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The impact of urban wetland landscape patterns on runoff: A comparative study of three Chinese cities with frequent extreme rainfall

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Abstract

Climate change is altering rainfall patterns and increasing the frequency of extreme rainfall events, thereby placing greater pressure on urban drainage systems and increasing flood risk. To improve urban stormwater management, China has actively promoted sponge city development, in which wetlands serve as important natural infrastructure for regulating urban runoff. However, understanding of how wetland landscape patterns influence the spatial variability of urban runoff remains limited. Therefore, this study examined three Chinese cities characterized by relatively low annual precipitation but frequent extreme rainfall events. Urban runoff was simulated using InfoWorks ICM under a unified rainfall scenario, and intercity differences in wetland landscape patterns were assessed. Ordinary least squares regression was then used to evaluate the contribution of wetland landscape characteristics to the spatial variability of runoff. The results revealed significant intercity differences in both runoff responses and wetland landscape patterns. After controlling for conventional urban environmental factors, wetland-related variables provided additional explanatory power for the spatial variability of urban runoff. Wetland cover, patch density, edge density, and connectivity were negatively associated with runoff, whereas landscape shape complexity was positively associated with runoff. These findings indicate that wetland landscape patterns explain additional variation in urban runoff beyond that accounted for by conventional urban environmental factors. Accordingly, urban stormwater management and spatial planning should consider not only wetland extent but also wetland landscape configuration, particularly spatial arrangement and connectivity, to strengthen flood resilience and climate adaptation in highly urbanized areas.

Keywords Urban wetland, Wetland landscape pattern, Urban runoff, InfoWorks ICM, Extreme rainfall

1. Introduction

Climate change is altering precipitation regimes and increasing the frequency and intensity of extreme rainfall events, thereby exacerbating urban flood risk (Dong et al. 2022; Zhou et al. 2024). In China, the 800mm annual precipitation isohyet is commonly regarded as an important geographical boundary separating the humid southern region from the relatively dry northern region. Recent studies have reported that this isohyet has shifted northward, suggesting that northern areas historically characterized by relatively low annual precipitation may become increasingly exposed to short-duration extreme rainfall events (Du et al. 2026; Tong et al. 2025). In recent years, several cities across the North China Plain have experienced severe flooding triggered by extreme rainfall. In July 2021, Zhengzhou was struck by an exceptionally intense rainstorm that caused catastrophic urban flooding, widespread transport disruption, substantial economic losses, and considerable loss of life. In July 2023, another extreme rainfall event resulted in extensive flooding

across the Beijing–Tianjin–Hebei region (Zhao et al. 2024). These events highlight that cities with relatively low long-term annual precipitation can nevertheless be highly vulnerable to flooding when intense rainfall is concentrated over a short period and exceeds the capacity of urban drainage and stormwater management systems. Nevertheless, compared with cities in the humid south, northern cities may remain less prepared for the increasing risks associated with extreme rainfall and urban flooding (Zhao et al. 2023).

To respond to the increasing urban flood risk associated with climate change, China has adopted the Sponge City (SC) concept as a national strategy to improve urban stormwater management through nature-based solutions designed to enhance rainwater retention, infiltration, and regulation (Chan et al. 2018; Li et al. 2026). Since the SC concept was introduced in 2013, SC projects have been progressively implemented across numerous provinces and cities. Among the various nature-based measures promoted under the SC initiative, urban wetlands represent an important component of green infrastructure (GI). However, existing studies have

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43 primarily focused on the hydrological effects of wetland
44 area and the number of wetland (Enu et al. 2025; Ferreira
45 et al. 2023), or have examined the relationship between
46 the overall spatial configuration of GI and flood
47 risk(Chen et al. 2024; Xie and Chui 2025). In contrast,
48 considerably less attention has been paid to the influence
49 of urban wetland spatial configuration on runoff
50 responses. This research gap is particularly pronounced
51 in cities characterized by relatively low long-term annual
52 precipitation but increasing exposure to short-duration
53 extreme rainfall events.

54 To address this research gap, this study aims to
55 examine the relationships between urban wetland
56 characteristics and urban runoff in cities characterized by
57 relatively low long-term annual precipitation, thereby
58 informing wetland based stormwater management and
59 climate-adaptive urban spatial planning.

60 2. Literature review

61 2.1. Urban wetland and runoff

62 Urban wetlands are a key component of GI and
63 provide a wide range of ecosystem services(Hansen and
64 Pauleit 2014; Zhao et al. 2021). Among these functions,
65 urban wetlands play a particularly important role in
66 regulating runoff processes because of their capacity to
67 store, detain, and gradually release stormwater(Acreman
68 and Holden 2013; Wu et al. 2020). Consequently,
69 wetlands have become an important nature-based
70 solution for enhancing urban resilience to flooding under
71 climate change. The physical characteristics of wetlands
72 also affect their mitigation effect on urban flooding.
73 Existing research shows that wetland cover area can
74 directly affect the timing of flood peaks and cumulative
75 runoff during rainfall events; a larger wetland area helps
76 delay flood peak arrival and reduce surface runoff
77 accumulation, thereby enhancing urban stormwater
78 regulation capacity (Enu et al. 2025; Tang et al. 2020).

79 However, wetland hydrological performance may
80 depend not only on wetland area but also on the spatial of
81 wetland configuration, suggesting that factors beyond
82 wetland area may also contribute to runoff regulation.

83 2.2. Wetland landscape pattern

84 The spatial configuration of urban green infrastructure
85 has been widely recognized as an important factor
86 influencing stormwater regulation and pluvial flood
87 mitigation. Higher Aggregation Index (AI) is generally
88 associated with lower flood risk, suggesting that greater
89 spatial aggregation and connectivity of green
90 infrastructure patches may enhance stormwater

91 regulation capacity. In contrast, higher Patch Density (PD)
92 is positively associated with flooding, indicating that
93 fragmented green infrastructure patterns may weaken
94 hydrological regulation functions(Wang et al. 2022;
95 Wang et al. 2025b). Among different landscape
96 characteristics, connectivity has received considerable
97 attention in both landscape ecology and hydrology.
98 Numerous studies distinguish connectivity into structural
99 connectivity and functional connectivity(Bracken and
100 Croke 2007). Structural connectivity refers to the spatial
101 arrangement and physical linkage among landscape
102 elements, whereas functional connectivity describes the
103 actual movement of water, runoff, and materials among
104 different spatial units during hydrological processes
105 (Turnbull et al. 2008; Zhang et al. 2021). Based on these
106 concepts, this study considers connectivity as one
107 component of wetland landscape configuration that
108 reflects the potential spatial linkage among wetland
109 patches within the urban runoff system. Rather than
110 interpreting connectivity solely as the physical continuity
111 between wetland patches, this study focuses on the spatial
112 relationships among wetland patches and their potential
113 relevance to urban runoff processes.

