

Article

Spatial Non-Stationarity in the Relationships Between Urban Surface Water Networks and Land Surface Temperature: Evidence from Fuzhou, China

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Abstract

Urban surface water networks are closely associated with the urban land surface thermal environment, but the spatial non-stationarity of their relationships with land surface temperature (LST) remains insufficiently understood. This study examined relationships between water network indicators and LST in Fuzhou. Following scale-sensitivity analysis to select the analytical grid scale, this study used global correlation and regression analyses to identify key indicators and applied multiscale geographically weighted regression (MGWR) to examine spatial non-stationarity in their relationships with LST. Based on the selected 150 m grid scale, the results showed the following: (1) Water coverage ratio (WCR), water body shape index (SI), and water network density (D) were retained as key explanatory variables, with WCR showing the strongest negative association with LST. (2) The relationships between water network indicators and LST showed spatial non-stationarity. WCR showed the most stable negative local association with LST, especially in built-up areas with higher background heat loads, whereas the local associations of SI and D were more context-dependent. These findings suggest that thermal-environment-oriented planning for urban surface water networks should prioritize water coverage while considering water network structure, water body morphology, the surrounding built environment and land cover conditions. These associations can inform spatially differentiated planning of urban surface water networks in comparable subtropical coastal cities.

Keywords: urban surface water networks; land surface temperature; spatial non-stationarity; multiscale geographically weighted regression



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1. Introduction

Rapid urbanization has reshaped urban land cover patterns by replacing vegetated and permeable surfaces with impervious materials [1]. This transformation alters surface energy exchange by reducing evapotranspiration and increasing heat storage, thereby raising urban temperatures relative to surrounding suburban areas and intensifying the urban heat island (UHI) effect [2,3]. The UHI effect not only increases urban energy consumption [4] and degrades air quality [5,6] but also reduces urban livability [7] and exposes residents to greater public health risks [8]. Therefore, regulating the urban climate and mitigating the UHI effect by optimizing urban surface structure has become a central concern in urban environmental science and landscape planning.

Urban heat island conditions are commonly examined from both surface and canopy-layer thermal perspectives. The surface urban heat island is often represented by land surface temperature retrieved from thermal infrared remote sensing, whereas the canopy urban heat island is mainly examined using near-surface air temperature from meteorological or microclimate observations [9,10]. For studies of urban surface cover and blue–green spaces, LST provides spatially continuous information for identifying surface thermal patterns and their relationships with different landscape elements [11,12]. Among the natural components of urban surface cover, blue–green spaces are widely regarded as important spatial elements associated with UHI mitigation [13–15]. Green spaces function as urban cooling sources through shading and transpiration [16,17], whereas water bodies regulate the surrounding thermal environment through heat storage, evaporative cooling, and thermal exchange between land and water [18,19]. Previous studies have shown that blue–green spaces can exhibit synergistic cooling patterns, and that higher proportional coverage generally corresponds to lower urban thermal intensity [14]. However, existing research has mainly focused on green spaces or on the combined thermal patterns of blue–green spaces, whereas quantitative assessments of blue spaces, particularly urban surface water networks, remain limited [20]. Although the thermal role of water bodies has been widely recognized, their associated spatial factors and spatial heterogeneity have not yet been systematically evaluated within an integrated framework [20,21]. Therefore, quantifying the relationships between urban surface water networks and the land surface thermal environment and revealing their spatial heterogeneity are important for understanding thermal patterns related to urban surface water networks and informing planning for the urban thermal environment.

Existing research on the thermal role of urban water bodies has mainly focused on two related aspects: cooling mechanisms and influencing factors [18,22]. Mechanistically, water bodies regulate the surrounding thermal environment through physical processes such as evaporative cooling, heat storage and release, sensible and latent heat exchange, and local air movement [23,24]. These processes jointly affect near-surface air temperature, humidity, and local wind conditions. However, the cooling patterns of water bodies often vary substantially across spatial contexts because urban surface structure is highly heterogeneous [25]. This variation is partly related to the intrinsic attributes of water bodies, including water area, width, shape complexity, water surface temperature, and spatial distribution [26–29]. It is also associated with surrounding environmental conditions, such as waterfront green-space configuration, land-cover structure, impervious surface proportion, building density, and building height [20,30–33]. Studies have shown that differences in water body morphology are associated with variations in the intensity and spatial extent of cooling around water bodies [20]. Open urban forms and continuous blue–green spaces can further facilitate the transport of cool air, allowing cooler air near water bodies to spread into adjacent built-up areas [34]. Therefore, the relationships between urban water bodies and the surrounding thermal environment should be understood by considering not only water body size, but also physical attributes, shoreline and green space conditions, spatial distribution, and surrounding urban morphology.

Although existing studies have made progress in identifying key physical indicators related to water body cooling [20,35], two major research gaps remain. First, most studies have examined individual water patches, areal water bodies, or linear river corridors, with emphasis on their cooling intensity, cooling extent, and influencing factors [34,36,37]. Complex urban surface water networks, however, remain insufficiently investigated [28]. Second, previous research has given considerable attention to cooling interactions within blue–green spaces or networks of cooling sources [38,39], whereas comprehensive evaluations of the physical and spatial indicators of water bodies themselves remain limited [35].

This limitation makes it difficult to clarify how the structural characteristics of urban surface water networks are related to thermal patterns around water bodies.

In addition, thermal patterns around water bodies vary across urban contexts and are closely associated with the surrounding urban surface structure [40–42]. Thermal conditions around water bodies may differ with building density, land use type, and impervious surface proportion [21,43]. For example, the same river may show different thermal conditions and dominant thermal processes when flowing through densely built areas and open park spaces [36]. Building obstruction and urban spatial form can modify local wind conditions and affect the dispersion of cool and moist air [33]. Surface materials and land-cover types, such as impervious materials, grassland, and vegetation, can also modify the local thermal conditions by altering heat storage, evapotranspiration, and surface energy exchange [44]. These spatially varying thermal responses suggest that the relationship between water bodies and the urban thermal environment may be spatially non-stationary. Neglecting these spatially varying relationships may therefore lead to a biased understanding of how water bodies are associated with urban thermal conditions.

Therefore, this study explores how the spatial and physical indicators of the urban surface water network are associated with the land surface thermal environment and how these relationships vary across space. Taking the main urban area of Fuzhou as a case study, this study combines global correlation and regression analyses with multiscale geographically weighted regression (MGWR) to examine the relationships between urban surface water network indicators and LST and their spatial non-stationarity. Specifically, this study aims to: (1) identify the key spatial and physical indicators of the urban surface water network that are closely associated with variations in LST; (2) examine the spatial non-stationarity in the relationships between key water network indicators and LST; and (3) translate the spatially varying associations revealed by MGWR into references for spatially differentiated planning of urban surface water networks and land cover optimization in subtropical coastal cities.

2. Materials and Methods

2.1. Research Framework

The research framework of this study is shown in Figure 1 and comprises five main steps. First, this study generated LST and urban surface water network datasets for the main urban area of Fuzhou. These datasets provided the basis for calculating water network indicators and examining their relationships with the land surface thermal environment. Second, an indicator system was constructed to characterize the urban surface water network across four dimensions: water coverage, water network structure, water body morphology, and water surface thermal properties. Third, this study established regular grids at multiple spatial scales, compared the relationships between water network indicators and LST across these scales, and selected an appropriate grid scale as the analytical unit for subsequent modeling. Fourth, this study identified key water network indicators through global correlation and regression analyses, and then used MGWR to examine the spatial non-stationarity in their relationships with LST. Finally, land cover, the built environment, and waterfront spatial characteristics were further considered to interpret spatial variations in the relationships between urban surface water network indicators and LST and to derive planning implications.

