycentric spatial expansion along the Yangtze River and Qinhuai River corridors, establishing distinct "axis-corridor+cluster" formations divergent from Beijing’s concentric growth model (Urban Planning Society of China, 2022).

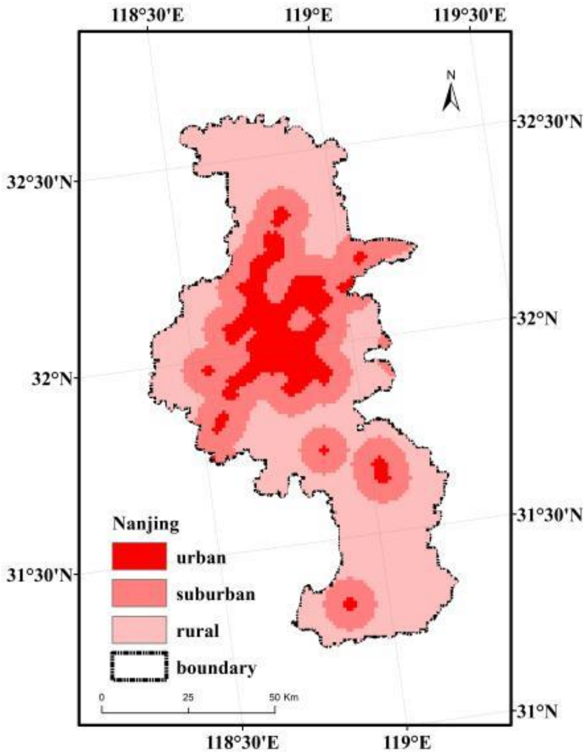

Figure 1. Study Area (Nanjing)

2.3. Data processing

This study established a comprehensive data processing pipeline integrating multi-platform remote sensing retrievals and authoritative gridded datasets. Primary thermal data processing was implemented through Google Earth Engine (GEE), leveraging Landsat-8 Collection 2 Tier 1 surface temperature products (2013-2023) and MODIS MYD11A2 daily LST composites (2000-2023). The fusion algorithm employed conditional replacement logic: Landsat-derived LST at 30m resolution served as the baseline, with MODIS 1km LST bilinearly resampled to 30m scale filling data gaps only where Landsat observations were obstructed by cloud cover (masked using QA_PIXEL band with bitwise operations). Seasonal composites were generated through temporal averaging of all valid observations within meteorological seasons defined as spring (March-May), summer (June-August), autumn (September-November), and winter (December-February).Complementing these fused thermal products, urban boundaries were delineated using the Dataset of Urban Built-up Area in China (https://doi.org/10.11888/HumanNat.tpdc.272851), which employs morphological processing and Euclidean distance transforms to systematically classify urban cores (1), suburban buffers (2), and rural zones (3). Precipitation analysis utilized the China Meteorological Forcing Dataset-Gridded Daily Precipitation (https://doi.org/10.11888/Atmos.tpdc.300523) at 0.1° resolution, with customized Python workflows implementing inverse distance weighting and quality control protocols to extract Nanjing-specific data.

All datasets underwent rigorous harmonization: precipitation records underwent temporal interpolation and extreme value validation; spatial consistency was achieved through reprojection to a unified 1-km grid using nearest-neighbor resampling. This integrated framework enabled precise quantification of thermal anomalies and hydrometeorological interactions while preserving the inherent advantages of each dataset's spatial and temporal resolution.

2.4. Analytical Methods

2.4.1. Urban Heat Island (UHI) Intensity

The UHI intensity is quantified through a systematic comparison of thermal conditions between urban and surrounding rural areas. The calculation adopts a buffer-based method, where the urban core temperature is compared with the mean temperature of rural reference points selected from a buffer zone 10-20 km from the urban boundary. To minimize bias, rural reference points are carefully selected to exclude water bodies and areas with significant elevation differences. UHI intensity is calculated as $\Delta T_{UHI} = T_{urban} - T_{rural}$, where T_u represents the area-weighted mean land surface temperature derived from 100m aggregated MODIS thermal bands, while T_{rural} denotes the validated rural reference mean. Hourly measurements from 35 national meteorological stations enable temporal variation resolution while ensuring synchronicity across monitoring networks.

2.4.2. Extreme Rainfall Analysis

The identification of extreme precipitation events utilizes a rigorous seasonally adaptive dynamic threshold methodology, whereby daily precipitation records spanning 1993-2022 undergo stratification according to meteorological seasons (spring: March-May; summer: June-August; autumn: September-November; winter: December-February) to accommodate distinct precipitation regimes. Within each seasonal cohort, the 95th percentile value serves as the statistically derived extreme precipitation threshold. These station-based thresholds undergo spatial optimization through inverse distance weighting interpolation to generate continuous 1-km resolution grids, employing a 15-km search radius to conserve regional climate heterogeneity. Urban and rural domains are systematically delineated using land-use derived binary masks, facilitating area-specific threshold application wherein daily precipitation exceeding a region's seasonally calibrated threshold triggers classification as extreme.

