



1 **Evaluating the effects of topography and land use change on**
2 **hydrological signatures: a comparative study of two adjacent**
3 **watersheds**

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7 **Abstract.** Watershed hydrological processes are significantly influenced by land use/land cover change (LULCC) and
8 watershed characteristics such as topography. This study comparatively investigates the impacts of terrain slope and
9 urbanization-driven LULCC on hydrological processes in two adjacent subtropical watersheds but with distinct terrain and
10 land-cover conditions within the Greater Bay Area (GBA) of China. We developed an Integrated Surface-Subsurface
11 Hydrological Model (ISSHM) using the Simulator for Hydrologic Unstructured Domains (SHUD), which was calibrated using
12 data from river and groundwater flow monitoring stations in the watersheds. The calibrated model facilitated simulations to
13 assess how terrain slope and LULCC affect surface runoff, subsurface flow, evapotranspiration (ET), and infiltration. Our
14 results indicate that slope impacts hydrological processes differently in watersheds with varying characteristics. In
15 mountainous areas, there are consistent high correlations between slope and annual surface runoff, infiltration, and subsurface
16 flow across all watersheds. However, at lower elevations, the hydrological responses of steeper watersheds correlate weakly
17 with local slope. Furthermore, urbanization (increase in impervious areas) has led to significant increases in annual surface
18 runoff and significant decreases in annual infiltration and ET across all watersheds, especially in those with steeper slopes. On
19 the other hand, in watersheds with gentler slopes, the annual increase in surface runoff is less than the percentage increase in
20 impervious area, suggesting a buffering capacity of these flatter watersheds against urbanization. However, this buffering
21 capacity is diminishing with increasing annual rainfall intensity.

22 **1 Introduction**

23 The effects of land use/land cover change (LULCC) and topographic variability on hydrological processes within a watershed
24 are widely recognized as critical issues in hydrology (e.g., Bosch and Hewlett, 1982; O'Loughlin, 1986; Costa et al., 2003;
25 Beven, 2011; Gwak and Kim, 2016; Larson et al., 2022; Sicaud et al., 2024). Urbanization has been demonstrated to
26 significantly impact hydrological processes such as surface runoff, evapotranspiration (ET), infiltration, and subsurface flow
27 by altering the conditions of the land surface (Olang and Fürst, 2011; Ayalew et al., 2015; Guan et al., 2015; Bai et al., 2020;



28 Yan et al., 2023; Liang and Guan, 2024). Furthermore, it is evident that topographic characteristics have a direct influence on
29 surface water flow paths and soil moisture, thereby affecting infiltration rates and groundwater recharge (Strahler, 1957; Hopp
30 and McDonnell, 2009; Mirus and Loague, 2013; Smith et al., 2018; Yang et al., 2019; Zhang et al., 2022a). However,
31 comprehending the diverse impacts of LULCC and topography on hydrological processes across disparate watersheds persists
32 as a significant challenge, due to the variability in watershed characteristics and the nonlinear nature of hydrological responses
33 (Niehoff et al., 2002; Brath et al., 2006; Thanapakpawin et al., 2007; Du et al., 2012; Pang et al., 2022; Yin et al., 2023; Guo
34 et al., 2023; Yan et al., 2024). In order to address these challenges, researchers employ various methodologies to dissect and
35 quantify these effects.

36 Statistical analysis techniques utilizing long-term monitoring data within a watershed are commonly used to examine the
37 effects of LULCC (Beven et al., 2008; Liu et al., 2017; Zhang et al., 2021; Zhang et al., 2022b; Kumar et al., 2022). However,
38 long-term changes in hydrological responses often reflect the combined impacts of climate change and LULCC, making it
39 complicated to isolate the impacts of LULCC (Beven, 2011). The paired catchments approach is another statistical method
40 commonly employed (Brown et al., 2005; Detty and McGuire, 2010; Yang et al., 2016; Van Loon et al., 2019), which compares
41 monitoring data from two watersheds with different land cover but similar physical characteristics (Li et al., 2009; Shao et al.,
42 2020). However, applying this approach in practice can be challenging due to the difficulty in identifying watersheds with
43 similar physical characteristics. Furthermore, recent studies have indicated that LULCC-induced hydrologic alterations exhibit
44 considerable spatial variability within watersheds, affecting upstream and downstream regions in disparate ways (Chu et al.,
45 2010; Garg et al., 2017). In this regard, statistical analysis methods that rely on gauging datasets often lack detailed spatial
46 resolution, employing methods that facilitate studies at finer spatial resolutions is essential for a comprehensive understanding
47 of these variations.

48 Similar challenges exist when investigating the effects of topography on watershed-scale hydrological processes due to
49 the diversity of geomorphic types and significant spatial variability within watersheds. One area where significant progress
50 has been made is the prediction of hydrologic connectivity through topographic indices to study rainfall-runoff responses in
51 watersheds (Jencso and McGlynn 2011). Topographic indices have become valuable tools for predicting soil moisture and
52 identifying saturated zones. Two successful examples are topographic wetness index (TWI; Beven and Kirkby, 1979; Sørensen
53 et al., 2006) and height above the nearest drainage (HAND; Nobre et al., 2011; Gao et al., 2019; Fan et al., 2019). However,
54 some studies reported TWI and groundwater levels exist distinct relations at different locations (Detty and McGuire, 2010;
55 Rinderer et al., 2014). Furthermore, the simulation results of HAND are highly depend on the pattern of observed saturated
56 zones and it perform better at gentler watersheds (Nobre et al., 2011; Gao et al., 2019). In addition, the predictive accuracy of



57 these indices decreases under dynamic conditions, such as at the onset of rainfall events (Seibert et al., 2003; Jarecke et al.,
58 2021).