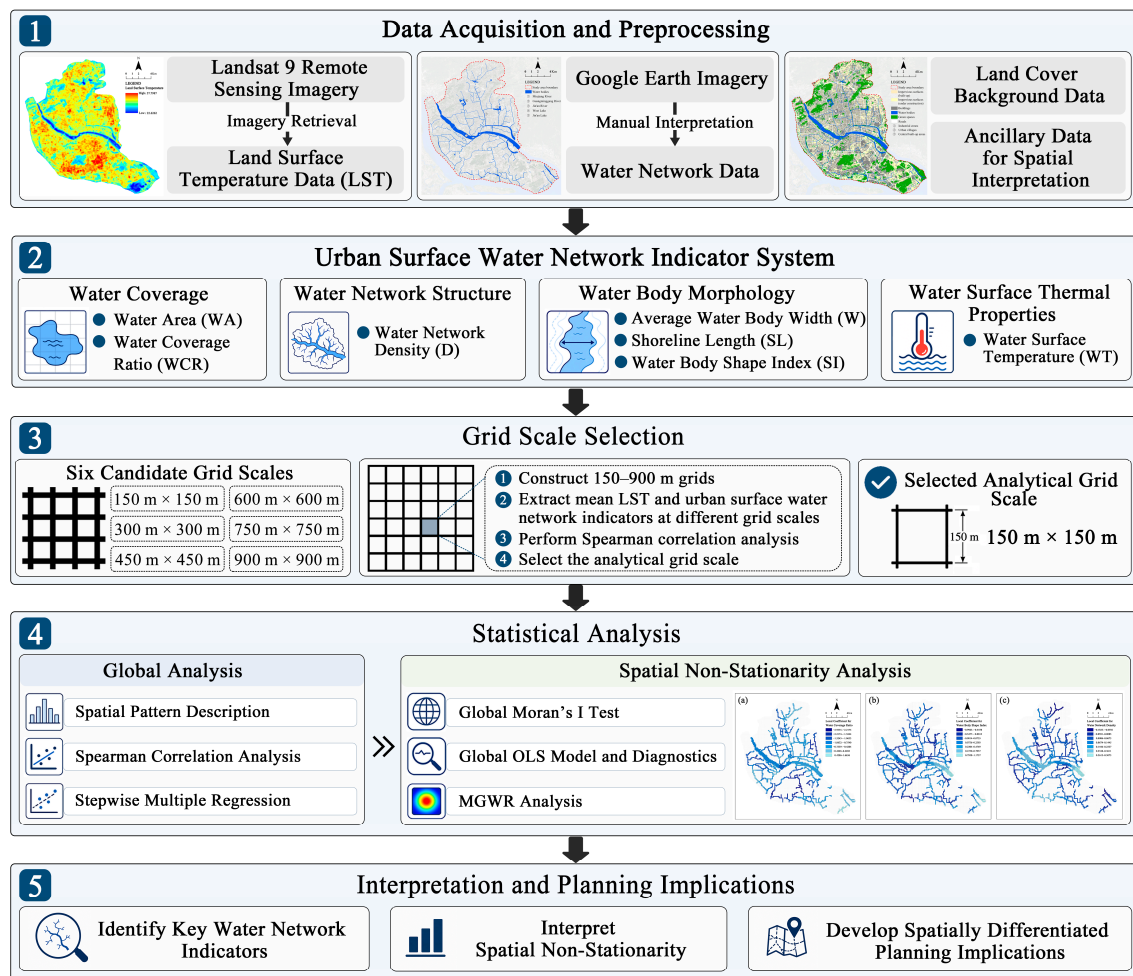


Figure 1. Research framework of the study. Note: LST, land surface temperature; WA, water area; WCR, water coverage ratio; D, water network density; W, average water body width; SL, shoreline length; SI, water body shape index; WT, water surface temperature; OLS, ordinary least squares; MGWR, multiscale geographically weighted regression.

2.2. Overview of the Study Area

Fuzhou is located on the eastern coast of Fujian Province, China, and has a subtropical monsoon climate characterized by hot and humid summers. With rapid urbanization in recent years, impervious surfaces have continued to expand in built-up areas, intensifying concerns regarding the urban thermal environment. The main urban area of Fuzhou also contains a dense surface water network, in which the Minjiang River and its tributaries form a complex urban water system. This setting provides a suitable case for examining the spatial relationships between urban surface water networks and the land surface thermal environment.

As shown in Figure 2, this study focuses on the main urban area of Fuzhou, including Gulou District, Taijiang District, Cangshan District, and the major built-up areas of Jin'an District. The main urban area of Fuzhou is characterized by high population density and intensive urban development, as well as a mosaic of blue, green, and gray land-cover types. Blue spaces include main river channels, urban tributaries, inner river systems, lakes, and other standing water bodies. Green spaces include urban parks, mountain green spaces, and waterfront green belts. Gray spaces are mainly composed of residential, commercial, industrial, transportation, and other impervious built-up areas. The coexistence of diverse land-cover types and a hierarchical surface water network gives the study area both an intensively developed urban setting and a complex water network structure. In recent

years, inner river improvement, waterfront space restoration, and water system connectivity projects have continued to reshape the surface water network and waterfront environment in the main urban area of Fuzhou. Together, the differentiated land-cover pattern and complex water network structure within the study area provide an important basis for interpreting the spatial non-stationarity in the relationships between the surface water network and LST and may offer a reference for urban surface water network planning and land cover optimization under similar climatic and spatial conditions.

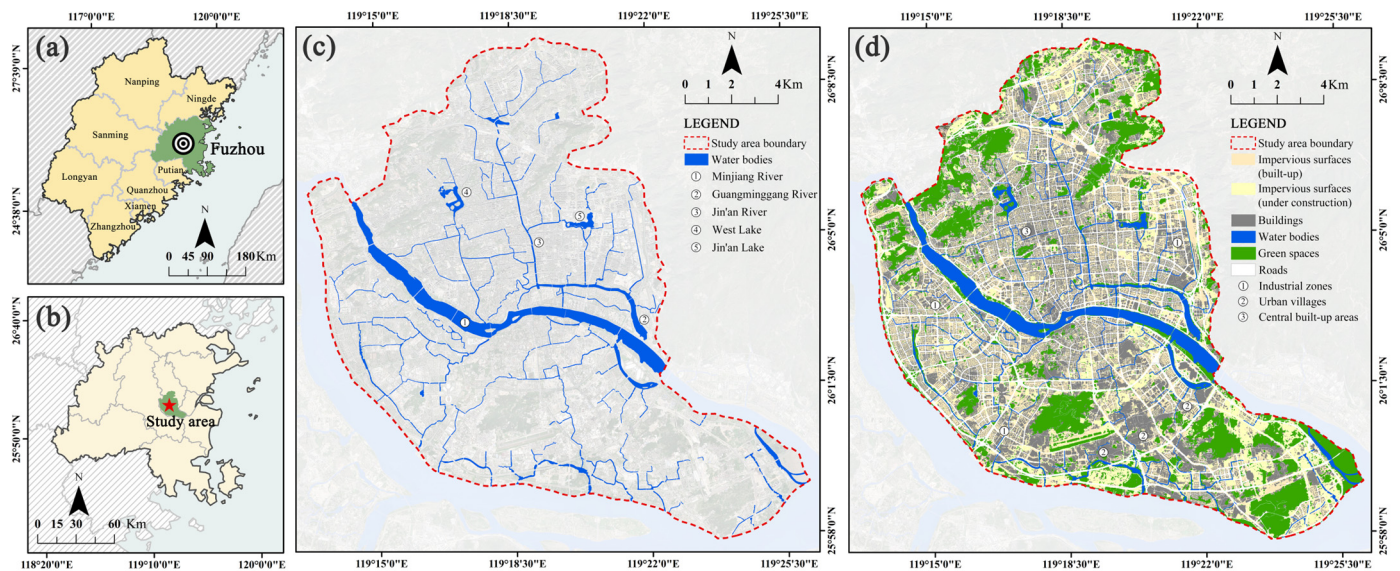


Figure 2. Location and spatial context of the study area. (a) Location of Fuzhou in Fujian Province, China; (b) location of the study area within Fuzhou; (c) urban surface water network in the study area; and (d) land cover background data in the study area.