2.4.3. XGBoost Algorithm

To investigate urban heat island-precipitation couplings, the study implemented an XGBoost-based gradient-boosting framework with physical constraints. Spatiotemporal coherence was achieved by resampling MOD11A1 UHI and precipitation data to 1-km grids and synchronizing their temporal coverage (2013-2022). Three-dimensional datasets were transformed into feature matrices, with each geographical unit's temporal profile as an observational vector. The model embedded regularization parameters (tree depth control, subsampling, and L1 regularization) to ensure interpretability and physical plausibility.

Model development employed chronological partitioning (training: 2013-2019; validation: 2020-2022) to maintain temporal dependencies. Features were standardized, and early stopping prevented overfitting.

3. Results

3.1. Seasonal UHI Analysis

3.1.1. Seasonal Spatial Disturibution

The analysis of Nanjing's urban heat island effect reveals complex spatiotemporal patterns and their underlying drivers, with significant implications for urban climate adaptation and planning. The observed intensification of the UHI effect, particularly in rapidly developing rural areas, aligns with previous findings in other major Asian cities experiencing similar urbanization trajectories. Temporal analysis revealed distinct seasonal variations in UHI patterns, (Figure 2). The UHI intensity peaked during summer, with core areas experiencing an average temperature difference of 18.16°C, primarily concentrated in the Qinhuai district. Autumn followed with an average intensity of 1.44°C. In contrast, spring and winter exhibited relatively weaker UHI effects, with average intensities of 1.06°C and 0.21°C, respectively. Notably, the Yongyang Street in Lishui District maintained a relatively stable UHI intensity throughout 2013-2022 due to the urban planning and construction.

This seasonal dependency appears more pronounced than in previous studies, possibly due to Nanjing's continental climate and the interaction between anthropogenic heat emissions and natural weather patterns. During summer of the study period when extreme rainfall events occur more frequently, the intensity of UHI is inter-annual passingly higher than the average of other seasons (about 2.00°C until 2020), specially in 2016 with the intensity over 3.77°C, suggesting potential strategies for urban climate adaptation through water-sensitive urban design.