59 Recent studies have shown that hydrological models based on the Richards equation not only simulate surface-subsurface
60 water interactions on hillslopes but also accurately describe hydrological processes under varying temporal conditions
61 (Camporese et al., 2019). The Integrated Surface-Subsurface Hydrological Model (ISSHM) is a type of Richards equation-
62 based fully distributed hydrological model (Shen and Phanikumar, 2010; Maxwell et al., 2014; Fatichi et al., 2016). Despite
63 being relatively new compared to other hydrological models, the ISSHM has demonstrated significant capabilities in
64 addressing the whole system of processes at watershed scales (Niu et al., 2017; Yu et al., 2022; Zanetti et al, 2024). By dividing
65 the land surface into grids, such models can represent the spatial variability of hydrological processes with high spatial accuracy.
66 They can also be solved with higher temporal accuracy by applying differential solutions to the physical governing equations.
67 Unlike monitoring data analysis methods, ISSHMs allow hydrologists to assess the impact of specific factors by implementing
68 designed scenarios and evaluating them across a comprehensive range of spatial and temporal scales. In recent years, ISSHMs
69 have been proven valuable for assessing LULCC and topographic impacts at the watershed scale. For instance, Im et al. (2009)
70 used the MIKE SHE model to show that urbanization increased total runoff by 5.5% and overland flow by 24.8% in a watershed.
71 Zhang et al. (2022a) explored how topography influences subsurface flow with the HydroGeoSphere, revealing that
72 topography plays a significant role in controlling penetration depths and stagnant zones.

73 While some studies have investigated the effects of LULCC and topography using the ISSHM approach, they are mainly
74 based on single and spatially homogeneous watersheds, hindering comparative studies. Herein, we showcase the behavior of
75 paired watersheds with heterogeneous patterns of both terrains and land cover, but are geographically adjacent to be compared
76 under the same subtropical climate regime. We simulate the hydrological processes of the two watersheds in the Greater Bay
77 Area (GBA), a crucial economic zone in China, using the Simulator for Hydrologic Unstructured Domains (SHUD) as an
78 ISSHM. It examines the influences of terrain slope and urbanization-driven LULCC on the hydrological components of surface
79 runoff, subsurface flow, ET, and infiltration at both daily and annual scales.

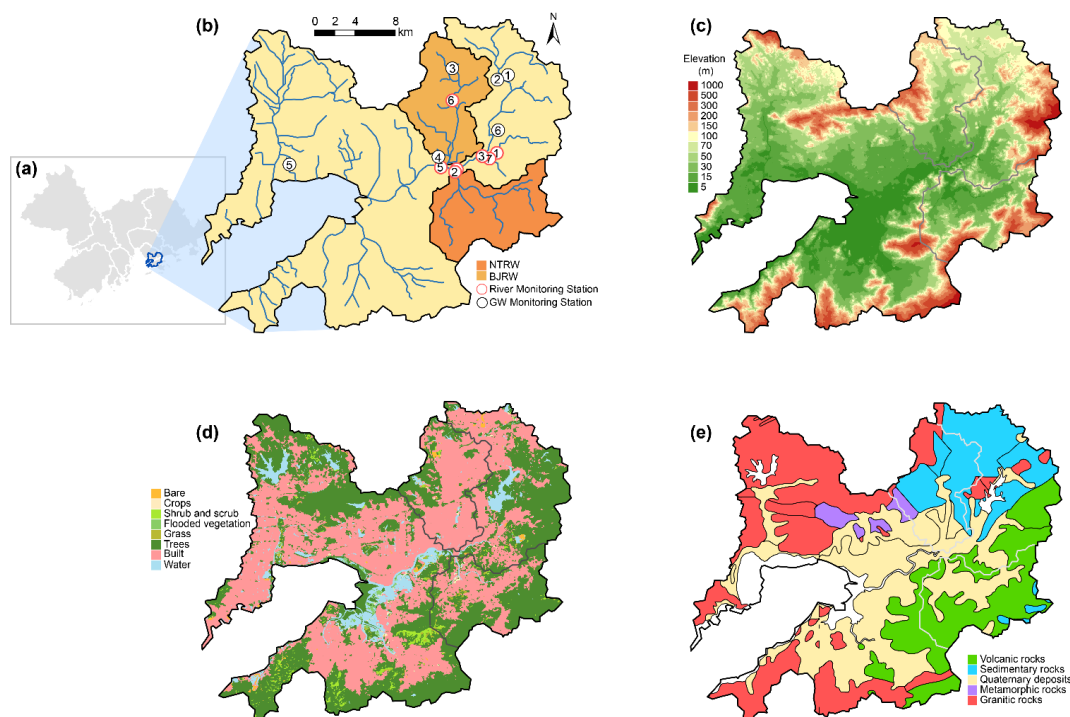
80 **2 Study site**

81 The study focuses on two neighboring watersheds within the Shenzhen River and Bay Basin (SRBB) in the Greater Bay Area
82 (GBA)—the Ng Tung River Watershed (NTRW) in Hong Kong and the Buji River Watershed (BJRW) in Shenzhen (Figs. 1a
83 and 1b). The NTRW encompasses an area of 70.7 km², while the BJRW covers 66.3 km². Situated in a subtropical region, the
84 SRBB experiences an average annual temperature of 23.3°C and receives a substantial amount of precipitation, averaging 1933
85 mm annually, with significant inter-annual variability. Notably, about 86% of this precipitation falls during the monsoon season



86 (April–September), with the region experiencing an average of 130 rainy days per year. The intensity of daily rainfall during
87 this period can be significant, reaching 289 mm and 382 mm for the 10-year and 50-year return period events, respectively.