114 2.3. Environmental factors affecting urban runoff

115 Geographic factors, such as elevation and slope, are
116 key determinants of urban flood risk, as they directly
117 influence surface runoff generation, flow direction, and
118 water accumulation processes(Kuller et al. 2018; Wang
119 et al. 2024). However, in cities characterized by complex
120 terrain or mountainous areas, mean elevation may
121 introduce bias when used as a comparative indicator,
122 because high-elevation mountainous zones can inflate
123 city scale elevation values and obscure the flood
124 susceptibility of low-lying urbanized areas. Therefore, in
125 this study, the average slope of each city was selected as
126 the primary topographic control variable for subsequent
127 analysis.

128 In addition to topographic conditions, human-induced
129 changes in landuse and landcover (LULC) and variations
130 in the Normalized Difference Vegetation Index (NDVI)
131 have been widely recognized as important factors
132 influencing urban runoff and flooding(Astuti et al. 2019;
133 Peng et al. 2024). Increases in impervious surfaces,
134 including roads, buildings, and other built-up areas, can
135 substantially alter natural hydrological processes by
136 reducing infiltration capacity, accelerating surface runoff,
137 and disrupting drainage pathways. Accordingly, building
138 density and road density were included in the analysis as
139 indicators of urban development intensity. In contrast,

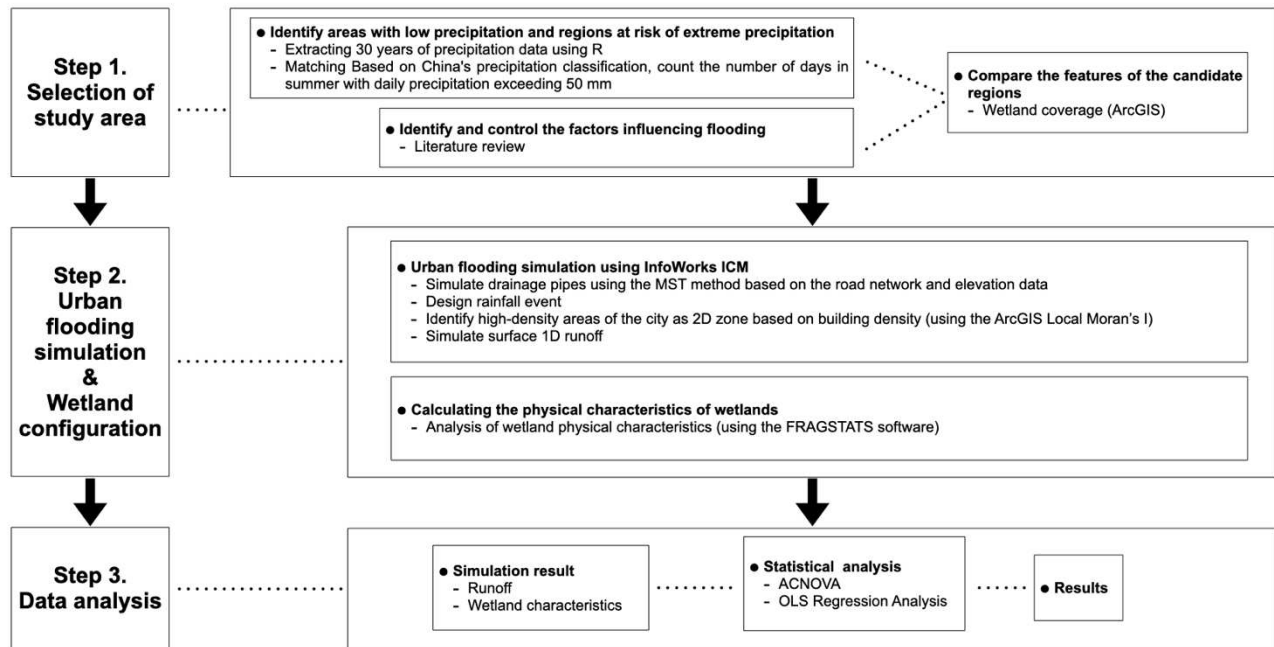


Fig.1 Research Methodology Framework

vegetation cover, represented by NDVI, can contribute to runoff mitigation by enhancing rainfall interception, promoting infiltration, and reducing surface runoff. Soil moisture conditions may also influence runoff generation by affecting antecedent infiltration capacity and the partitioning of rainfall into infiltration and runoff (Wang et al. 2025b; Wasko and Nathan 2019). Furthermore, hydrological characteristics, including river density and proximity to rivers, may affect runoff accumulation and drainage efficiency by altering flow pathways and the conveyance of surface water (Li et al. 2022; Mård et al. 2018). Accordingly, NDVI, soil moisture, river density, and distance to the nearest river were included in the analysis to account for their potential associations with runoff variation.

Socioeconomic conditions may also influence flood impacts by affecting exposure and vulnerability. Regional disparities in economic development and population distribution can exacerbate flood-related losses in densely populated or economically concentrated areas (Lindersson et al. 2023). However, because socioeconomic factors primarily influence flood vulnerability rather than runoff generation, they were considered only during the selection of the study cities to improve intercity comparability and were not included in the subsequent statistical analyses.

3. Methods

This study consists of three main steps (Fig.1). First, candidate cities were screened based on precipitation characteristics and geographical and socioeconomic

conditions associated with urban flooding. Second, urban runoff simulations were conducted using InfoWorks ICM under the designed rainfall scenario. FRAGSTATS was employed to quantify the spatial configuration of urban wetlands. Third, the simulation results were statistically analyzed together with wetland pattern indicators to examine the relationship between urban wetland patterns and runoff variation.