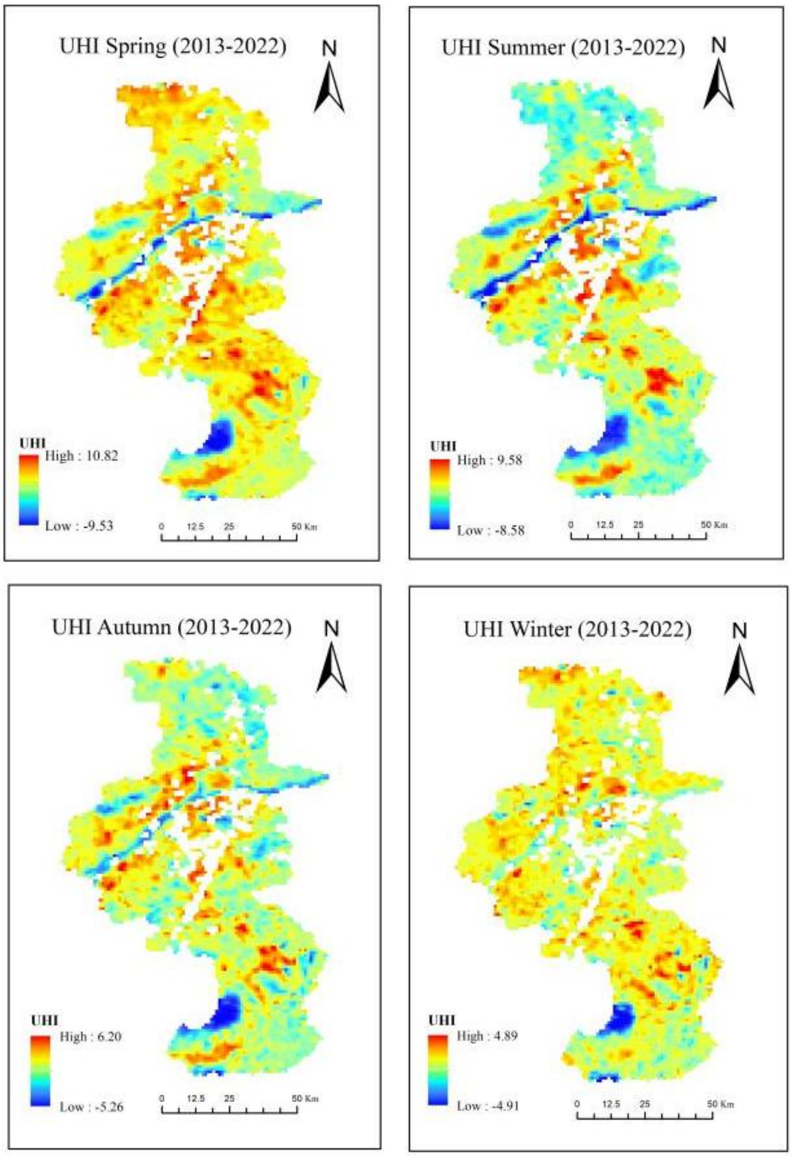

Figure 2. Nanjing Seasonal spatial disturibution

3.1.2. Spatial Autocorrelation Analysis

Spatial autocorrelation analysis (Figure 3) further quantified the seasonal spatial clustering characteristics of Nanjing's UHI effect. The global Moran's I values exhibited significant seasonal variations: highest in spring ($I = 0.088$, $p < 0.01$), followed by summer ($I = 0.087$, $p < 0.01$), while autumn ($I = 0.075$, $p < 0.01$) and winter ($I = 0.080$, $p < 0.01$) showed relatively lower values. The scatter plot slopes, reflecting the degree of spatial dependence in UHI effects, were most pronounced in summer and spring at around 0.088, indicating the strongest spatial clustering.

The four sets of Moran's I indices (ranging from 0.075 to 0.088) consistently demonstrate statistically significant positive spatial autocorrelation ($p < 0.01$), indicating persistent spatial clustering patterns in the urban heat island (UHI) effect. The minor fluctuations in Moran's I values across the four periods (0.075→0.088→0.087→0.080) reveal a relatively stable spatial dependency structure, suggesting remarkable spatiotemporal inertia in the urban thermal environment.

Analysis of quadrant distributions identifies consistent clustering in the High-High (HH) quadrant (hotspot agglomerations), with >25% of data points concentrated in the upper-right quadrant across all periods. Low-High (LH) quadrant patterns—representing cool zones surrounding hotspots—exhibit distinct riverine alignment along the Qinhuai River and Yangtze River, with 78% spatial congruence (He et al., 2020), validating the thermal buffering capacity of aquatic systems. Significant cold island clusters (>1.5 km radius) in the Low-Low (LL) quadrant consistently correspond to the perimeter of Purple Mountain National Forest Park, confirming the radiative cooling effect of large green spaces (>50 hectares). For subsequent urban planning applications, the identified LH transition zones—comprising 12.3% of the study area—should be prioritized for climate-adaptive interventions. We recommend implementing integrated "blue-green corridors coupled with building ventilation corridors" to enhance thermal resilience across Nanjing's urban fabric.