88 Despite their proximity and similar climatic conditions, the NTRW and BJRW exhibit distinct differences in topography
89 and land use patterns. The NTRW is characterized by steep slopes, with an average gradient of 12.3° and elevation variations
90 ranging from 0.5 to 611.6 m (average elevation 97.1 m). In contrast, the BJRW features relatively flatter terrain, with an
91 average slope of 7.5° and elevation ranging from 0.5 to 435.3 m (average elevation 70.6 m) (Fig. 1c). These watersheds reflect
92 the rapid urbanization occurring in both Shenzhen and Hong Kong since the 1980s; however, urbanization has progressed
93 more rapidly in the BJRW. Initially, the BJRW had limited construction areas with forests predominating (Cheng et al., 2023).
94 By 2020, built-up land in the BJRW had increased to 71%, while in the NTRW, forests remain dominant and built-up areas
95 constitute 37% of the land (Fig. 1d).



96
97 **Figure 1.** Location and characteristics of the Ng Tung River Watershed (NTRW) and Buji River Watershed (BJRW): (a) location of the
98 Shenzhen River and Bay Basin (SRBB) within the Greater Bay Area (GBA), (b) location of the NTRW (dark orange) and BJRW (light
99 orange) within the SRBB (yellow), along with channels (blue), calibration river monitoring stations (numbered 1–7, red circles), and
100 calibration groundwater monitoring stations (numbered 1–6, black circles), (c) DEM (FABDEM V1-2), (d) land cover map of 2020, (e)
101 geological map.



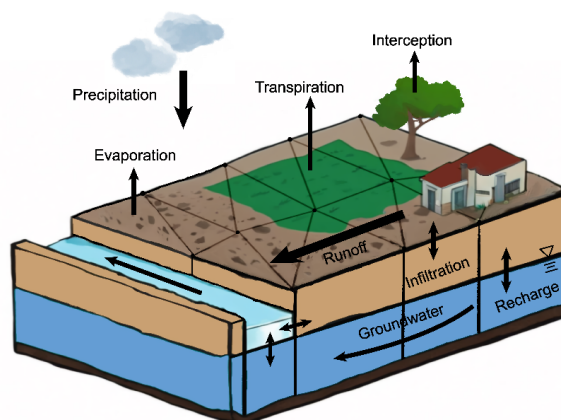
102 3 Methodology

103 3.1 Hydrological model

104 The hydrological model employed in this study is SHUD (Shu et al., 2020), which evolved from the well-known Penn State
105 Integrated Hydrologic Model (PIHM; Qu and Duffy, 2007; Kumar, 2009; Kumar et al., 2009). SHUD is an open-source model
106 that incorporates a user-friendly data preprocessing toolkit, rSHUD (Shu et al., 2024), designed to simplify tasks such as grid
107 partitioning, data integration, and model setup, addressing common challenges faced by hydrologists when working with
108 ISSHMs. By integrating the parallel programming framework OpenMP, SHUD achieves high computational efficiency and
109 has demonstrated superior robustness in solving problems at the watershed scale compared to PIHM, thus confirming its
110 effectiveness in hydrological modeling (Shu et al., 2020).

111 As illustrated in Fig. 2, the hydrological processes simulated by SHUD include rainfall, surface water ponding storage,
112 surface water infiltration, surface runoff, ET, changes in unsaturated layer moisture, groundwater flow, and river flow processes.
113 The model represents the land domain using unstructured triangular elements and trapezoid segments for the river network.
114 Each triangular element is vertically discretized into three layers: the top layer represents the land surface, the middle layer
115 represents the unsaturated zone, and the bottom layer represents the saturated aquifer. The model employs the finite volume
116 method to spatially discretize the partial differential equations of hydrological states into ordinary differential equations,
117 enabling detailed simulation of hydrological dynamics.

118 For a more comprehensive understanding of the four hydrological processes analyzed in this study, we provide the
119 relevant assumptions and computational formulas used in SHUD in Appendix A. Further details on the mathematical and
120 algorithmic structure of SHUD are available in the referenced papers (Shu et al., 2020; Shu et al., 2024) and on the SHUD
121 Book website (SHUD Book, 2024).

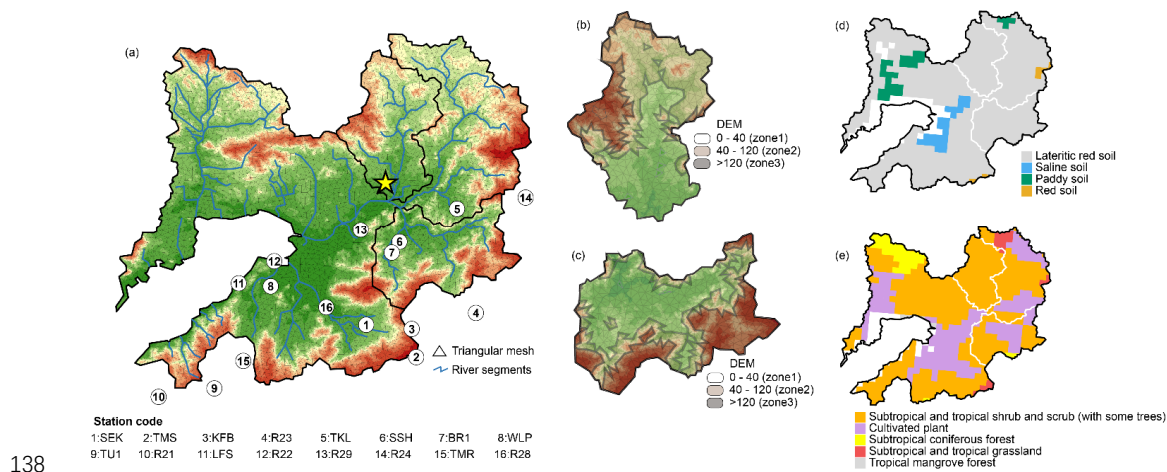


122
123 **Figure 2.** Model schematic of hydrological processes in the SHUD model.