3.1. Select study area

(1) Screening criteria based on precipitation

The temperature and precipitation indices developed by ETCCDI (Expert Team on Climate Change Detection and Indices) are widely used in climate change research. Some of these precipitation indices are defined based on specific thresholds (e.g., 10 mm, 20 mm, or user-defined thresholds), with precipitation amounts exceeding these thresholds being classified as extreme precipitation events (Anagnostopoulou and Tolika 2012). According to existing studies, precipitation definitions are generally categorized into absolute and relative thresholds. Absolute thresholds are set according to specific precipitation indices, whereas relative thresholds are calculated using percentile methods. It has been demonstrated that calculating precipitation amounts using relative thresholds is more reasonable than using absolute thresholds (Fu et al. 2024; Gimeno et al. 2022). To identify Chinese cities located in relatively low-precipitation regions, this study used daily precipitation records from 1994 to 2023. The median of the 30-year

199 mean annual precipitation was used as the threshold, and
 200 areas with annual precipitation below this threshold were
 201 classified as low precipitation zones. Although these
 202 areas receive less total annual rainfall, extreme
 203 precipitation events are concentrated in summer, where
 204 consecutive days of heavy rainfall readily trigger urban
 205 flooding (Li et al. 2012; Stein et al. 2020). According to
 206 China's precipitation classification standards, 24-hour
 207 precipitation exceeding 50 mm is defined as a rainstorm.
 208 Therefore, this study uses 50 mm/day as the threshold for
 209 rainstorm events and extracts the number of days
 210 exceeding this threshold in summer as a surrogate
 211 indicator of potential urban flooding risk, thus supporting
 212 the initial screening of the study area.
 213 This study obtained 30 years of daily precipitation
 214 records from the National Oceanic and Atmospheric
 215 Administration (NOAA) global precipitation dataset and
 216 used RStudio software to extract and process
 217 precipitation records for the Chinese region.

218 **(2) Determination of the study area**

219 Following the preliminary screening based on
 220 precipitation conditions, the factors described in Section
 221 2 were further incorporated as secondary screening
 222 criteria to ensure that the selected cities shared
 223 comparable precipitation backgrounds, geographical
 224 settings, and socioeconomic conditions while exhibiting
 225 differences in wetland characteristics for comparative
 226 analysis. Based on this process, Zhengzhou (Henan
 227 Province), Qingdao (Shandong Province), and Xuzhou
 228 (Jiangsu Province), all located within the North China
 229 Plain, were ultimately selected as the study areas. The
 230 specific characteristics of these three cities are shown in
 231 Table 1, and their spatial locations are shown in Figure 2.
 232 Zhengzhou is located in north-central Henan Province
 233 and serves as the provincial capital. It lies within the
 234 Yellow River–Huai River basin system and is

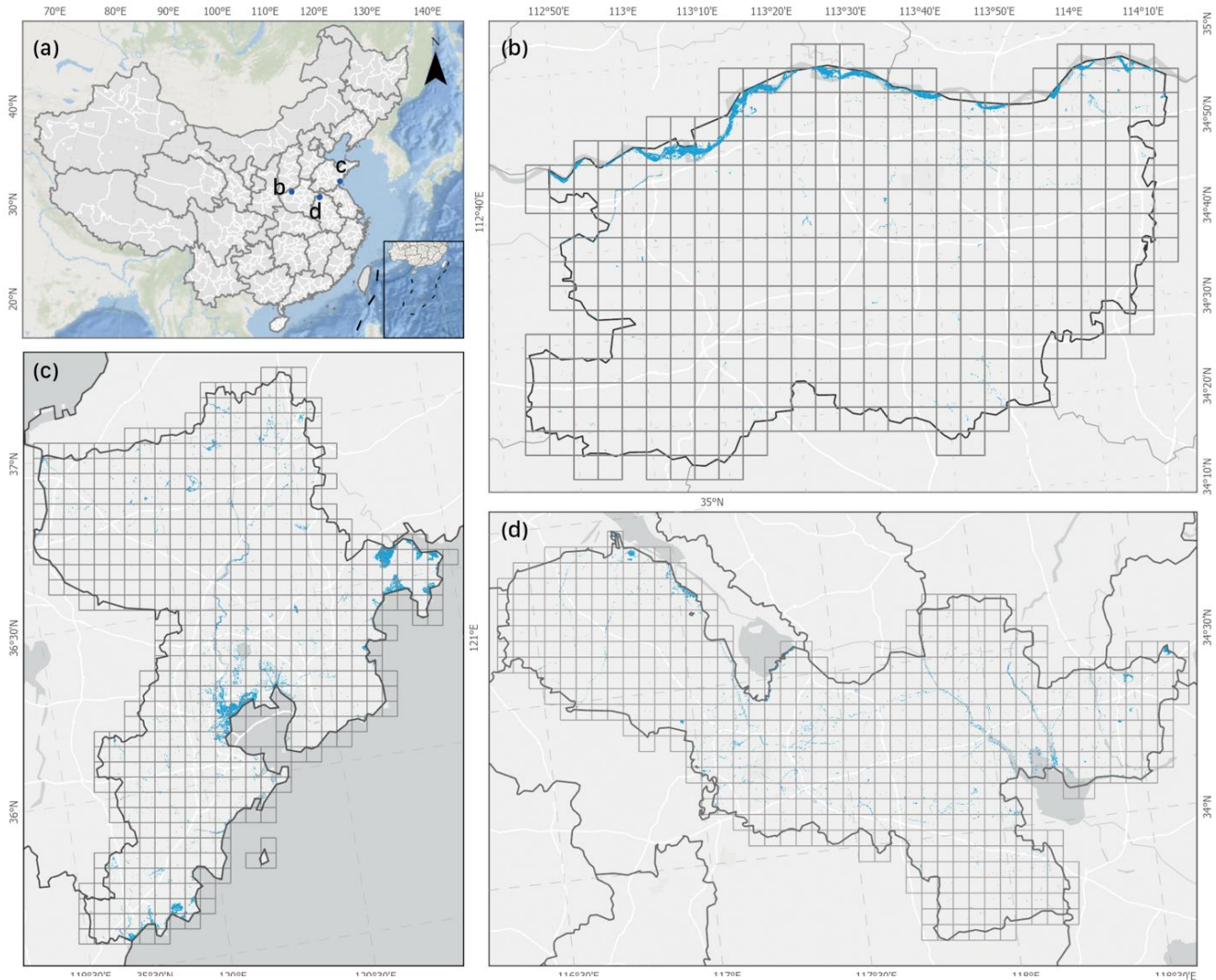


Fig.2 Study area. (a) China map showing the locations of the study cities; (b) Zhengzhou; (c) Qingdao; (d) Xuzhou.