2.3. Data Sources and Preprocessing

2.3.1. Land Surface Temperature Data

This study used summer Landsat 9 OLI-2/TIRS-2 imagery acquired under clear-sky conditions as the data source for LST retrieval. The Landsat 9 image was obtained from the USGS and corresponds to path/row 119/42. The TIRS-2 thermal infrared data have a native ground sampling distance of 100 m and are resampled to 30 m in the delivered Landsat product. The image was acquired on 7 July 2023 at a scene-center time of 10:32 local time in Fuzhou. On the acquisition date, Fuzhou was characterized by high air temperature, relatively high humidity, and no measurable precipitation. The daily maximum air temperature was 38.9 °C, the daily mean air temperature was 32.7 °C, the mean relative humidity was 64.1%, the mean wind speed was 2.6 m/s, and the prevailing wind direction was southeast. The cumulative precipitation during the three days before image acquisition was 0.0 mm. These conditions are consistent with a typical summer daytime thermal background in Fuzhou. These meteorological data were obtained from the NOAA Integrated Surface Database for the Fuzhou station (WMO station ID: 58847). According to the Landsat metadata, the land cloud cover was 6.47%, indicating minimal cloud interference over the study area. LST was retrieved using the radiative transfer equation, with land surface emissivity and atmospheric parameters, including atmospheric transmittance, upwelling radiance, and downwelling radiance [45,46]. The imagery was first subjected to radiometric calibration and atmospheric correction. Thermal infrared band data and the corresponding atmospheric parameters were then used to calculate the true land surface temperature, T_s , according to Equations (1)–(3). The retrieved LST raster was used as a 30 m gridded output for subsequent grid-level spatial aggregation and analysis.

The retrieved LST was used to characterize the surface thermal environment of the study area and to examine its spatial relationships with urban surface water network indicators.

The thermal infrared radiance received by the satellite sensor, L_λ , can be expressed using the radiative transfer equation as follows:

$$L_\lambda = [\varepsilon B(T_s) + (1 - \varepsilon)L_d]\tau + L_u \quad (1)$$

The blackbody radiance in the thermal infrared band, $B(T_s)$, corresponding to the surface temperature T_s , can then be derived as follows:

$$B(T_s) = \frac{L_\lambda - L_u - \tau(1 - \varepsilon)L_d}{\tau\varepsilon} \quad (2)$$

The land surface temperature was finally obtained using Planck's law and converted to degrees Celsius ($^{\circ}\text{C}$):

$$T_s = \frac{K_2}{\ln\left(\frac{K_1}{B(T_s)} + 1\right)} - 273.15 \quad (3)$$

In these equations, L_λ denotes the radiance received by the sensor, and T_s represents the true land surface temperature. $B(T_s)$ is the blackbody radiance; ε is the land surface emissivity; τ is the atmospheric transmittance in the thermal infrared band; L_u is the atmospheric upwelling radiance; and L_d is the atmospheric downwelling radiance. K_1 and K_2 are the thermal calibration constants, obtained from the image metadata file.

2.3.2. Urban Surface Water Network Data and Indicator Selection

Urban surface water network vector data were manually interpreted and digitized from high-resolution Google Earth imagery, and the water body boundaries were subsequently checked and refined. Based on the final water network vector data, a multidimensional indicator system was constructed to characterize the spatial and physical properties of the urban surface water network from four dimensions: water coverage, water network structure, water body morphology, and water surface thermal properties.

Specifically, water area (WA) and water coverage ratio (WCR) were used to represent water coverage at the grid scale. Water network density (D) was used to describe the density and structural characteristics of the water network. Shoreline length (SL), average water body width (W), and water body shape index (SI) were used to characterize the boundary and planform morphology of water bodies. Water surface temperature (WT) was used to represent the thermal state of the water surface. The definitions and calculation methods of these indicators are presented in Table 1.

Table 1. Definitions of spatial and physical indicators of the urban surface water network.

Indicators of the Urban Surface Water Network		Indicator Meaning	Unit
Water coverage	Water area (WA)	Total area of all water bodies within a grid cell.	m^2
	Water coverage ratio (WCR)	Ratio of water area to the total area of a grid cell.	-
Water network structure	Water network density (D)	Ratio of the total water network length to grid-cell area	m/m^2
Water body morphology	Shoreline length (SL)	Total length of shorelines within a grid cell.	m
	Average water body width (W)	Average width of water bodies within a grid cell.	m
	Water body shape index (SI)	Normalized perimeter-area ratio used to characterize the planform complexity of water bodies within a grid cell.	-

Table 1. Cont.

Indicators of the Urban Surface Water Network		Indicator Meaning	Unit
Water surface thermal properties	Water surface temperature (WT)	Mean water surface temperature within a grid cell.	°C

2.3.3. Land Cover Background Data

Land cover background data were used as an ancillary background layer to describe the blue, green, and gray spatial context of the study area and to support the interpretation of the results. They were not used as explanatory variables in the quantitative analyses. The base layer was derived from the 2021 EcoVision submeter urban land cover dataset. Produced from submeter remote sensing imagery, this dataset provides detailed land cover information for urban areas and has an overall classification accuracy of 83.6% [47]. Because the core analysis in this study was based on 2023 LST and urban surface water network indicators, the 2021 EcoVision dataset was checked against high-resolution Google Earth imagery from 2023. Local updates were made only where land cover changes could be clearly identified through visual interpretation. Specifically, water body boundaries in the background layer were replaced by the urban surface water network vector data manually interpreted from high-resolution Google Earth imagery in 2023. Local areas with evident changes in water bodies and green spaces, such as Jin'an Lake and its surrounding green spaces, were also updated using the 2023 imagery. For relatively stable built environment categories, including roads, buildings, and other impervious surfaces, the original EcoVision classifications were retained. The resulting land cover layer was used only for study area mapping and qualitative spatial interpretation in the discussion section. It was not included in the Spearman correlation analysis, stepwise multiple regression, or MGWR model.

2.3.4. Grid Processing and Scale Sensitivity Analysis

Spatial relationships between LST and its explanatory factors are sensitive to spatial aggregation and the definition of analytical units [29,43,48]. Previous studies have shown that the thermal influence of water bodies also shows scale dependence and generally diminishes with distance from the shoreline [43]. Therefore, the study area was divided into regular grids at multiple spatial scales. Six candidate scales were predefined by considering the spatial characteristics of the Landsat-derived LST raster, the spatial pattern of the water network and urban blocks in the main urban area of Fuzhou, and the distance-related attenuation of the thermal influence of water bodies. The six grid scales were 150 m × 150 m, 300 m × 300 m, 450 m × 450 m, 600 m × 600 m, 750 m × 750 m, and 900 m × 900 m. These scales were used to compare how the relationships between water network indicators and LST changed under different levels of spatial aggregation.

For each grid cell, mean LST was extracted and the statistical values of the water network indicators were calculated within the same spatial unit. The grid cells were used as spatial aggregation units for examining grid-level relationships between water network indicators and LST. Spearman correlation coefficients between each water network indicator and LST were then calculated at each scale to examine the scale sensitivity of these relationships. Scale selection was based on statistical significance, directional consistency, correlation strength, and the spatial interpretability of the scale. The selected scale was then used as the primary analytical unit for subsequent global regression and MGWR analyses.

2.4. Statistical Analysis

2.4.1. Global Correlation Analysis and Identification of Key Indicators

Spearman correlation analysis was conducted in IBM SPSS Statistics 25 to examine the relationships between each water network indicator and LST across the entire study area. This analysis was used to identify the direction and strength of the associations between different indicators and the land surface thermal environment. Based on the meanings of the indicators and the correlation results, spatial indicators significantly associated with LST were considered as candidate variables and entered into a stepwise multiple linear regression model. This model was used to identify key water network indicators and evaluate their relative importance at the global scale. The regression model was estimated using ordinary least squares (OLS). Multicollinearity among predictors was assessed using the variance inflation factor (VIF), with a threshold of 5 used to indicate acceptable collinearity. The coefficient of determination, R^2 , was used to evaluate model fit, with higher values indicating stronger explanatory performance. Indicators retained in the regression model at $p < 0.05$ were identified as key indicators associated with urban LST.