124 **3.2 Data collection and model setup**

125 We set up the model domain as the entire SRBB, rather than focusing solely on its smaller two watersheds. This decision was
 126 driven by two strategic considerations. Firstly, the limited availability of monitoring data within the two watersheds
 127 necessitated a broader spatial framework to ensure a comprehensive dataset for robust hydrological analysis. Secondly, the
 128 similar characteristics of geology (Fig. 1e), soil (Fig. 3d), and vegetation (Fig. 3e) across the SRBB and its subbasins supported
 129 the feasibility of this extensive modeling approach. The SRBB, covering an area of 596 km², was discretized into 6,602
 130 triangular meshes. Specifically, the NTRW and the BJRW were represented by 819 and 793 triangular grids, respectively (Fig.
 131 3a). In the model, the outer boundary of the SRBB was designated as a zero-flow boundary, meaning no water flows across
 132 this boundary. Additionally, the land and river boundaries along the concave boundary in the southwestern part of the basin
 133 were set as a fixed head value, corresponding to the local sea level. This fixed-head boundary was established at 1.5 m, based
 134 on annual tidal observations from the Hong Kong Observatory (HKO). While this fixed-head approximation does not account
 135 for the precise daily tidal fluctuations, it represents a reasonable compromise for hydrological modeling purposes. Given that
 136 the two watersheds are situated significantly inland from the ocean, their hydrological processes are minimally affected by
 137 tidal variations.



138 **Figure 3.** Map of meteorological site locations and triangular meshes of two watersheds, black circles (numbered 1-16) represent rainfall
 139 sites located in Hong Kong, and yellow star represent the Shenzhen Meteorological Station (SMS), (a) three zones delineated for BJRW (b)
 140 three zones delineated for NTRW (c), soil map (d), and vegetation map (e).
 141

142 The Digital Elevation Model (DEM) for the study area was sourced from the FABDEM V1-2 dataset (Neal and Hawker,
 143 2023) and offers a resolution of 30 meters. Land cover data for 2020, with a spatial resolution of 10 meters, were acquired
 144 from the Dynamic World Project via Google Earth Engine (Brown et al., 2022). Data on soil types and vegetation were obtained



145 from the Data Center for Resources and Environmental Sciences at the Chinese Academy of Sciences (RESDC, 2024), and
 146 geological information was sourced from the China Geological Survey (GeoCloud, 2024). Satellite imagery was utilized to
 147 determine river channel widths. Determining the appropriate soil depth remains a significant challenge, and as highlighted by
 148 Fan et al. (2019), weathering fractures notably influence hydrological activities. Based on the geological data from the study
 149 site, extensive weathering is noted in the mountainous regions. Consequently, the aquifer depth was modeled to vary gradually
 150 from 18 meters in the upslope areas to 9 meters downstream.

151 Additionally, driving force data were collected for two distinct periods. The first period, from 2020 to 2021, included
 152 hourly meteorological data from the Shenzhen Meteorological Station (SMS), provided by the Meteorological Bureau of the
 153 Shenzhen Municipality. This dataset included records of precipitation, temperature, relative humidity, and wind speed. Hourly
 154 precipitation data for the same period were also gathered from 16 additional gauging sites in Hong Kong, sourced from the
 155 HKO (Fig. 2a). The second period, from 1993 to 2021, involved collecting precipitation data from the R29 station via the
 156 HKO. Moreover, monitoring data of daily river discharge from seven stations and daily or weekly groundwater table depths
 157 from six stations were gathered from the Water Authority of the Shenzhen Municipality for the period of 2020–2021. A
 158 comprehensive summary of all datasets and related information is provided in Table 1.

159 **Table 1.** Summary of collected datasets and related information.

Data	Source	Resolution	Time period	Purpose
DEM	FABDEM V1-2	30 m		
Land cover type	Dynamic World Project	10 m	2020	
Soil type	RESDC	1000 m		Model mesh grid attributes
Geology	China Geological Survey (GeoCloud)	100 m		set up
River characteristics	Google Earth			
Meteorological data of the Shenzhen Meteorological Station (SMS)	Meteorological Bureau of the Shenzhen Municipality	Hourly	2020–2021	(1) Model calibration phase driving force inputs; (2) Model scenarios 1 and 2 driving force inputs
Precipitation of 16 Hong Kong stations	Hong Kong Observatory (HKO)	Hourly	2020–2021	Model calibration phase driving force inputs
Precipitation of the R29 station	Hong Kong Observatory (HKO)	Hourly	1993–2021	Model scenarios 3 and 4 driving force inputs
Streamflow monitoring data of 7 sites	Water Authority of the Shenzhen Municipality	Daily	2020–2021	
Groundwater table depth monitoring data of 6 sites	Water Authority of the Shenzhen Municipality	Daily or weekly	2020–2021	Model calibration