Tabel 1 Comparison of area characteristics

		Zhengzhou (Henan)	Qingdao (Shandong)	Xuzhou (Jiangsu)
Geographical factors	Area of the district	7567.2km ²	11039.4km ²	11765km ²
	Average slope ^a	4.6°	3.1°	1.5°
	Average NDVI (May to September 2024) ^a	0.27	0.26	0.34
	Wetland cover (%) ^a	1.42	2.64	1.19
Socioeconomic factors	Population (10,000 people) ^b	1300.8	1037.2	1035.3
	Average GDP 2019 to 2023 (100 million yuan) ^b	10864.1	12003.7	7094.3
Climate and environment factor	Koppen climate classification ^c	Cwa	Cwa	Cwa
	Annual average precipitation (1994 to 2023)	741.52mm	778.59mm	924.05mm
	Extreme Precipitation Events	22	34	28

a. Calculated using ArcGIS Pro

b. Based on the statistical yearbooks of various cities

c. Obtain it from the website Climate-Data.org

characterized by a southwest-to-northeast topographic gradient. Zhengzhou was designated as a provincial Sponge City demonstration city. Qingdao is situated in the southern part of the Shandong Peninsula along the Yellow Sea and is an important coastal and port city. It was selected as one of the second batch of national Sponge City pilot cities. Xuzhou is located in northern Jiangsu Province and serves as the central city of the Huaihai Economic Zone as well as a national comprehensive transportation hub. The Beijing–Hangzhou Grand Canal passes through the city, and an extensive river network is distributed throughout the municipal area. Xuzhou was also designated as a provincial Sponge City demonstration city. Although the three cities share the same Koppen climate classification, they differ in topography, wetland distribution, and urban development characteristics. These similarities and differences provide an appropriate basis for comparative analysis of runoff variation and wetland landscape patterns under a unified analytical framework.

Although watershed-based units are commonly used in hydrological analysis, differences in watershed size and boundary configuration reduce the comparability of spatial units among cities. Therefore, a fixed 5×5 km grid was adopted as the analytical unit, allowing runoff simulation results and wetland landscape metrics to be compared across cities at a consistent spatial scale.

3.2. Urban runoff simulation

Hydraulic modeling is widely applied in urban flood-risk assessment. The widely used Storm Water Management Model (SWMM) evaluates subsurface drainage performance by simulating the conveyance capacity of urban sewer networks. In contrast, InfoWorks ICM is an integrated hydrologic–hydraulic modeling platform that

couples 1D pipe-network dynamics with 2D overland flow simulation, enabling a more comprehensive representation of urban flood processes.

(1) Construction of a simulated 1D pipeline network

Drainage pipe network data are typically not publicly accessible. Given these constraints, we adopted a generalized simulation approach to construct a representative drainage pipe network. Prior studies have demonstrated the feasibility of using generalized drainage networks, showing that the spatial distribution of drainage networks is significantly correlated with road network patterns, and that the simulated maximum inundation extent based on generalized networks closely corresponds to results derived from actual pipe network data (Du et al. 2023; Mair et al. 2017). Following the methodological framework established in previous studies, this study constructed a simplified drainage network using road network data as the spatial basis (Montalvo et al. 2024; Reyes-Silva et al. 2023). The invert elevations of manholes were derived from Digital Elevation Model (DEM) data. Subsequently, the Kruskal algorithm was applied to generate a minimum spanning tree, which was used to identify the minimum pipeline network required to connect all manholes to the outfall. Road network data were obtained from OpenStreetMap (OSM), and extracted major road classes, including motorway, trunk, primary, secondary, and tertiary roads. To maintain consistency in model settings across the three study cities, the stormwater pipe diameter was uniformly set to 800 mm, with reference to the construction guidelines of Zhengzhou. In addition, each grid was defined as an individual subcatchment, and one drainage inlet was assigned to each subcatchment to ensure that every drainage node had an associated

303 contributing area and to support subsequent grid scale
304 statistical analysis.

305 (2) Rainfall Design

306 InfoWorks ICM provides two precipitation input
307 options: one constructs rainfall events directly from
308 observed monitoring records, whereas the other specifies
309 design rainfall hyetographs derived from long-term
310 precipitation datasets(Wei et al. 2024). However, when
311 conducting simulations across multiple cities, observed
312 rainfall records may not provide consistent simulation
313 conditions because rainfall timing, duration, and intensity
314 vary among cities. Therefore, to ensure comparability
315 across the three case cities, this study adopted the
316 Chicago hyetograph method to generate design rainfall
317 events, The other parameters were referenced from the
318 Zhengzhou City Design Rainstorm Intensity Formula,
319 which is expressed as follows:

$$320 \quad q = \frac{001.829(1+3.264lgP)}{(t+24.8)^{0.856}}$$

321 where q represents the design rainfall intensity [L/
322 (hm² · S)], t represents the rainfall duration (min), and
323 P represents the design return period (years). As this
324 study does not focus on the simulation of extreme or
325 disaster-scale precipitation events, a 2-year return period
326 was selected to characterize a typical rainfall scenario
327 with the potential to induce surface runoff. Short duration
328 high intensity rainfall may increase the hydraulic burden
329 on urban drainage systems, thereby contributing to
330 surface water accumulation. Accordingly, the rainfall
331 time step was set to 5 min, the total rainfall duration was
332 set to 120 min, and the rainfall peak coefficient was set to
333 0.433.

334 (3) 1D-2D coupling for surface overflow simulation

335 The coupling between the 1D pipe network and the 2D
336 surface runoff model is achieved through stormwater
337 manholes. Surface runoff can enter the drainage network
338 through the inlets, and when the network is overloaded,
339 water can overflow from the inlets to the 2D
340 surface(Wang et al. 2025a).

341 The 2D zone was restricted to high density urban areas,
342 where impervious surfaces and drainage demand are
343 concentrated and rainfall induced runoff is more likely to
344 occur(Mair et al. 2017). This restriction helped focus the
345 surface flooding simulation on highly urbanized areas
346 and reduced the influence of low development landcover
347 types, including forests, grasslands, and other urban green
348 spaces. Building density was used as an indicator of urban

349 development intensity, and Local Moran's I was applied
350 to identify high-high clusters of building density, where
351 both the target grid and its neighboring grids have
352 relatively high building density values(Yang and Whang
353 2024). Therefore, the node corresponding to each grid
354 within the identified high-high clusters was assigned the
355 "2D" inlet flood type in ICM, thereby enabling hydraulic
356 exchange between 1D pipe flow and 2D surface flooding.
357 It should be note that he 2D zone was used only to define
358 the area of 1D-2D hydraulic exchange in the
359 hydrodynamic model and was not included in the
360 subsequent statistical analyses, which focused on runoff.

361 3.3. Wetland pattern metrics

362 Landscape metrics can be calculated at the class level
363 and the landscape level(McGarigal 2015). Class level
364 metrics quantify the compositional and configurational
365 characteristics of a specific landcover class within a
366 landscape, whereas landscape level metrics describe the
367 overall structure of the landscape composed of all
368 landcover classes. Because this study aims to examine
369 how wetland patches are spatially distributed and
370 connected within urban landscapes, wetlands were
371 treated as the target landcover class. Accordingly, class-
372 level metrics were used to characterize wetland landscape
373 configuration, including fragmentation, aggregation,
374 shape complexity, isolation, edge characteristics, and
375 connectivity (Table 2). Wetland areas were extracted
376 from 10m resolution LULC data, and FRAGSTATS v4.3
377 was used to quantify the spatial patterns of wetland
378 patches.