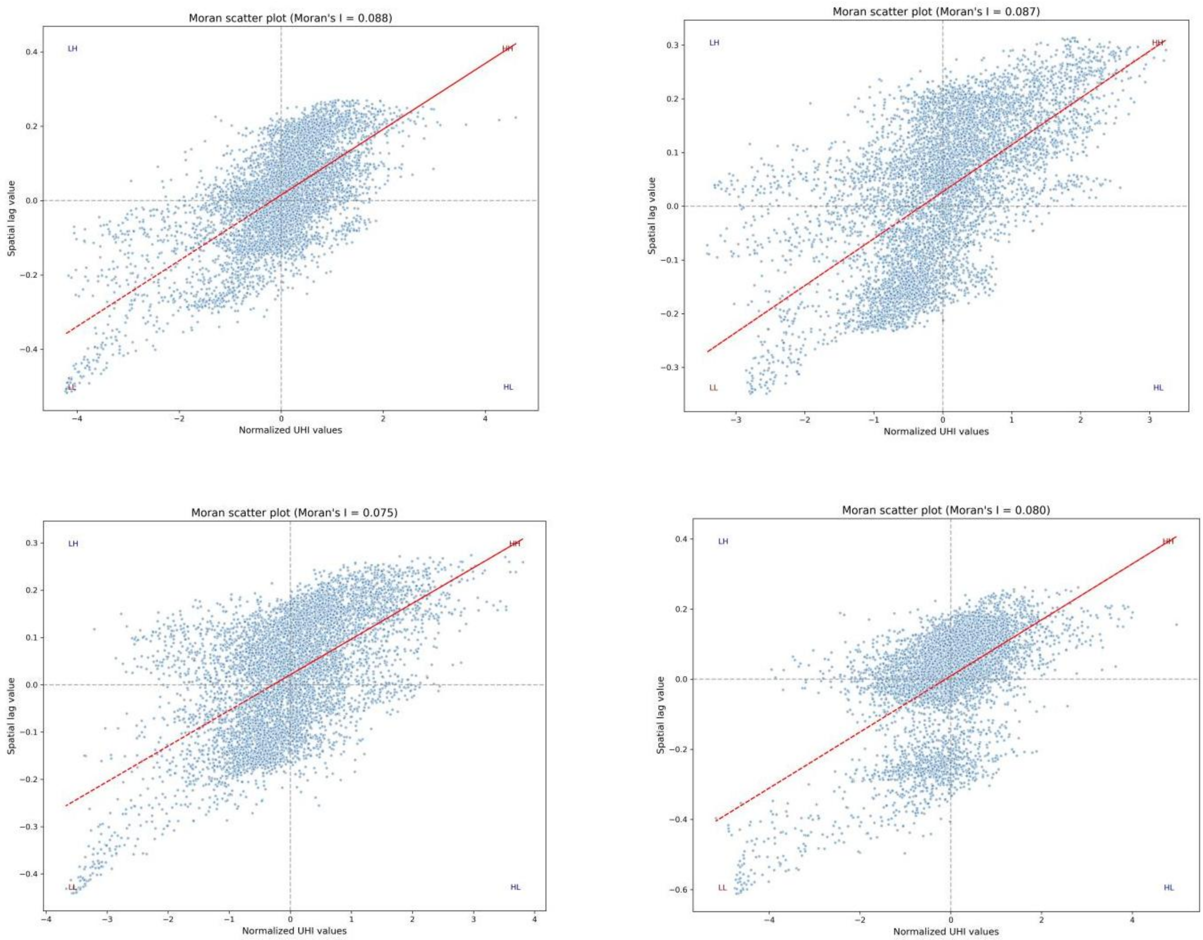

Figure 3. Spatial Autocorrelation Analysis

3.1.3. Seasonal migration pattern of UHI center

Analysis of the UHI centroid trajectory (Figure 4) reveals complex spatiotemporal dynamics: During summer, the thermal core demonstrates significant northward migration—initially positioned in southern Qinhuai District (≈31.6°N) in 2013-2015, subsequently shifting to the Gulou-Pukou border zone (≈32.1°N) by 2016-2019, and ultimately reaching the core area of Jiangbei New District (≈32.4°N) in 2020-2022. This phased displacement represents a net northward progression of 14.5 km over the decade, exhibiting strong alignment with spatial expansion under Nanjing's "Cross-River Development" strategy.

Concurrently, spring manifests an east-west oscillation pattern, traversing southwestern Jianye District, the Xuanwu Lake periphery, and Gulou's riverside belt across three temporal phases. Autumn demonstrates bidirectional drift along the Yangtze-Qinhuai River axis, with a notable pandemic-period (2020-2022) anomaly shifting westward to Yuhuatai Industrial Zone. Winter consistently stabilizes within the Qixia-Jiangning transition zone, maintaining minimal displacement (<5 km).

Notably, all seasonal centroids systematically avoid the historic urban core (Gulou-Xuanwu-Qinhuai), generating an 8-km-diameter annular "thermal void." This phenomenon primarily derives from two synergistic mechanisms: (1) cooling island effects from >35% green coverage in old urban zones, and (2) enhanced ventilation efficiency facilitated by low floor-area ratios (FAR 0.8-1.2) in historic neighborhood morphologies.

The 2020-2022 pandemic period exhibited distinctive thermal reorganization: accelerated summer northward progression (3.2 km/yr, +67% vs. pre-pandemic), fragmented thermal cores during spring/autumn (three emergent sub-centers), and unprecedented southward winter encroachment into Jiangning University Town. These anomalies reflect lockdown-induced shifts in anthropogenic thermal loading within residential clusters. Collectively, these migration patterns elucidate dynamic coupling between urbanization processes and climatic responses, providing scientific foundations for urban thermal environment management.