160 **3.3 Model calibration**

161 We employed rainfall data from 17 sites covering the period from 2020 to 2021 to drive the model during the calibration
162 process. To distribute the rainfall data effectively across all 17 sites, we utilized the Thiessen multi-polygon method, allocating
163 the data to corresponding triangular grids. Due to limitations in data availability, meteorological parameters such as
164 temperature, relative humidity, and wind speed were sourced solely from the SMS for the entire basin. The initial setup of the
165 model parameters was informed by field data, the general features of the model structure, and past modeling experience. The
166 model underwent multiple spin-up sessions using 2020 meteorological data to establish an initial condition that closely mirrors
167 the monitoring datasets. Given the heterogeneity of the basin, effective auto-calibration was challenging, leading to a
168 preference for manual calibration as a common practice for ISSHMs (Shi et al., 2014; Thornton et al., 2022; Brandhorst and
169 Neuweiler, 2023). We leveraged previous uncertainty analysis and parameter sensitivity studies (Baroni et al., 2010; Song et
170 al., 2015; Liu et al., 2020) to select the most crucial parameters for this hands-on calibration process. Monitoring data from
171 the entire period were utilized for calibration, focusing on enhancing model performance. Our calibration efforts concentrated
172 on both streamflow and groundwater table depths to ensure a comprehensive evaluation of the model. The selected parameters
173 and the final calibrated results are discussed in Sect. 4.1.

174 **3.4 Scenario design and evaluation methods**

175 We developed four modeling scenarios differentiated by time span and land use pattern (Table 2). Scenarios 1 and 2 analyze
176 hydrological processes at daily and annual temporal resolutions, respectively, using continuous meteorological data provided
177 by the SMS for the years 2020–2021. These scenarios aim to determine how watershed topography and urbanization conditions
178 influence daily and annual hydrological responses. Scenarios 3 and 4 extend the analysis to a 29-year period (1993–2021),
179 utilizing rainfall data from the R29 station. This approach enriches our understanding of how annual rainfall variability
180 influences topographic slope and LULCC on hydrological processes.

181 For the LULCC assessment, we considered two land use patterns: Historical Land Use (HLU) and Current Land Use
182 (CLU). The HLU pattern involves reverting all built-type land uses in both watersheds to their pre-construction conditions,
183 corresponding to the forest type evident in the 1979 satellite images from Google Earth. The CLU pattern reflects the land use
184 as of 2020.

185 To isolate the impact of slope from LULCC effects, we analyzed slope impacts within the two watersheds exclusively
186 under the HLU pattern. We conducted a thorough examination of model outputs across three distinct elevation zones within
187 the watersheds. Zone 1 encompasses low-elevation regions with DEM values below 40 m, primarily consisting of flat areas.



188 Zone 2 includes areas with DEM values ranging from 40 m to 120 m, situated at the foothills of the mountains. Zone 3
189 comprises primarily high-elevation regions with DEM values exceeding 120 m (Figs. 3b and 3c).

190 **Table 2.** Designed four scenarios.

Scenario	Driving force inputs time span	Land use pattern
1	2020–2021	HLU
2	2020–2021	CLU
3	1993–2021	HLU
4	1993–2021	CLU

191

192 In this study, the model outputs are exclusively positive, indicating water outflow, and are measured in meters to represent
193 the depth of outflow over a specified period within each local grid. We used the Spearman rank correlation method (Seibert et
194 al., 2003; Hauke and Kossowski, 2011) to analyze the results of Scenario 1, quantifying the relationship between the slope and
195 four model outputs. To assess the impact of LULCC, we applied the Kolmogorov-Smirnov (KS) two-sample test (Lilliefors,
196 1967) between Scenario 1 and Scenario 2. In all simulations, the output results are recorded at a one-day time interval. When
197 analyzed on a daily scale, the results can be directly examined. For annual evaluations, the output results are aggregated by
198 year. Detailed equations used for these assessments are provided in Appendix B to facilitate comprehensive understanding. To
199 explore potential variations in the impact of slope due to annual rainfall fluctuations, we established a simple linear regression
200 model. This model was used to examine the correlation between 29-year annual rainfall data and the Spearman correlation
201 coefficients derived from Scenario 3. Additionally, a separate simple linear regression model was implemented to assess the
202 relationship between 29-year annual rainfall and KS test values between Scenario 3 and Scenario 4. This approach aims to
203 evaluate how annual rainfall fluctuations might influence LULCC.

204 **4 Results and discussion**

205 **4.1. Model performance**

206 Due to spatial heterogeneity within the watersheds, the calibrated values for each parameter are formed as a matrix. For clarity,
207 only the median values is displayed (Table 3). The first four parameters, K_s , θ_{ss} , α and β , are primarily associated with the
208 vadose zone and significantly influence the hydraulic processes in the soil layer. The last three parameters K_g , θ_{gs} and θ_{gr} ,
209 govern the hydraulic processes in the aquifer layer. All these parameters fall within reasonable ranges, as supported by previous
210 studies (Das, 1990; Freeze and Cherry, 1979; Bear, 2013; Van Genuchten, 1980).