2.4.2. Spatial Non-Stationarity Analysis Using MGWR

Before the MGWR analysis, Global Moran's I was calculated for grid-level LST using a row-standardized spatial weights matrix to diagnose spatial autocorrelation. This diagnostic test was used to assess whether LST exhibited significant spatial clustering before spatially varying relationships were examined using MGWR. Based on the indicators retained from the stepwise regression, the final global OLS model was used to characterize the average relationships between water network indicators and LST across the study area, provide model diagnostics, and serve as a global reference for the subsequent MGWR analysis. Using the same retained indicators, MGWR was further used to examine the spatial non-stationarity in the relationships between key water network indicators and LST. Unlike global regression models, MGWR allows regression coefficients to vary across space. It also permits different explanatory variables to operate at different spatial scales. This makes it suitable for identifying spatially varying relationships that cannot be captured by a single global coefficient [40]. In this study, the MGWR model was implemented using MGWR 2.0 software (Spatial Analysis Research Center, Arizona State University, Tempe, AZ, USA) with an adaptive bisquare kernel function. The optimal bandwidth was selected using the corrected Akaike information criterion (AICc). The MGWR results were used to identify the spatial heterogeneity in the relationships between urban surface water network indicators and LST. They also supported the interpretation of how water network structure and morphology are linked to the land surface thermal environment.

3. Results

3.1. Spatial Patterns of LST and Urban Surface Water Network Indicators

On 7 July 2023, LST in the main urban area of Fuzhou ranged from 22.6262 °C to 57.7987 °C and showed clear spatial differentiation (Figure 3a). Areas with high LST were mainly concentrated in densely built central areas, industrial land clusters in the eastern and western parts of the study area, urban villages along the southern fringe of the central urban area, and areas surrounding major road corridors, transport nodes, and large impervious land cover patches. In contrast, areas with low LST were mainly distributed along main river channels, lakes and other large water bodies, and contiguous green spaces. The Minjiang River and Jin'an River corresponded to relatively continuous linear low-LST zones, whereas Jin'an Lake, West Lake, large urban parks, and extensive green spaces appeared as more concentrated low-LST patches. Overall, the spatial pattern of LST showed clear correspondence with land cover types. Intensively developed impervious areas were

generally associated with high LST clustering, whereas water bodies and vegetated areas were the main spaces with relatively low LST in the study area.

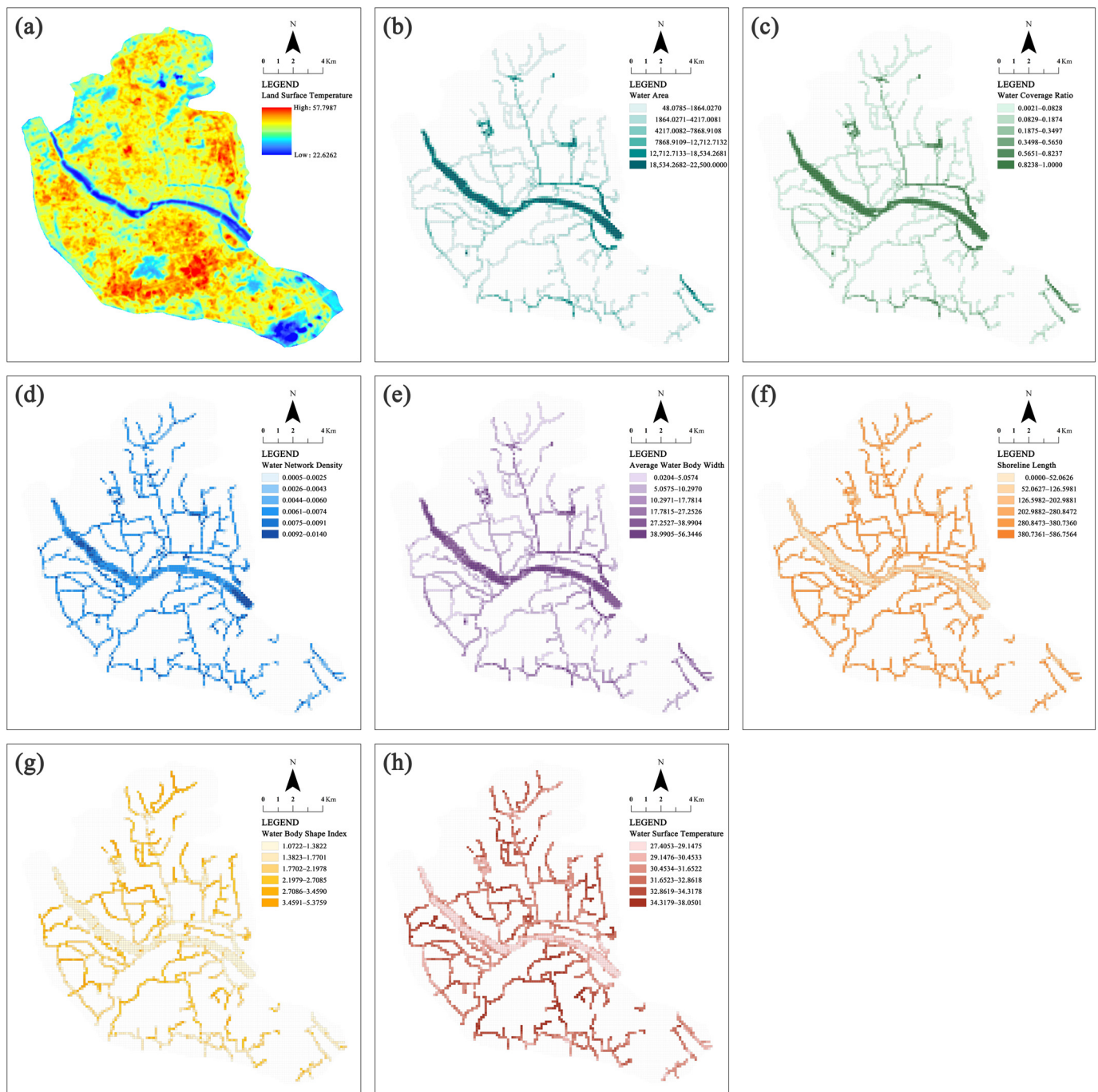


Figure 3. Spatial distributions of retrieved land surface temperature (LST; 30 m spatial resolution) and urban surface water network indicators calculated at the selected 150 m × 150 m grid scale. (a) LST; (b) water area (WA); (c) water coverage ratio (WCR); (d) water network density (D); (e) average water body width (W); (f) shoreline length (SL); (g) water body shape index (SI); and (h) water surface temperature (WT).

As shown in Figure 3b–h, the spatial and physical indicators of the urban surface water network showed clear spatial heterogeneity within the study area. In terms of water coverage, areas with high WA and WCR values were mainly distributed along major river channels, including the Minjiang River, and around large water bodies, including Jin'an Lake and West Lake. Water coverage in the study area was mainly concentrated in large

and continuous water bodies. For water network structure, high D values were mainly distributed in areas with dense tributaries and interconnected inner rivers. For water body morphology, high W values were concentrated along wide water bodies, including the main channel of the Minjiang River and Guangminggang River. SL values were higher in areas where tributaries converged, shorelines were sinuous, and water body boundaries were fragmented, but lower along wide and relatively straight main river reaches. High SI values mainly occurred in narrow tributaries, upstream water systems, and terminal branching river sections, where local planform morphology was more complex. WT was higher in small or narrow water bodies adjacent to areas dominated by dense buildings and impervious surfaces, but lower in large open water areas.

Overall, the spatial distribution of water network indicators showed clear correspondence with the LST pattern. Large and continuous water bodies and their surrounding areas mainly overlapped with low LST clusters, whereas narrow and fragmented water bodies adjacent to areas dominated by dense buildings and impervious surfaces were often located near areas with relatively high LST. These spatial patterns provided the basis for the subsequent correlation analysis, global regression, and spatial heterogeneity analysis.