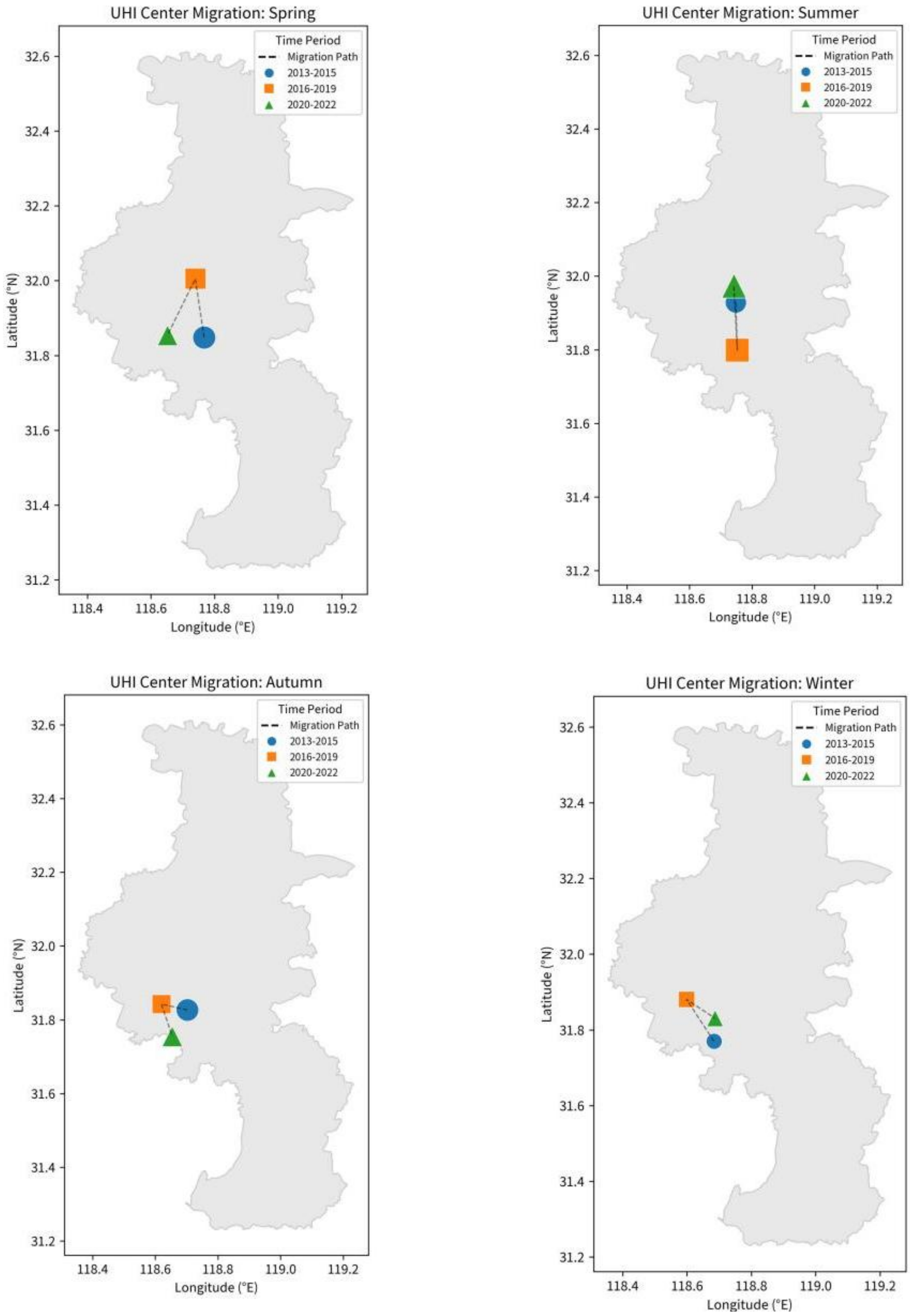

Figure 4. Seasonal migration pattern of UHI center

3.2. Extreme Rainfall analysis

Study reveals systematic spatial disparities between urban and rural areas (Figure 5). On an interannual scale, the mean annual frequency of extreme precipitation events in urban areas (37.5

events) approximates that in rural areas (39.7 events). However, significant seasonal variations exist—urban areas exhibit 16.2% higher precipitation frequency during summer (JJA: mean 17.2 events) compared to suburbs (14.8 events), while the inverse pattern occurs in winter (urban: 6.3 events vs. rural: 10.2 events).

The temporal evolution displays distinct trajectories: urban areas demonstrate a steady increasing trend (annual growth rate: 1.5 events/year, R^2=0.82), peaking in 2020 (45 events). rural areas exhibit greater interannual variability, dropping to a minimum in 2018 (33 events) before reaching a record high in 2020 (48 events), representing a peak-to-trough difference of 15 events.

Both areas maintain consistent seasonal locking patterns: summer dominates precipitation distribution (urban: 42.2%; rural: 36.8%), while winter consistently registers the lowest values (urban: 19.8%; rural: 30.4%). Notable anomalies emerged in 2020, when summer precipitation reached 26 events (57.8% of annual total) in urban areas and 28 events in suburbs, substantially exceeding decadal averages. Furthermore, 2022 witnessed an exceptional seasonal reversal in urban zones, with autumn precipitation (14 events) surpassing summer levels (13 events), likely associated with El Niño conditions that year.