211 Figures 4a–c display the hydrographs of daily simulated and observed streamflow at various river gaging stations within
212 the BJRW (Site 6; Fig. 4c), at the upstream of the watersheds (Site 1; Fig. 4a), and at the downstream of the watersheds (Site



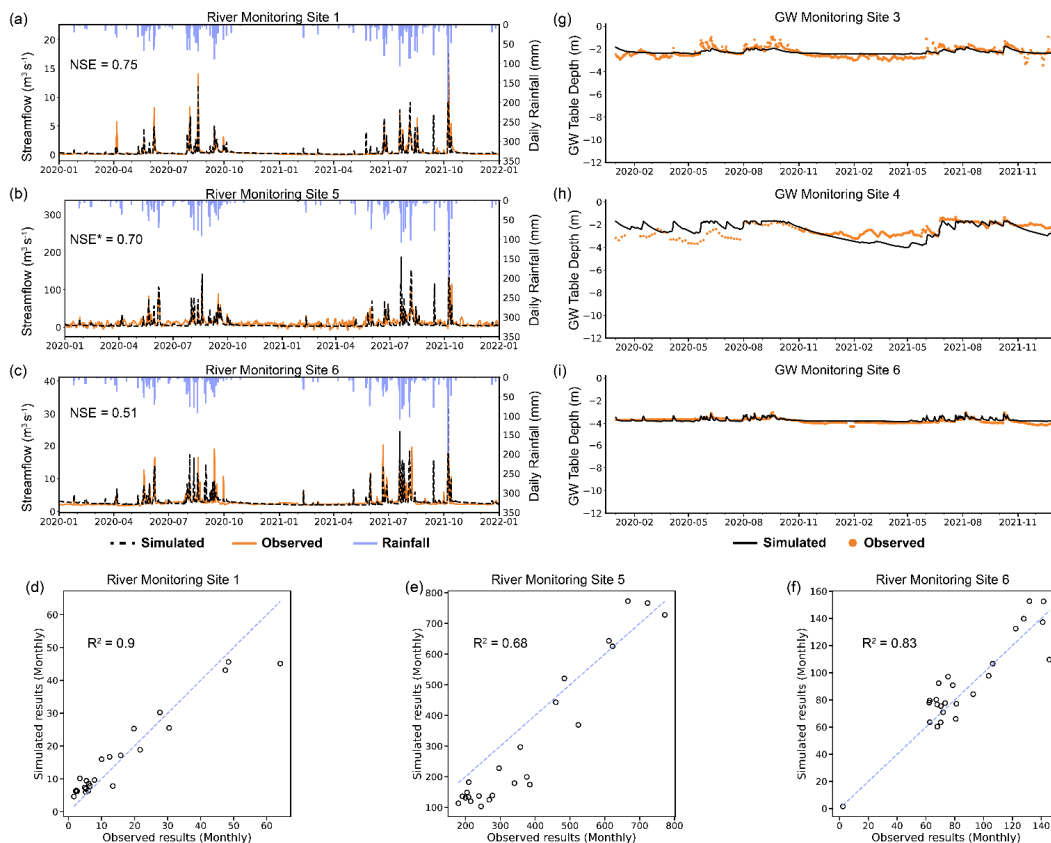
213 2; Fig. 4b), respectively. The Nash-Sutcliffe Efficiency (NSE) indices, computed for the entire simulation period, demonstrate
214 satisfactory model performance, except for Site 2 where the observed dataset shows daily fluctuations in river flow during
215 rain-free periods due to tidal influences. Therefore, for such sites, we specifically calibrated the discharge during rainy days
216 and calculated the NSE index using data from those days. The simulation results exhibit satisfactory performance with NSE
217 indices greater than 0.5, indicating a reasonable accuracy in streamflow predictions.

218 Furthermore, the monthly calibration results reinforce the robust performance of the calibrated model, exhibiting R^2
219 values exceeding 0.6 (Figs. 4d–f; Moriasi et al., 2007). This strong correlation suggests a consistent and reliable model behavior
220 over a longer time scale. Figures 4g–i present the comparisons between the simulated and observed groundwater data. It is
221 challenging to evaluate the assessment indices of groundwater calibration for such long durations. However, our calibration
222 outcomes indicate a marked concordance between the model outputs and observed data trends, and the modeled groundwater
223 table depth closely aligns with the measured depths, underscoring the model’s accuracy in reflecting actual groundwater
224 conditions. Overall, the model exhibits satisfactory performance on both surface and subsurface water flows. Additional sites’
225 calibration results are available in Fig. C1.

226 **Table 3.** Refined parameters for the watershed after calibration.

Parameter	Description	Allowable value range	Median value after calibration	Unit
K_s	Soil saturated infiltration conductivity	10^{-3} – 10^4	0.045	m day ⁻¹
θ_{ss}	Soil saturated water content	0.25–0.7	0.531	-
α	van Genuchten parameter	>0	5.23	m ⁻¹
β	van Genuchten parameter	>1	1.29	-
K_g	Groundwater hydraulic conductivity	10^{-5} – 10^4	2.6	m day ⁻¹
θ_{gs}	Groundwater saturated water content	0.0–0.5	0.3	-
θ_{gr}	Groundwater residual water content	0.0–0.5	0.01	-

227



228

229 **Figure 4.** Calibration performance of SHUD model across daily river discharge in the river monitoring sites 1, 5 and 6 (a)–(c), and monthly
 230 river discharge in the river monitoring sites 1, 5 and 6 (d)–(f), and groundwater table depth in the groundwater monitoring sites 3, 4 and 6
 231 (g)–(i).