379 PD measures the number of wetland patches per unit
380 area and is usually expressed as the number of patches per

Table 2 Calculation of wetland pattern indicators

Wetland pattern metrics	Unit	Formula
Patch Density (PD)	Numbe r/ 100ha	$\frac{n_i}{A} (10000)(100)$
Edge Density (ED)	m/ha	$\frac{\sum_{k=1}^m e_{ik}}{A} \times 10000$
Aggregation Index (AI)	%	$\left[\frac{g_{ii}}{\max \rightarrow g_{ii}} \right] (100)$
Nearest Neighbor Distance (ENN_MN)	m	$ENN = h_{ij}$
Landscape Shape Index(LSI)	-	$\frac{0.25 \times E^*}{\sqrt{A}}$
Connectance Index(CONNECT)	%	$\left[\frac{\sum_{j \neq k}^{n_i} c_{ijk}}{n_i(n_i - 1)} \right] \times 100$

100 ha; higher values generally indicate greater wetland fragmentation. ED quantifies the total length of the edge of a wetland patch per unit area. A higher value indicates more edge interfaces and a more complex landscape shape(Li et al. 2011). AI measures the degree of spatial aggregation among wetland patches, with higher values indicating stronger aggregation. ENN_MN represents the mean Euclidean nearest-neighbor distance among wetland patches and is used to characterize spatial isolation, where larger values indicate greater isolation(Xie and Chui 2025). LSI measures the shape complexity of wetland patches based on the relationship between total edge length and patch area, with higher values indicating more complex and irregular patch shapes. CONNECT assesses the functional connectivity between landscape types; a higher value indicates stronger connectivity(Shi et al. 2019).

3.4. Statistical analysis and data collection

To identify the potential factors associated with urban runoff differences across the three cities, this study used the 1D runoff simulated by InfoWorks ICM as the dependent variable. Wetland landscape metrics, built-environment characteristics, topographic factors, and natural environmental factors were included as explanatory variables to examine their associations with simulated runoff variation.

In addition, hierarchical ordinary least squares (OLS) regression was conducted to assess the associations between different groups of explanatory variables and simulated runoff variation and to evaluate the additional explanatory contribution of wetland landscape metrics. All statistical analyses were performed using SPSS Statistics 29.0.

4. Results

4.1. Simulated runoff differences among three cities

The Under a uniform rainfall scenario, the simulated runoff of the three cities exhibited different distribution characteristics at the grid scale, and significant spatial variability also existed between different grids within the same city. Based on the skewed distribution characteristics of the runoff data, this study used the Kruskal–Wallis test to compare the original runoff distributions of the three cities and used ANCOVA to compare the corrected mean runoff after controlling for spatial covariates such as built environment factors, topographic conditions, and wetland patterns.

The Kruskal–Wallis test results showed that there were significant differences in the original runoff distributions of the three cities ($H = 18.665$, $p < 0.001$). Bonferroni-corrected pairwise comparisons showed that Zhengzhou's runoff was significantly higher than that of Xuzhou ($p < 0.001$) and Qingdao ($p = 0.001$), while the difference between Xuzhou and Qingdao was not significant (Figure 3a). The ANCOVA results showed that, after controlling for spatial covariates, the corrected mean runoff of the three cities still showed significant differences ($F = 91.19$, $p < 0.001$). The estimated marginal means show that Zhengzhou has the highest mean, followed by Xuzhou, and Qingdao has the lowest. Bonferroni-corrected pairwise comparisons further show that Qingdao is significantly lower than both Xuzhou ($p < 0.001$) and Zhengzhou ($p < 0.001$), while the difference between Xuzhou and Zhengzhou is not significant ($p = 0.109$)(Figure 3b). This indicates that, after controlling for spatial covariates, the runoff difference pattern between cities is not entirely consistent with the original distribution results.

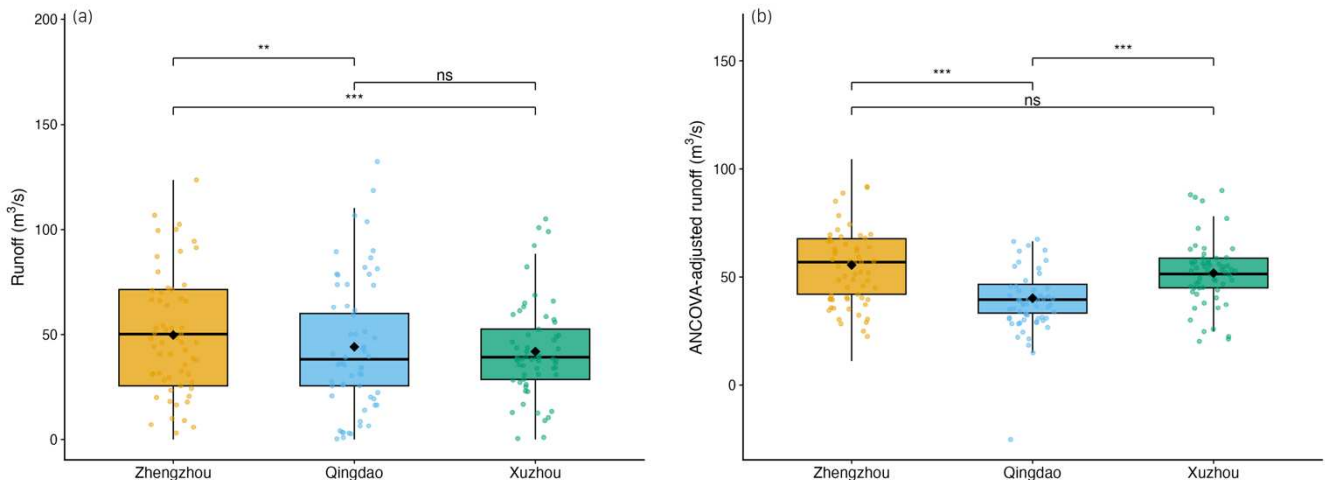


Fig.3 Comparison of ICM simulation results. (a) Distribution of grid scale 1D runoff across the three cities; (b) Wetland pattern differences after controlling the built environment. The black diamond indicates the mean values. Points represent randomly sampled grid cells for visualization. Box plots generated using R.