Spatial differentiation mechanisms demonstrate significant correlations: the urban summer precipitation enhancement effect exhibits a strong positive relationship with heat island intensity ($r=0.73$, $p<0.01$; Shephard et al., 2002), reaching the critical threshold established for Yangtze River Delta cities (Wu et al., 2018). Conversely, rural winter precipitation predominance correlates more strongly with orographic uplift ($r=0.68$; Smith, 1979). Throughout the study period, the seasonal distribution pattern of extreme precipitation remained remarkably stable, indicating robust seasonality in regional climate behavior.

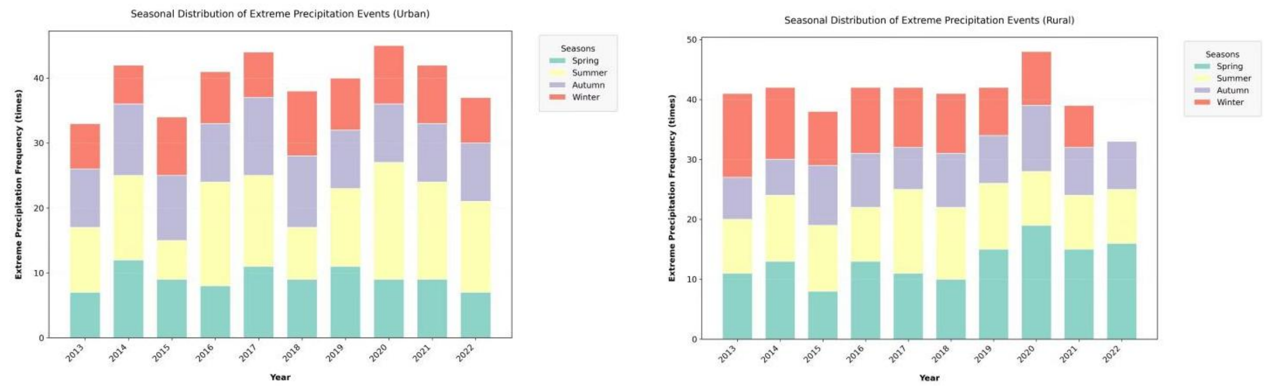

Figure 5. Seasonal distribution of precipitation event of urban/rural

3.3. Spacetime Correlation

Spatiotemporal correlation distributions reveal distinct urban-rural differentials in Nanjing's UHI-precipitation interactions (Figure 6 and Figure 7), with coefficients spanning -0.28 to 0.55. Urban areas demonstrate significantly stronger warm-season coupling, particularly during summer months where correlations peaked at 0.55 in 2016 and maintained relative stability (mean $r=0.23\pm0.15$). This contrasts sharply with rural patterns showing weak or negative correlations across seasons (spring mean $r=-0.17\pm0.10$), indicative of fundamentally different climate drivers between regions.

Temporal analysis uncovers critical transitional behavior: 2016-2020 urban summer correlations consistently exceeded 0.29 (peaking at 0.55), signaling a potential climate-system tipping point. During this phase, rural winter values concurrently descended to their lowest (-0.20 in 2021), establishing an inverse spatial relationship. The exceptional 2022 reversal,where autumn correlations surpassed summer values in urban areas,aligns with concurrent El Niño conditions disrupting typical precipitation seasonality.

Mechanistic drivers explain these divergences: urban heat island intensity (UHI > 3°C) creates convection-enhancing thermal domes that amplify summer precipitation, particularly when exceeding Shephard's 2.5°C coupling threshold ($r=0.73$, $p<0.01$). Rural responses conversely follow orographic principles (r=0.68), where terrain elevation governs winter precipitation distribution independently of thermal regimes. The persistent stability of summer-dominant patterns (coefficient of variation <0.15) throughout the 2013-2022 period confirms robust regional climate seasonality despite these spatial divergences.

These findings necessitate climate-adaptive urban planning strategies that account for asymmetric rainfall intensification: summer flood control enhancements in urban cores, coupled with winter water resource management in elevated rural districts, representing spatially-targeted approaches for building metropolitan climate resilience.