3.2. Global Relationships and Key Water Network Indicators at the Selected Grid Scale

Spearman correlation analysis across different grid scales showed clear scale differences in the bivariate relationships between urban surface water network indicators and LST, mainly reflected in directional stability, changes in correlation strength, and changes in statistical significance (Table 2). Within the predefined candidate scales, stronger correlations were generally observed at smaller grid sizes, with higher directional consistency and statistical stability. Specifically, WA, WCR, W, SI, and WT maintained relatively stable correlation directions across different grid sizes. WA, WCR, and W were consistently negatively correlated with LST, whereas SI and WT were consistently positively correlated with LST. As the grid size increased, some indicators showed reduced correlation strength or statistical significance: the correlation strengths of WA, WCR, W, and WT with LST generally weakened; SL remained significant only at the 150 m and 300 m scales and became non-significant at grid sizes of 450 m and above; and D was significantly negatively correlated with LST at the 150 m, 300 m, and 450 m scales, but the correlation weakened at larger grid sizes and shifted to weak positive correlations at the 750 m and 900 m scales. Among the candidate grid sizes tested in this study, all water network indicators were significantly correlated with LST at the 0.01 level at the 150 m scale, and the relationships showed stronger directional consistency and statistical stability overall. Considering that the thermal influence of urban water bodies generally diminishes with distance from the shoreline and is often concentrated within a range of several hundred meters, the 150 m grid effectively captured local differences between the water network and surrounding urban surface structure while maintaining stable statistical relationships. It was therefore suitable for capturing local spatial relationships among the urban surface water network, roads, and urban blocks in the main urban area of Fuzhou. Accordingly, the 150 m grid was selected as the primary spatial aggregation unit for subsequent global regression and spatial heterogeneity analyses by considering directional stability, changes in statistical significance, scale sensitivity, and the ability to retain local spatial differences. In this sense, this scale selection should be understood as specific to the data conditions and urban context of this study, rather than directly generalizable to all cities or climatic regions.

At the 150 m scale, WT, SL, and SI showed significant positive correlations with LST, whereas WA, WCR, D, and W showed significant negative correlations with LST. Among these indicators, WT had the strongest positive correlation with LST, while WCR and WA showed the strongest negative correlations.

Table 2. Spearman correlations between land surface temperature and urban surface water network indicators at different grid sizes.

Grid Size (m)	WA	WCR	D	SL	W	SI	WT
150 × 150	−0.714 **	−0.714 **	−0.285 **	0.338 **	−0.658 **	0.643 **	0.977 **
300 × 300	−0.605 **	−0.605 **	−0.174 **	0.104 **	−0.605 **	0.520 **	0.931 **
450 × 450	−0.570 **	−0.570 **	−0.159 **	0.008	−0.615 **	0.489 **	0.889 **
600 × 600	−0.464 **	−0.464 **	−0.057	0.036	−0.557 **	0.503 **	0.873 **
750 × 750	−0.383 **	−0.383 **	0.004	0.068	−0.529 **	0.539 **	0.842 **
900 × 900	−0.391 **	−0.391 **	0.062	0.087	−0.525 **	0.560 **	0.795 **

Note: (1) ** indicates the correlation is significant at the 0.01 level. (2) D, water network density; WCR, water coverage ratio; WA, water area; W, average water body width; SL, shoreline length; WT, water surface temperature; SI, water body shape index.

However, WT differs fundamentally from the other spatial configuration indicators of the water network. WT characterizes the thermal state of water surfaces, whereas WCR, D, and SI describe water coverage, water network structure, and water body planform morphology, respectively. Because WT and LST were both retrieved from the same Landsat thermal infrared image acquired on the same date and were summarized at the same grid scale, their strong association may partly reflect their shared data source and synchronous observation conditions. If WT were included together with the spatial configuration indicators in the stepwise regression model, the strong association between WT and LST could dominate the model results and weaken the selection and coefficient interpretation of spatial configuration indicators. Therefore, WT was not treated as an independent planning indicator. It was used only to characterize the thermal state of water surfaces and was not included as a candidate variable in the stepwise multiple regression based on OLS estimation.

After excluding WT, the stepwise multiple regression used LST as the dependent variable and WA, WCR, D, W, SL, and SI as candidate explanatory variables. The results showed that WCR, D, and SI were retained as key spatial water network indicators significantly associated with LST (Table 3). All retained variables had VIF values below 3, indicating that severe multicollinearity was not present in the final model. The standardized coefficient of WCR was negative, whereas those of D and SI were positive. The scatterplot matrix in Figure 4 further shows the bivariate relationships between the variables retained in the model and LST. WCR showed a strong negative correlation with LST, SI showed a strong positive correlation with LST, and D showed a weaker negative correlation with LST.

Table 3. Stepwise multiple linear regression results at the 150 m × 150 m grid scale.

Predictor	Parameter of Model				
	B	Standardized β	t	p-Value	VIF
Constant	43.212	-	211.646	<0.001	-
WCR	−11.486	−0.847	−45.174	<0.001	2.796
D	147.592	0.084	5.536	<0.001	1.849
SI	0.347	0.054	3.276	<0.001	2.203

Note: (1) The dependent variable is land surface temperature. (2) B represents the unstandardized regression coefficient, and β represents the standardized regression coefficient. (3) Adjusted $R^2 = 0.715$, $F = 1897.185$, $p < 0.001$. (4) WCR, water coverage ratio; D, water network density; SI, water body shape index.

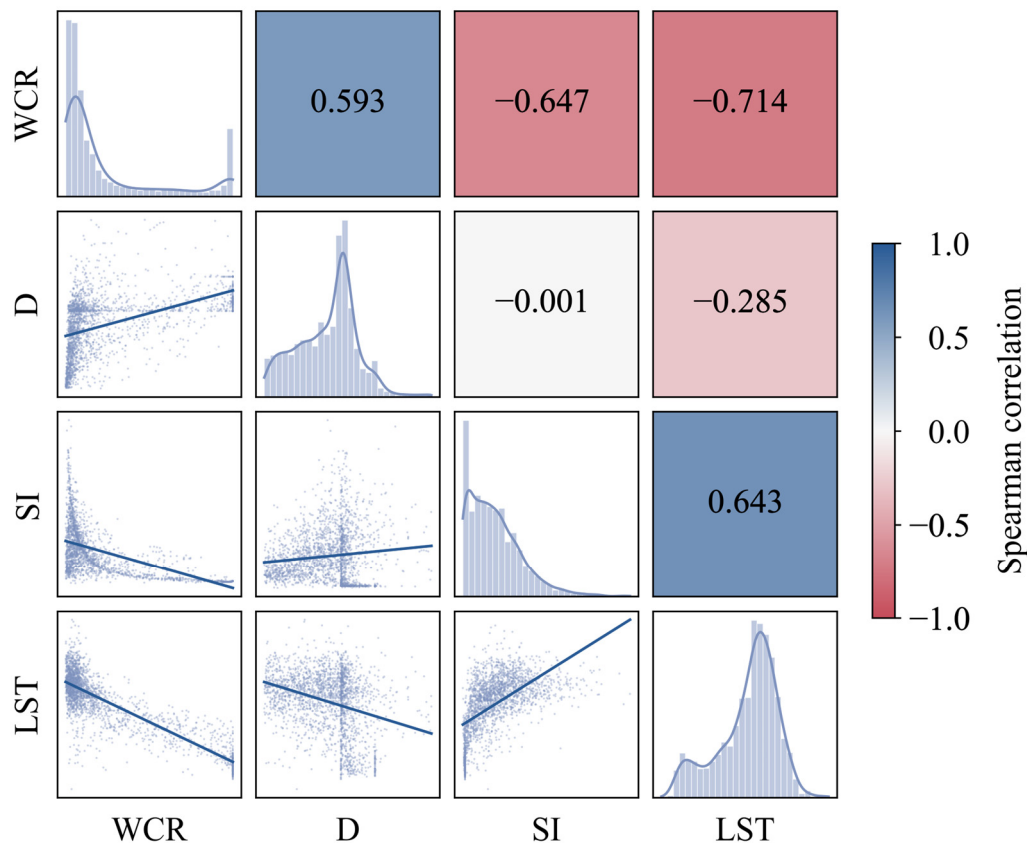


Figure 4. Scatterplot matrix of key water network indicators and land surface temperature. Note: The variables include water coverage ratio (WCR), water network density (D), water body shape index (SI), and land surface temperature (LST). The diagonal panels show variable distributions, the lower triangle shows pairwise scatterplots, and the upper triangle shows Spearman correlation coefficients.