4.2. Wetland pattern differences

Wetland patterns differed significantly among the three cities (Fig. 4). Descriptive statistics showed that the mean values of PD, ENN_MN, and ED were consistently higher than their corresponding medians (Table 3), indicating right skewed distributions driven by a small number of grids with exceptionally high values. The Kruskal–Wallis tests further confirmed significant differences among the three cities for all wetland landscape metrics examined (all $p < 0.001$). Bonferroni-adjusted pairwise comparisons revealed distinct intercity patterns across the wetland landscape metrics.

PD, ED, and LSI exhibited broadly consistent patterns. The median PD values in Qingdao and Xuzhou were both 1.44, significantly higher than that in Zhengzhou (0.60; adjusted $p < 0.001$), whereas no significant difference was observed between Qingdao and Xuzhou (adjusted $p = 0.568$). Similarly, the median ED values in Qingdao and Xuzhou (5.75 and 5.08, respectively) and their median LSI values (7.29 and 7.64, respectively) were significantly higher than those in Zhengzhou (ED = 2.20; LSI = 5.17; adjusted $p < 0.001$). No significant difference in LSI was found between Qingdao and Xuzhou. Collectively, these results indicate that Qingdao and Xuzhou were characterized by higher wetland patch

Table 3 Statistical description of wetland patterns and the Kruskal–Wallis test result

Wetland metric	Zhengzhou		Qingdao		Xuzhou		Kruskal–Wallis H
	Mean (SD)	Median (IQR)	Mean (SD)	Median (IQR)	Mean (SD)	Median (IQR)	
PD	2.05(6.02)	0.60(1.42)	3.16(5.59)	1.44(2.02)	2.42(2.93)	1.44(2.78)	77.64***
ENN_MN	237.46(434.65)	85.03(181.95)	266.89(278.33)	194.58(225.72)	304.92(551.27)	110.89(218.26)	69.18***
CONNECT	52.90(29.11)	44.44(46.62)	28.65(19.91)	21.97(17.61)	31.29(20.22)	25.57(20.33)	95.59***
AI	79.13(11.88)	79.29(16.01)	80.52(8.71)	81.21(10.21)	76.44(9.88)	77.79(11.12)	49.90***
ED	8.72(19.55)	2.20(7.07)	14.05(22.82)	5.75(11.88)	10.52(18.67)	5.08(11.53)	63.70***
LSI	5.79(3.36)	5.17(4.48)	8.23(4.77)	7.29(4.76)	8.57(4.98)	7.64(7.53)	83.66***

Note: *** $p < 0.001$

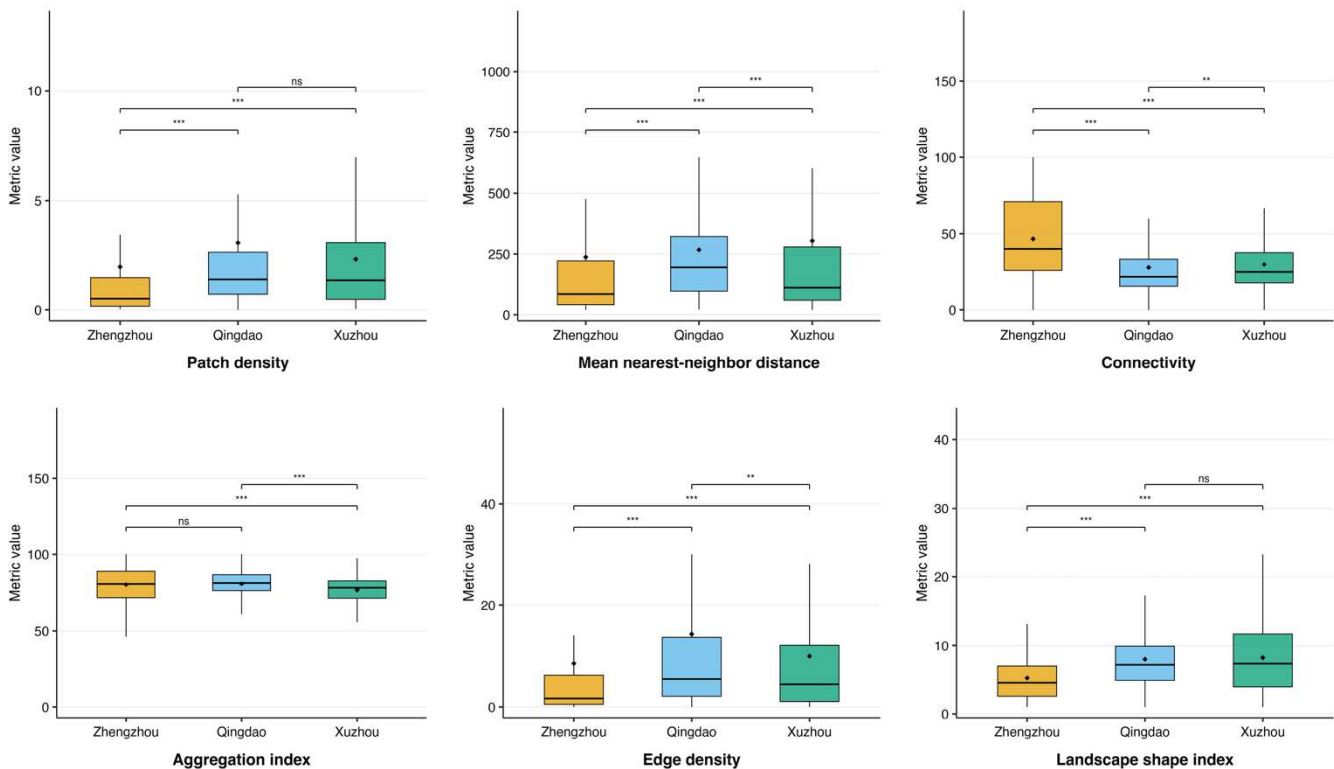


Fig.4 Differences in wetland patterns among the three cities. Boxplots illustrate the distributions of wetland landscape pattern indicators across the three cities, with black diamonds representing mean values. To improve the readability of intercity distributional differences, outliers were not displayed, and the plotting range was adjusted based on the upper whisker (ns indicates no significant difference, ** $p < 0.01$, *** $p < 0.001$). Box plots generated using R.

density, greater edge density, and more complex patch shapes than Zhengzhou.

ENN_MN and CONNECT exhibited contrasting intercity patterns. Qingdao had the highest median ENN_MN (194.58), followed by Xuzhou (110.89) and Zhengzhou (85.03). All pairwise comparisons were statistically significant (adjusted $p < 0.001$), indicating that wetland patches in Qingdao were, on average, more widely separated. In contrast, the median CONNECT value was highest in Zhengzhou (44.44), followed by Xuzhou (25.57) and Qingdao (21.97). Significant differences were observed among all three cities (adjusted $p < 0.01$), indicating that Zhengzhou had the highest structural connectivity among wetland patches.