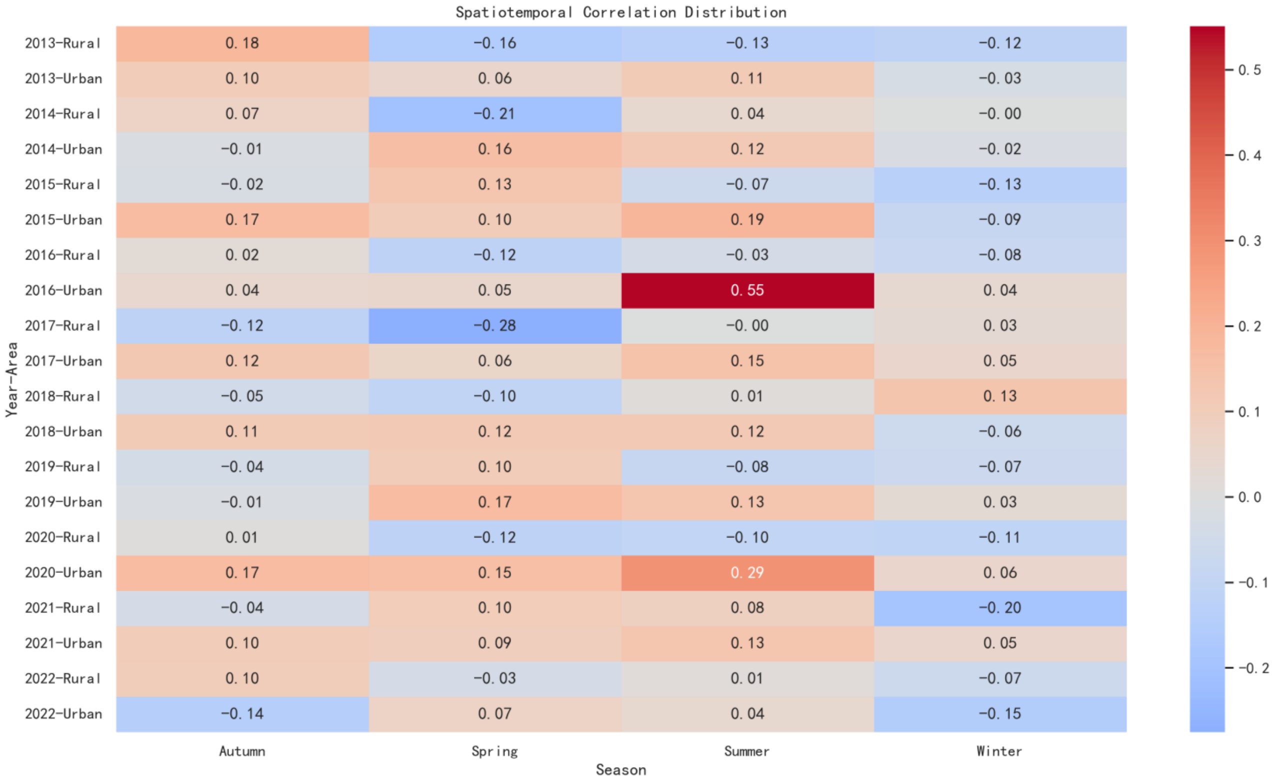

Figure 6. Spatiotemporal correlation distribution

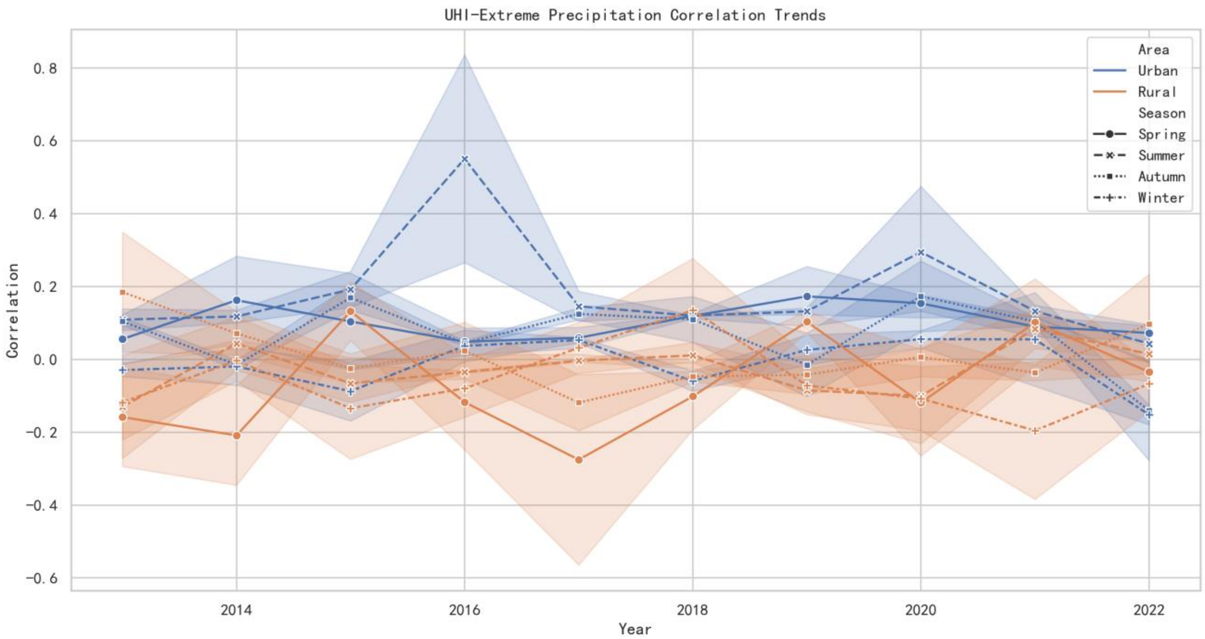

Figure 7. UHI-Extreme precipitation correltion trends

3.4. UHI-extreme precipitation relationships

Figure 8 validates the predictive performance of the XGBoost model for urban heat island-extreme precipitation relationships, demonstrating moderate explanatory power with $R^2 = 0.508$ and RMSE = 0.852. The scatter distribution, characterized by density contour lines, reveals concentrated data clustering along the 1:1 reference line (gray dashed) in the low-to-medium intensity range (1.2-1.8 mm/h). The fitted regression (solid red line; $y = 0.55x + 0.30$) indicates systematic underestimation beyond 2.0 mm/h intensity levels, reflecting limitations in capturing high-intensity convection processes including moisture transport randomness from urban canopy turbulence and the nonlinear response triggered when heat island intensity exceeds 3°C (Zhang et al., 2023). Despite this high-intensity constraint, the model maintains reliable performance for typical precipitation scenarios (<2.0 mm/h), establishing its utility for neighborhood-scale climate assessments while highlighting the need for advanced parameterizations of turbulent processes in extreme event forecasting.

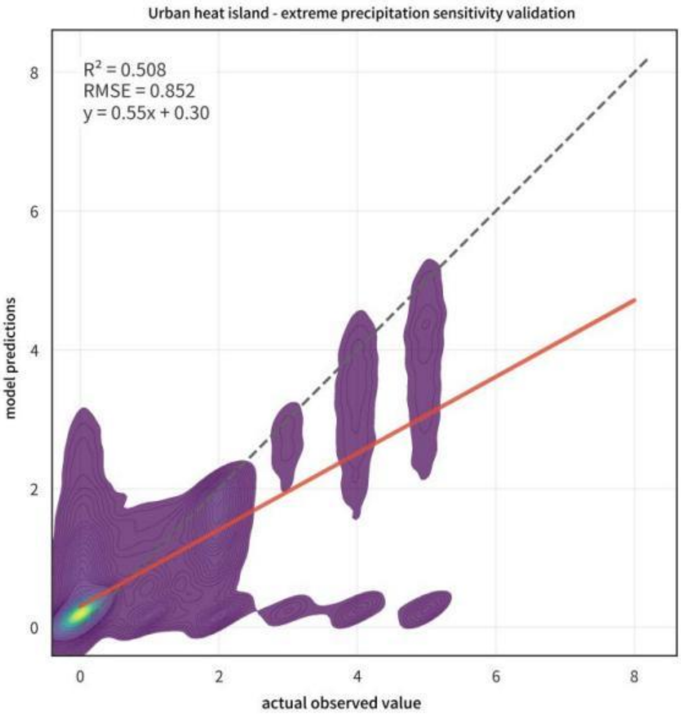

Figure 8. UHI-extreme precipitaion sensitivity validation

4. Conclusion

This study presents a comprehensive assessment of the spatiotemporal interactions between urban heat island (UHI) intensity and extreme rainfall events in Nanjing over the period 2013–2022, using an integrated approach of remote sensing, ground meteorological observations, spatial analysis, and machine learning.