3.3. Spatial Non-Stationarity in the Relationships Between Key Water Network Indicators and LST

Global Moran's I was first used to test the spatial autocorrelation of LST at the 150 m grid scale. The results showed significant spatial clustering of LST in the study area (Moran's I = 0.8468, z-score = 53.4760, $p < 0.001$). This spatial autocorrelation provided a basis for using MGWR to examine local differences in the relationships between water network indicators and the land surface thermal environment.

Based on the stepwise multiple linear regression results, a global OLS model was further constructed with LST as the dependent variable and WCR, SI, and D as explanatory variables. This model was used for comparison with the MGWR model and for model diagnostics. The OLS diagnostics indicated that severe multicollinearity was not present, providing a basis for the subsequent spatial regression analysis. Because the global OLS model only represents the average relationships across the study area and cannot reveal local spatial differences in the relationships between water network indicators and LST, WCR, SI, and D were further included in the MGWR model to identify spatial non-stationarity in their relationships with LST.

The MGWR model showed a higher adjusted coefficient of determination (Adj. $R^2 = 0.865$) than the global OLS model (Adj. $R^2 = 0.715$). This result showed that MGWR provided a better model fit and captured spatial variation in the relationships between water network indicators and LST. The bandwidths and summary statistics of the local regression coefficients for each variable are presented in Table 4, and the spatial distributions of the local coefficient estimates are shown in Figure 5.

Table 4. Summary statistics and bandwidths of MGWR local coefficients.

Variables	Mean	STD	Min	Median	Max	Bandwidth
WCR	−0.866	0.529	−2.933	−0.803	1.664	43
SI	0.107	0.265	−0.996	0.058	1.176	43
D	0.090	0.119	−0.183	0.060	0.507	89

Note: WCR, water coverage ratio; SI, water body shape index; D, water network density.

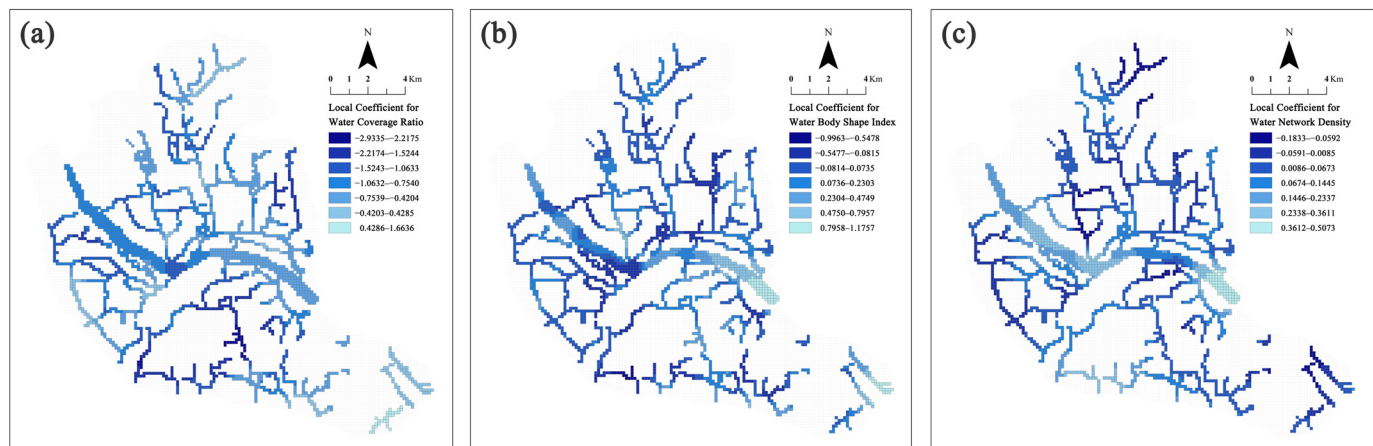


Figure 5. Spatial distributions of local coefficients estimated by multiscale geographically weighted regression (MGWR), with land surface temperature (LST) as the dependent variable: (a) local coefficient for water coverage ratio (WCR); (b) local coefficient for water body shape index (SI); and (c) local coefficient for water network density (D). The color classes indicate the direction and magnitude of the estimated local associations with LST after accounting for the other explanatory variables. These maps are mainly used to visualize spatial variation patterns rather than statistical significance in individual grid cells.

The bandwidths differed across water network indicators. WCR and SI both had bandwidths of 43, corresponding to more localized spatial relationships with LST. By contrast, D had a bandwidth of 89, corresponding to a smoother and more spatially extensive relationship. These bandwidth differences showed that the relationships between water network indicators and LST varied across spatial scales. It should be noted that Figure 5 presents MGWR local coefficient estimates rather than coefficients filtered by statistical significance. Therefore, the interpretation of Figure 5 focuses on the overall spatial patterns, coefficient signs, and relative magnitudes of the local relationships, not on statistical significance in individual grid cells.

The mean local coefficient of WCR was −0.866, and the median was −0.803. These values showed an overall negative relationship between WCR and LST across the study area, with higher water coverage generally associated with lower LST. The local coefficients of WCR ranged from −2.933 to 1.664, with a standard deviation of 0.529, showing substantial spatial variation in coefficient magnitude. The local coefficient map in Figure 5a showed that stronger negative WCR coefficients were mainly located in built-up areas with dense buildings and impervious surfaces, including industrial land and urban villages along the fringe of the central urban area. In these areas, higher WCR values were more strongly associated with lower LST. By contrast, around large open water bodies, terminal tributary sections, and urban fringe areas, the negative coefficients tended to be weaker. Only a limited number of edge or local grid cells showed positive coefficients, and these did not change the dominant negative pattern of the relationship between WCR and LST. Overall, WCR had the most stable negative relationship with LST among the three MGWR variables, but the magnitude of this relationship varied across the study area.

The mean local coefficient of SI was 0.107, and the median was 0.058, showing an overall weak positive average relationship with LST. The local coefficients ranged from -0.996 to 1.176 , with a standard deviation of 0.265 . These values showed that the direction and magnitude of the relationship between SI and LST varied substantially across space. The local coefficient map in Figure 5b showed that positive SI coefficients were broadly observed along the Minjiang River and urban river segments within the built-up areas of the study area. In these areas, higher SI values were associated with higher LST. By contrast, negative SI coefficients appeared only in limited areas, mainly around some large water bodies such as Jin'an Lake, river segments near the urban fringe, and several river confluence areas. Overall, SI showed a weak positive average relationship but did not exhibit a stable unidirectional local coefficient pattern, indicating that the relationship between SI and LST varied across spatial locations.

The mean local coefficient of D was 0.090 , and the median was 0.060 , showing a weak positive average conditional relationship with LST. The local coefficients ranged from -0.183 to 0.507 , with a standard deviation of 0.119 . Compared with WCR and SI, D had smaller variation in local coefficient values. D also had a larger bandwidth than WCR and SI, and its local coefficients showed a smoother spatial distribution. The local coefficient map in Figure 5c showed that positive local coefficients of D were widely distributed across the study area, especially within the built-up areas of central Fuzhou. Weak positive coefficients were mainly distributed along tributary and canal segments within the built-up areas on both sides of the Minjiang River, including many finer urban water network segments in the study area. By contrast, stronger positive coefficients were mainly concentrated along and around the broad main corridor of the Minjiang River. Negative coefficients, however, appeared only in a limited number of scattered local areas and did not form a continuous spatial cluster. These results indicate that the relationship between D and LST varied across space. Although the positive average relationship of D was generally consistent with the dominant positive local coefficient pattern, the global model could not fully capture the spatial differences in local coefficient magnitude or the limited local negative variations.