Intercity differences in AI were comparatively modest. The median AI was highest in Qingdao (81.21), followed

by Zhengzhou (79.29) and Xuzhou (77.79). Xuzhou differed significantly from both Qingdao and Zhengzhou (both $p < 0.001$), whereas no significant difference was observed between Qingdao and Zhengzhou. These results indicate that wetland patches in Xuzhou were relatively less aggregated.

Overall, the three cities exhibited distinct wetland landscape configurations. Zhengzhou was characterized by relatively continuous and well-connected wetland patches with lower fragmentation, whereas Qingdao exhibited the greatest spatial isolation among wetland patches. Xuzhou shared fragmentation characteristics similar to Qingdao but maintained intermediate levels of connectivity and nearest-neighbor distance.

Table 4 Hierarchical OLS regression model summary

Model	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change
1	0.036	0.034	25.26624468	0.036	20.248***
2	0.622	0.619	15.87120791	0.587	211.010***
3	0.724	0.719	13.61448313	0.102	56.747***

Note: *** $p < 0.001$.

Table 5 Analysis results of OLS regression model 3

Variable	Unstandardized Coefficients		Standardized Coefficients	t	Collinearity Statistics	
	B	Std. Error	Beta		Tolerance	VIF
Xuzhou dummy ^a	10.876	1.104	0.208***	9.856	0.572	1.748
Zhengzhou dummy ^a	17.498	1.738	0.271***	10.067	0.354	2.828
DEM	-0.033	0.010	-0.120**	-3.198	0.182	5.500
Slope	2.878	0.301	0.294***	9.555	0.270	3.709
Building density	1.852	0.110	0.436***	16.879	0.384	2.604
Road density	18.599	2.515	0.178***	7.395	0.440	2.275
NDVI	-60.044	6.224	-0.258***	-9.647	0.358	2.796
Soil wetness	15.037	12.406	0.022	1.212	0.777	1.287
Distance to river	0.000	0.001	-0.009	-0.411	0.510	1.963
River Density	6.400	39.037	0.004	0.164	0.490	2.040
PD	-0.814	0.174	-0.140***	-4.672	0.286	3.492
ENN_MN	0.001	0.001	0.023	1.115	0.613	1.633
CONNECT	-0.111	0.024	-0.100***	-4.658	0.557	1.795
AI	-0.019	0.047	-0.007	-0.407	0.753	1.328
ED	-0.166	0.045	-0.131***	-3.694	0.204	4.892
LSI	2.140	0.143	0.398***	14.945	0.361	2.769
Wetland coverage	-0.424	0.134	-0.079**	-3.173	0.408	2.451

Note: ** $p < 0.05$, *** $p < 0.001$

a. Qingdao was used as the reference category for the city dummy variables. The coefficients for Xuzhou dummy and Zhengzhou dummy indicate differences relative to Qingdao.

503 4.3. Relationship between wetland pattern and runoff

504 To further explore the relationship between wetland
505 patterns and surface runoff, this study employed
506 hierarchical ordinary least squares (OLS) regression
507 analysis to assess the additional explanatory power of
508 wetland variables after controlling for city level
509 differences, natural environmental conditions, and built
510 environment factors. Model 1 included only city dummy
511 variables, Model 2 added natural environmental and built
512 environment variables to Model 1, and Model 3 further
513 incorporated wetland related variables, including wetland
514 area proportion and wetland landscape pattern indices.
515 The results indicate that the explanatory power of the
516 models increased significantly as additional groups of
517 variables were introduced (Table 4). Model 1 had limited
518 explanatory power for runoff variability ($R^2 = 0.036$),
519 suggesting that city level differences alone explained
520 only a small portion of runoff variation. In Model 2, R^2
521 increased to 0.622, indicating that natural environmental
522 and built environment factors significantly enhanced the
523 model's explanatory power. After incorporating wetland
524 related variables into Model 3, R^2 further increased to
525 0.724, and this change in R^2 was statistically significant
526 ($\Delta R^2 = 0.102$, $p < 0.001$). This indicates that wetland area
527 proportion and wetland landscape pattern indices
528 provided an additional 10.2% of explanatory power
529 beyond city level, natural environmental, and built
530 environment variables, demonstrating the important
531 supplementary explanatory role of wetland variables in
532 explaining runoff variation.

533 The final OLS model showed that grid scale runoff
534 was associated with multiple variables related to the
535 urban built environment, topography, vegetation cover,
536 and wetland patterns (Table 5). Among all predictor
537 variables, building density had the highest positive
538 standardized coefficient ($\beta = 0.436$, $p < 0.001$), followed
539 by LSI ($\beta = 0.398$, $p < 0.001$) and slope ($\beta = 0.294$, $p <$
540 0.001). Road density also showed a significant positive
541 association with runoff ($\beta = 0.178$, $p < 0.001$), indicating
542 that grid cells with more intensive built-environment
543 conditions tended to correspond to higher runoff levels.
544 In contrast, NDVI showed a significant negative
545 association with runoff ($\beta = -0.258$, $p < 0.001$), suggesting
546 that areas with better vegetation cover tended to
547 correspond to lower runoff levels. Some wetland pattern
548 variables also showed significant associations with runoff.
549 Wetland coverage ($\beta = -0.079$, $p < 0.05$) and PD ($\beta = -$
550 0.140 , $p < 0.001$) were negatively associated with runoff,
551 indicating that greater wetland extent and higher patch
552 density were associated with lower runoff levels. ED, and
553 CONNECT were also significantly negatively associated

554 with runoff, whereas LSI exhibited a strong positive
555 association. In particular, the positive coefficient for LSI
556 suggests that more irregular wetland spatial morphology
557 was associated with higher runoff levels, which may
558 reflect the co-occurrence of complex wetland
559 configurations and more highly urbanized contexts. In
560 contrast, soil wetness, distance to river, river density,
561 ENN_MN, and AI were not significantly associated with
562 grid scale runoff in the final model.