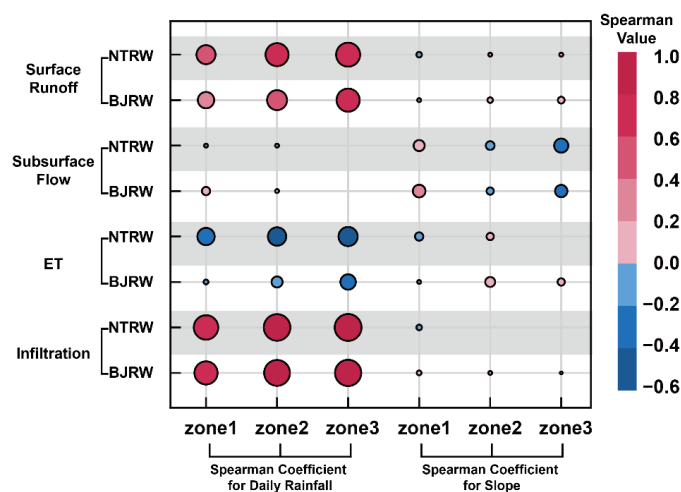
232 **4.2 Daily and annual scale hydrological responses**

233 **4.2.1 Stronger correlation between slope and daily subsurface flow**

234 Figure 5 depicts the correlation between four hydrological processes and terrain slope on a daily scale, with all depicted
 235 markers being statistically significant ($p\text{-value} \leq 0.05$). The analysis primarily emphasizes slope, but also explores the influence
 236 of daily rainfall to provide additional insights. The Spearman correlation analysis indicates slight correlation coefficients
 237 between surface runoff, infiltration, and slope, which lie between -0.2 and 0.2 in all zones of the two watersheds. In contrast,
 238 coefficients associated with daily rainfall range from -0.6 to 1. Notably, during rainy days, daily subsurface flow demonstrates
 239 a more pronounced correlation with slope (coefficients between -0.4 and 0.2) than with daily rainfall (coefficients between -
 240 0.2 and 0.2). Specifically, in Zone 1, a positive correlation is observed between daily subsurface flow and slope, while Zones
 241 2 and 3 exhibit a negative correlation.



242 Consistent with the findings in existing literature, this result underscores the critical role of topographical factors in
 243 influencing groundwater dynamics during rainfall events (Hopp and McDonnell, 2009; Detty and McGuire, 2010; Jencso and
 244 McGlynn, 2011; Singh et al., 2021). The observed negative correlations between slope and subsurface flow in the middle and
 245 high elevations of the two watersheds can be attributed to the predominantly accretive state of groundwater in these areas. In
 246 these higher elevations, lower slopes contribute to enhanced groundwater retention and accumulation, thus enhancing
 247 subsurface flow. Conversely, in the lower elevations of both watersheds, the positive correlation between slope and subsurface
 248 flow may be explained by the tendency of groundwater to move towards surface water more readily after rainfall events. The
 249 flatter topography in these lower areas facilitates this transferring process, thereby reducing the total amount of subsurface
 250 flow retained within the soil.



251
 252 **Figure 5.** Comparative analysis of slope influence and daily rainfall on four hydrological variables. Marker size denotes the absolute value
 253 of the Spearman correlation coefficients, while marker color indicates the direction of the relationship between slope or rainfall and the four
 254 model outputs. Generally, red represents a positive correlation, whereas blue denotes a negative correlation.

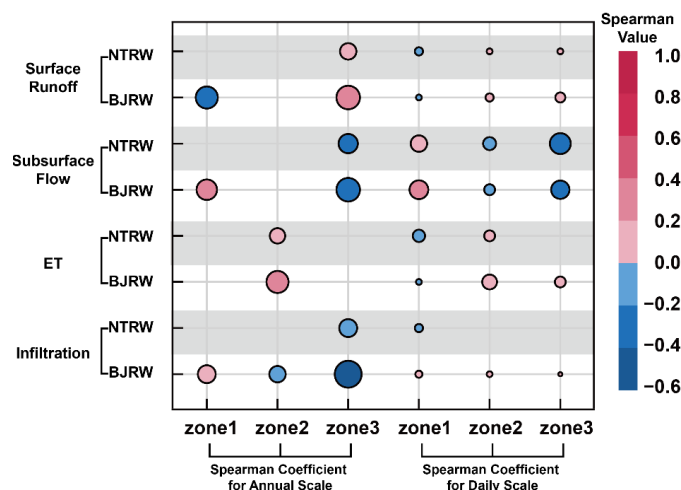
255 **4.2.2 Faint slope-flow relationship in NTRW's lower zone**

256 Figure 6 presents the comparative results of terrain slope at daily and annual scales. The findings suggest that slope has a more
 257 pronounced relationship with annual surface runoff, subsurface flow, and infiltration at higher elevations compared to daily
 258 scales, highlighting the pivotal role of slope in redistributing water post-rainfall events. This aligns with the observations by
 259 Seibert et al. (2003) and Rinderer et al. (2014), who noted that topographic indices more accurately reflect hydrological
 260 responses under steady-state conditions. Specifically, Rinderer et al. (2014) reported from their analysis of data from 51
 261 groundwater wells in a Swiss catchment that the ability of the TWI to predict water table distributions diminishes under
 262 unsteady conditions.



263 Concerning the direction of correlation, surface runoff in mountainous areas exhibits a positive correlation with slope at
 264 both daily and annual scales, whereas subsurface flow shows a negative correlation. On a daily scale, this pattern may be
 265 primarily due to the direct influence of slope on water flow paths. However, on an annual scale, variations in infiltration play
 266 a more substantial role (Table C1). The results indicate that in both watersheds, infiltration rates decrease at higher elevations
 267 as slopes increase, leading to increased surface water runoff and reduced subsurface flow in areas with steeper slopes.