4. Discussion

4.1. Global Relationships Between Water Network Indicators and LST

This study found significant associations between the spatial and physical indicators of the urban surface water network and LST, but their thermal implications and interpretive values differed across indicators. WA and WCR were negatively correlated with LST, showing that greater water coverage was generally associated with lower land surface temperatures. D also showed a negative correlation with LST, indicating that areas with denser water networks tended to have lower LST in the bivariate correlation analysis. Among the water body morphology indicators, W was negatively correlated with LST, whereas SL and SI were positively correlated with LST. This contrast suggests that the thermal implications of water body morphology depend on the specific morphological metric, rather than following a single directional pattern. The strong positive correlation between WT and LST mainly reflected the covariation between the thermal state of the water surface and the surrounding land surface thermal environment.

The negative correlations of WA, WCR, W, and D with LST are generally consistent with evidence from Shanghai's urban river network, where river width, WCR, and river network density were identified as important factors associated with lower-LST patterns in river network areas [28]. The present results extend this evidence to the main urban area of Fuzhou, showing that larger water area, higher WCR, greater average water body width, and greater water network density were generally associated with lower LST. However, the stepwise regression results showed that these bivariate relationships should

not be interpreted as independent explanatory relationships. After WT was excluded from the candidate spatial explanatory variables, WCR, D, and SI were retained in the final model, among which WCR showed the clearest coverage-related association with LST. The exclusion of WA and W from the final model should not be interpreted as evidence that water area and water body width are unrelated to LST. Rather, under the 150 m grid scheme used in this study, WCR, D, and SI were more informative for characterizing global associations with LST when shared variance among indicators was considered. This pattern is consistent with previous studies showing that urban thermal analyses are sensitive to spatial scale, and that the relationships among landscape composition, urban morphology, and LST can vary with the analytical unit [49].

D showed a weak positive coefficient after WCR and SI were included. This shift indicates that the negative bivariate relationship between D and LST was not independent of water coverage and water body morphology. Therefore, D should be interpreted cautiously in the global model. It does not indicate a uniform association with lower LST, but more likely reflects a conditional structural relationship with LST. This result also suggests the need to further examine whether the relationship between D and LST varies across space.

The positive bivariate correlations of SL and SI with LST show that longer shorelines and more complex planform morphology of water bodies do not necessarily indicate a stronger association with lower LST. As geometric metrics, SL and SI mainly describe shoreline length and water body planform complexity, and a stable association with lower LST should not be inferred from these metrics alone. SI was retained in the stepwise regression model, indicating that water body planform morphology remained statistically associated with LST after water coverage and water network density were considered. However, this result should not be interpreted as evidence that SI alone represents a stronger association with lower LST. Instead, it suggests that the thermal meaning of water body planform morphology depends on its relationship with water coverage, water network structure, and the surrounding urban context. Previous studies in Wuhan have shown that the thermal conditions around water bodies are closely associated with surrounding two-dimensional and three-dimensional urban morphology [21]. Further evidence from Changsha indicates that land cover, building spatial configuration, and landscape pattern are also closely associated with river-related thermal patterns [50]. Consistent with these studies, the present results suggest that morphological indicators alone do not provide a sufficient basis for explaining lower LST.

The strong positive correlation between WT and LST should be interpreted differently from the relationships observed for other spatial and physical indicators. WT is not an independent spatial pattern indicator. It represents the thermal state of the water surface derived from the same LST retrieval used to characterize the land surface thermal environment. Because WT and LST were obtained from imagery acquired on the same date and processed through comparable spatial aggregation procedures, their strong positive correlation partly reflects consistency in data source and analytical scale. Therefore, the relationship between WT and LST should not be interpreted as an independent driving effect of water surface temperature on surrounding LST. It is better understood as parallel variation between the thermal state of the water surface and the overall thermal environment within the corresponding grid cell. Accordingly, WT is useful as a diagnostic indicator for identifying the thermal state of water bodies and their surroundings, but it should not be treated as an independent planning variable of the same nature as spatial pattern indicators such as WCR, D, and SI.

Taken together, the global results show the value of treating urban surface water networks as an integrated spatial system. This approach extends previous studies that examined individual water bodies, single river corridors, or river network density alone. By

bringing water coverage, water network structure, and water body morphology into a single framework, this perspective helps distinguish how different water network dimensions are globally related to the land surface thermal environment. These global patterns also indicate the need to examine spatial non-stationarity in the relationships between water network indicators and LST.

4.2. Spatial Non-Stationarity in the Relationships Between Water Network Indicators and LST

The global regression model describes the average relationships across the study area, whereas the MGWR results show the spatial non-stationarity in the relationships between urban surface water network indicators and LST. WCR and SI had relatively small bandwidths, indicating more localized relationships with LST. By contrast, D had a larger bandwidth, consistent with a smoother and more spatially extensive relationship between water network density and LST.

The local coefficients of WCR were predominantly negative across the study area, indicating that WCR showed the most spatially stable negative association with LST among the MGWR variables. A qualitative comparison between the land cover background in Figure 2d and the local WCR coefficient map in Figure 5a suggests that the negative relationship between WCR and LST was more pronounced around areas dominated by dense buildings and impervious surfaces, including industrial land and urban villages along the fringe of the central urban area. This spatial pattern indicates that the local relationship between WCR and LST was closely conditioned by the surrounding spatial and thermal context. Previous studies have shown that the thermal patterns around water bodies are associated not only with the thermal state of the water bodies themselves, but also with the thermal contrast between water bodies and surrounding land surfaces [36]. In areas with higher impervious surface proportions and stronger background heat accumulation, a larger thermal gradient may form between water bodies and adjacent impervious surfaces. Under these conditions, higher water coverage was more clearly associated with lower LST, which is reflected in stronger negative local coefficients. A study of urban blue space optimization in Beijing found that the thermal patterns of blue spaces were spatially heterogeneous and that responses to optimization were more pronounced in areas with dense buildings [35]. Studies on industrial heat islands have also shown that the size of landscape patches around industrial areas is related to surrounding LST intensity, and that larger water patches are generally associated with lower LST [51]. Together with the present results, these findings indicate that the negative local relationship between WCR and LST can be strengthened in built environments with higher background heat loads. By contrast, the negative relationship between WCR and LST tended to be weaker around large open water bodies, some terminal tributary reaches, and urban fringe areas. This does not mean that water bodies in these areas were unrelated to the spatial pattern of LST. Large water bodies usually coincide with a relatively stable low LST background [52], while terminal tributary reaches and urban fringe areas often have higher vegetation coverage or lower impervious surface proportions [15]. These conditions may reduce the thermal contrast between water bodies and surrounding land surfaces, leading to smaller absolute WCR coefficients in these areas.

The local coefficients of SI showed spatial inconsistency in both direction and magnitude. This pattern indicates that the thermal implications of water body planform morphology varied across urban spatial contexts. The positive local SI coefficients were mainly distributed around the Minjiang River reaches and urban river segments within the built-up areas of the study area. In these areas, higher SI values were generally associated with higher LST. Together with the land cover background data, this pattern suggests that, under intensive urban development, higher SI values may reflect irregular, fragmented,

or channelized water body boundaries embedded in dense buildings and impervious surfaces, rather than more open or ecologically functional waterfront forms. These water bodies may be surrounded by hardened shorelines, waterfront roads, limited open space, or discontinuous blue–green spaces. Such spatial conditions may be less favorable for the outward dispersion of cooler air because they can constrain air movement and reduce the spatial contact between water bodies and adjacent open areas [21,36]. By contrast, negative SI coefficients appeared only in limited areas, mainly around some large water bodies such as Jin'an Lake, river segments near the urban fringe, and several river confluence areas. In these contexts, higher SI may indicate a more complex water–land interface in surroundings that are less continuously built up. Large water bodies can form relatively stable low-temperature backgrounds [20], and waterfront areas near lakes, confluences, or urban fringe zones may be more likely to include open spaces or connected green spaces. Under such conditions, greater water body edge complexity may increase the contact interface between water bodies and adjacent spaces, which may be more favorable for the local dispersion of cooler air [53]. However, this negative relationship was spatially limited and should not be generalized to all high-SI water bodies. Overall, because WCR and D were included in the MGWR model, the local coefficients of SI should be interpreted as a conditional morphological relationship after water coverage and water network density were considered. SI should not be interpreted as a standalone indicator of lower LST. Rather, it mainly represents the planform irregularity or edge complexity of water bodies, and its thermal meaning depends on the surrounding urban spatial context.