563 5. Discussion

564 5.1. Drivers of intercity runoff variation

565 The intercity runoff differences revealed by the
566 simulation results indicate that significant runoff risks
567 may still arise under extreme rainfall conditions, even in
568 areas with low-precipitation backgrounds. The original
569 runoff distribution showed that Zhengzhou had higher
570 runoff than Qingdao and Xuzhou, whereas the difference
571 between Qingdao and Xuzhou was not significant. This
572 suggests that, even among low precipitation cities with
573 relatively comparable precipitation backgrounds, runoff
574 responses to the same rainfall input may differ
575 substantially. Existing research supports this
576 interpretation, showing that urban runoff and flood risk
577 are influenced not only by rainfall conditions, but also by
578 built environment intensity, impervious surface
579 proportion, landcover structure, and topographic
580 conditions. In particular, higher built environment
581 intensity and impervious surface proportion may shorten
582 hydrological response time and increase flood risk (Feng
583 et al. 2021; Zhu et al. 2024). The inconsistency between
584 the adjusted runoff results and the original runoff
585 distribution indicates that the pattern of inter-city runoff
586 differences changed after controlling for selected spatial
587 covariates. Specifically, Qingdao showed the lowest
588 adjusted runoff, while Xuzhou became more comparable
589 to Zhengzhou. This change suggests that intercity runoff
590 differences cannot be simply explained as fixed city scale
591 attributes but are closely related to the internal spatial
592 conditions and spatial heterogeneity of each city. The
593 OLS regression results further support this interpretation.
594 City dummy variables alone had limited explanatory
595 power for runoff variation, whereas the inclusion of
596 natural environmental and built environment variables
597 substantially improved model explanatory power.
598 Existing studies have also shown that the effects of
599 topography, land cover, the built environment, and
600 landscape pattern on urban runoff or flooding are not
601 spatially uniform but instead exhibit significant spatial
602 heterogeneity (Qi et al. 2020; Wang et al. 2022).

5.2. Implications of wetland landscape configuration for urban runoff

The OLS regression results indicate that wetland related variables provide additional explanatory power for grid-scale runoff variation beyond conventional urban environmental factors. More importantly, the negative association between wetland patch density and runoff suggests that wetland fragmentation does not necessarily weaken runoff regulation in highly urbanized environments, highlighting the importance of wetland spatial configuration in urban hydrological processes.

Specifically, wetland coverage, patch density, edge density, and connectivity were negatively associated with runoff. The negative association of wetland coverage is consistent with the general function of wetlands in stormwater retention, storage, and regulation (Enu et al. 2025; Tang et al. 2020). From the perspective of urban wetland connectivity, the negative associations of PD and ED with runoff suggest that higher wetland patch density does not necessarily represent ecological fragmentation but may instead reflect a more dispersed distribution of wetland patches across urban space. Contrary to the conventional expectation that greater fragmentation weakens ecological functioning, higher wetland patch density was associated with lower runoff, suggesting that fragmented wetlands may still contribute to runoff regulation in highly urbanized environments. Similarly, higher edge density increases the interface between wetlands and surrounding land-cover types, potentially facilitating runoff exchange and temporary water storage at wetland boundaries. The negative association between CONNECT and runoff further indicates that spatially connected wetlands may regulate runoff more effectively than isolated wetland patches. This finding is consistent with previous research suggesting that, compared with isolated wetland patches, more connected wetland networks may be more effective in mitigating urban flood risk (Li and Kim 2022).

However, the negative association between wetland patch density and runoff partly differs from some studies on general green infrastructure. Previous studies have suggested that higher greenspace patch density may be associated with greater flood risk because excessive fragmentation can weaken the continuity and hydrological regulation capacity of green spaces (Kim and Park 2016; Liu et al. 2026). This discrepancy may be related to differences in research objects and spatial scales. Compared with ordinary green spaces, wetlands are inherently designed or naturally function as stormwater retention and storage elements, making

dispersed wetland patches potentially more effective than equally fragmented GI patches.

In contrast, LSI was positively associated with runoff, indicating that more irregular wetland shapes were generally related to higher runoff levels. A higher LSI may reflect wetlands embedded in more fragmented and spatially constrained urban environments, where wetland patches are affected by surrounding roads, buildings, and impervious surfaces, leading to shape modification, or disturbance. Therefore, wetland shape complexity may indicate not only increased boundary interaction, but also stronger built environment pressure, and its hydrological implications need to be interpreted in relation to surrounding built environment conditions and runoff pathways.

5.3. Limitations

Although this study obtained relatively stable analytical results, it still has several limitations. First, the runoff simulation was based on a generalized drainage network rather than a complete actual drainage system. Therefore, the simulation results could not be further validated or calibrated using actual drainage network data. Second, this study adopted a unified design rainfall scenario for the three cities to improve the comparability of simulation results across cities. However, actual rainfall events differ in terms of temporal distribution, rainfall peak timing, rainfall intensity, and spatial variability, and a single rainfall scenario cannot fully reflect the complexity of real extreme rainfall events. Future research could include multiple rainfall scenarios or historical extreme rainfall events to test the robustness of the results. Third, this study used a uniform grid scale for the analysis, wetland landscape pattern indicators and runoff responses may be scale dependent. Therefore, the results may differ when examined at finer or coarser spatial scales. Finally, this study selected only Zhengzhou, Qingdao, and Xuzhou as case cities. Given the significant differences among cities in climatic conditions, topographic characteristics, urban development patterns, drainage systems, and wetland types, caution should be exercised when generalizing the findings to other cities or different climate zones.

6. Conclusion

This study compared three Chinese cities with relatively low annual precipitation but frequent extreme rainfall events to investigate the relationships between urban wetland characteristics and the spatial variability of urban runoff under a unified rainfall. First, despite similar annual precipitation backgrounds, the three cities

exhibited significantly different runoff responses under the same rainfall scenario. After controlling for urban environmental factors, the pattern of intercity runoff differences changed, indicating that urban runoff variability is influenced not only by climatic background but also by the spatial heterogeneity of urban environmental conditions. Second, the three cities exhibited significant differences in wetland landscape patterns. After accounting for conventional urban environmental factors, wetland-related variables provided additional explanatory power for urban runoff variability. Wetland cover, patch density, edge density, and connectivity were negatively associated with runoff, whereas landscape shape complexity showed a positive association.

These findings demonstrate that urban runoff is influenced not only by wetland cover but also by wetland landscape characteristics. Urban flood mitigation and stormwater management should therefore consider wetland landscape patterns, particularly their spatial distribution and connectivity, to enhance climate adaptation and flood resilience in highly urbanized areas. Future research should expand the analysis to cities with different climatic conditions and urban development stages and evaluate the robustness of these relationships across multiple spatial scales and rainfall scenarios.

Declarations

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Author contributions

Conceptualization: Yaoxue Li and Youngmin Kim; Methodology: Yaoxue Li and Youngmin Kim; Software: Yaoxue Li; Validation, Yaoxue Li; Formal analysis and investigation, Yaoxue Li.; Data curation: Yaoxue Li.; Writing-original draft preparation: Yaoxue Li; Writing-review and editing: Youngmin Kim; Visualization, Yaoxue Li. All authors read and approved the final manuscript.

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