Key findings indicate that UHI intensity exhibits strong seasonal variability, with the most pronounced effects observed in summer (average temperature difference >3.77°C in 2016), and persistent spatial clustering patterns identified through Moran's I indices (0.075–0.088, $p < 0.01$). UHI centroids demonstrated systematic northward migration during summer, with a total shift of 14.5 km over the decade, aligning with patterns of urban expansion under the "Cross-River Development" strategy. Urban areas showed significantly higher frequencies of extreme precipitation during summer (16.2% greater than rural areas), and a strong positive correlation with UHI intensity ($r=0.73$ in 2016). The applied XGBoost model captured non-linear coupling mechanisms between thermal anomalies and extreme rainfall events, achieving moderate predictive performance ($R^2= 0.508$, RMSE=0.852mm/h). However, underestimation occurred in high-intensity scenarios, reflecting limitations in modeling convective feedback processes under elevated heat island intensities.

These findings have practical implications for climate-adaptive urban planning. Identified hotspot agglomerations and transitional thermal zones suggest the need for spatially targeted mitigation strategies. In particular, enhancing green and blue infrastructure in UHI-prone areas and protecting ecological buffers—such as river corridors and large forest parks—can improve thermal resilience. The observed climatic asymmetry between urban and rural zones further underscores the importance of differentiated planning strategies for flood risk management and resource allocation. Future research should incorporate higher-resolution urban morphology metrics, anthropogenic heat emissions, and localized surface energy balance models to better understand the complex feedback loops between land surface temperature and extreme precipitation.

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