The results for D further indicate a contrast between its bivariate correlation with LST and its coefficients in the regression and MGWR models. One possible explanation is related to the 150 m grid-based representation of D. In the bivariate analysis, some grids along the broad Minjiang River corridor contained extensive low-temperature water surfaces and relatively high D values, which may have strengthened the overall negative correlation between D and LST. After WCR was included in the stepwise regression model, the low-temperature variation associated with water coverage was largely accounted for. Therefore, the coefficients of D in the stepwise regression and MGWR models mainly represent the additional relationship between water network density and LST after water coverage and water body planform morphology have been considered. Previous research on the urban river network of Shanghai identified network density as one of the factors associated with lower LST patterns in river network areas. However, the role of network density needs to be interpreted together with river width, water coverage, and water network morphology [28]. The present results support this view by showing that higher water network density alone was not consistently associated with lower LST after WCR and SI were included in the model. In relation to the land cover background, positive D coefficients were widely distributed, especially within the built-up areas of central Fuzhou and in parts of the Minjiang River corridor, whereas negative coefficients occurred only in a limited number of scattered local areas. This pattern suggests that D should not be interpreted as a stable planning indicator in isolation. Research on Hangzhou has also shown that the thermal role of water network structure should be interpreted in relation to the morphology of the surrounding built environment [29]. Therefore, the spatial heterogeneity of D reflects the distinction between water network density and effective thermal connectivity. Its planning interpretation should not focus solely on the density of channels. It should also consider whether the water network provides open and continuous spatial conditions that are favorable for the spread of cooler air toward surrounding urban areas.

4.3. Spatially Differentiated Planning Implications for Urban Surface Water Networks

The MGWR analysis revealed spatial non-stationarity in the relationships between water network indicators and LST. The following planning implications therefore focus on WCR, SI, and D as spatially differentiated references for urban surface water network planning.

The MGWR results showed that WCR was the most stable coverage-related indicator for planning interpretation, and that its negative association with LST was stronger in built-up environments with higher background heat loads. Therefore, effective water coverage should be treated as a general priority in urban water network planning for the land surface thermal environment, especially in industrial areas and urban villages. In these areas, planning should prioritize the protection of existing water bodies and water corridors, avoid water body infilling and channel narrowing, and, where local conditions allow, maintain or enhance effective water coverage by restoring water surfaces and improving water space along river corridors.

The spatially varying SI coefficients identified by MGWR suggest that the planning interpretation of SI is strongly context-dependent. Planning should instead examine what higher SI represents in specific urban contexts. In dense built-up areas, higher SI may reflect fragmented, channelized, or hardened waterfront edges embedded in impervious urban surfaces. In such areas, planning should give greater attention to improving the continuity of water bodies and water corridors, reducing artificial fragmentation, enhancing shoreline ecological quality, and maintaining open interfaces between land and water.

The broader spatial scale of the D relationship identified by MGWR suggests that water network density should be treated as a structural reference, rather than as a standalone target for increasing channel density. Planning should not simply pursue denser water networks. Instead, D should be considered together with effective water coverage, river corridor scale, and the surrounding land cover. In narrow tributaries, fragmented canal systems, hardened shorelines, and areas dominated by impervious surfaces, increasing water network density alone may have limited value as a standalone reference for lower LST.

These implications are derived from the spatially varying associations revealed by MGWR and should be understood as references for spatially differentiated planning, rather than as direct estimates of the effects of planning interventions. For subtropical coastal cities with extensive surface water networks similar to Fuzhou, specific planning strategies should therefore be adapted to local water network patterns, development intensity, land cover conditions, and waterfront functions.

4.4. Limitations and Future Research

This study has several limitations. First, the LST data were retrieved from a single summer Landsat image acquired under clear-sky daytime conditions. The results therefore mainly represent the land surface thermal environment at the time of the Landsat overpass and cannot fully capture diurnal variation, seasonal differences, interannual variability, or heatwave-related thermal dynamics. In addition, LST characterizes land surface thermal conditions and does not directly represent canopy-layer air temperature, pedestrian heat exposure, or human thermal comfort. Future studies could combine thermal infrared data with finer spatial resolution, multi-temporal satellite imagery, UAV thermal images, and field meteorological or microclimate observations to support more detailed spatiotemporal analyses. Such multi-temporal and field-based data would not only improve the temporal resolution of the analysis by providing repeated observations across different dates, seasons, and diurnal periods, but also help test whether the relationships between urban surface water network indicators and LST identified from the single-date Landsat image remain stable over time. Geographically and temporally weighted regression (GTWR) could also

be used to further examine spatiotemporal variations in the relationships between water network indicators and LST [54].

Second, this study characterized urban surface water bodies mainly through indicators of spatial pattern, planform morphology, and water surface thermal state. However, the thermal conditions associated with water bodies may also be affected by water body type and hydrological and hydrodynamic conditions. This study did not further distinguish between flowing and stagnant water bodies, nor did it incorporate water depth, flow velocity, water-level variation, tidal influence, or hydrological connectivity into the analysis. Future studies could integrate hydrological monitoring, tidal records, water-level observations, and field-based microclimate measurements to better explain the thermal differences among different types of urban water bodies.

Third, this study revealed spatially varying relationships between urban surface water network indicators and LST, providing spatial evidence for understanding the relationships between urban water bodies and the land surface thermal environment. However, thermal responses associated with water bodies may also be shaped by land cover, development intensity, and surrounding urban form. Because this study focused mainly on water network indicators and grid-level spatial relationships, the role of three-dimensional urban form factors, such as building height, street canyon geometry, enclosure, sky view factor, building density, and building spacing, remains to be further examined [34,36]. Furthermore, the regression and MGWR results should be interpreted as spatially varying statistical associations rather than estimates of causal effects, and they are not sufficient on their own to isolate the independent associations of individual water network indicators with LST. Future studies could combine three-dimensional urban morphology data, field-based microclimate observations, matched comparison analyses, and numerical simulations, such as ENVI-met and computational fluid dynamics (CFD), to further test the mechanisms and thermal responses under different water network optimization scenarios [55,56].

5. Conclusions

Taking the main urban area of Fuzhou as a case study, this study examined the relationships between urban surface water network indicators and the land surface thermal environment. The results showed that the relationships between water network indicators and LST varied across the candidate grid scales, and spatial non-stationarity was further identified at the selected 150 m grid scale.

The global regression results identified WCR, SI, and D as the main explanatory variables associated with variations in LST. Among them, WCR showed the strongest standardized explanatory association and relatively clearer planning relevance among the retained spatial indicators. By contrast, SI and D require more context-dependent interpretation and should not be treated as stable or independent planning indicators. WT had a strong bivariate association with LST, but it mainly reflected parallel variation between the thermal state of the water surface and the grid-level thermal environment. It should therefore not be interpreted as an independent planning variable.

The MGWR results further showed spatial non-stationarity in the relationships between key water network indicators and LST. WCR and SI showed more localized relationships with LST, whereas D operated at a broader spatial scale. WCR showed the most stable negative relationship with LST, and this relationship was more pronounced in built-up environments with higher background heat loads. In contrast, the local meanings of SI and D depended more strongly on spatial context. Their thermal implications should be understood together with the background level of water coverage, river corridor scale, shoreline conditions, blue–green continuity, and the surrounding built environment.

Overall, planning for urban surface water networks should not simply pursue more complex water body shapes or higher water network density. Instead, priority should be given to effective water coverage, while also considering the scale of river corridors, shoreline openness, the continuity of blue and green spaces, and surrounding land cover conditions. These findings provide spatially explicit references that may inform thermal-environment-oriented planning of urban surface water networks and land cover optimization in similar subtropical coastal cities.

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