268 When examining annual flow processes at lower elevations, a significant correlation between terrain slope and
 269 hydrological behavior is evident in the gently sloping BJRW. In contrast, such correlation is notably faint in the steeper NTRW.
 270 This disparity may be attributed to the fact that water flow in steeper watersheds tends to be quicker (Fan et al., 2019; Singh
 271 et al., 2021), leading to hydrological processes at lower elevations being primarily influenced by rapid upstream inflows rather
 272 than the local topography. On the other hand, the gentler slopes of other watersheds facilitate slower flow processes, allowing
 273 topographic features at lower elevations to continuously influence water flow paths over time, thus maintaining a consistent
 274 hydrological impact.



275
 276 **Figure 6.** Comparison of hydrological responses to slope variability on annual and daily scales in NTRW and BJRW.

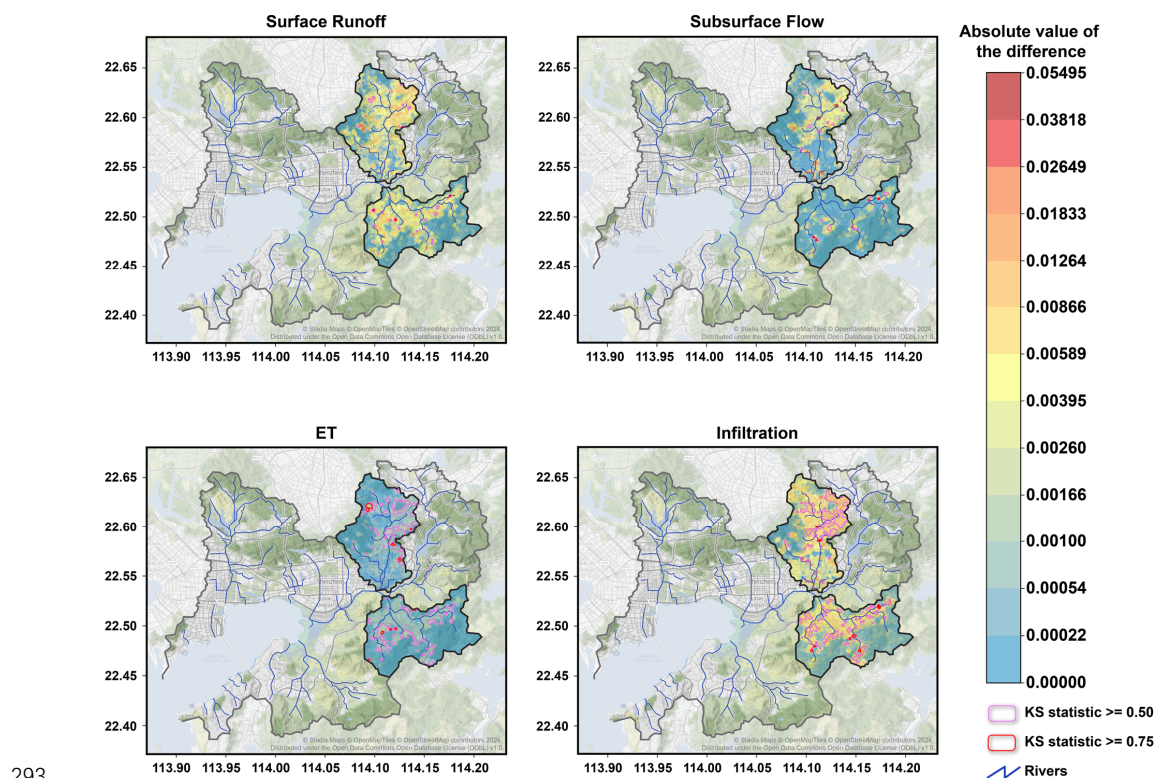
277 **4.2.3 Dominant impact of LULCC on daily infiltration**

278 Figure 7 illustrates the absolute mean differences in hydrologic outputs between the HLU and CLU patterns for each grid cell.
 279 Employing the KS statistic, significant alterations in the cumulative distribution function (CDF) of daily hydrologic outputs
 280 were identified, highlighting the substantial impacts of LULCC. Among the hydrological processes examined, daily infiltration
 281 exhibits the most pronounced and widespread differences, underscoring the dominant influence of LULCC.



282 When considering only absolute mean differences, surface runoff and subsurface flow are identified as the second and
 283 third most influenced processes, respectively. However, when focusing exclusively on the results from the KS statistical test,
 284 ET emerges as the second most affected process. This indicates that land use changes significantly alter ET patterns on rainy
 285 days, despite the smaller mean differences observed.

286 This finding aligns with the results of Chu et al. (2010) and Diem et al. (2021), which underscore the extensive impact of
 287 urbanization on surface runoff through changes in infiltration. Notably, the distribution of affected subsurface flow in both
 288 watersheds closely correlates with the areas exhibiting the most significant changes in infiltration. Compared to the steeper
 289 NTRW, the flatter BJRW shows broader changes in subsurface flow as a result of LULCC. This disparity likely stems from
 290 the prolonged water-soil contact in flatter terrains, which enhances infiltration. Consequently, this enhanced infiltration process
 291 leads to a more extensive distribution of soil moisture throughout the watershed, influencing both surface and subsurface
 292 hydrological dynamics.



293

294 **Figure 7.** Map of absolute mean differences at each grid between HLU and CLU patterns, with significant variations in daily hydrologic
 295 output CDFs marked according to the KS statistic. The color coding represents the absolute value of the differences in these outputs, and the
 296 pink and red circles indicate areas where the KS statistic is significant.



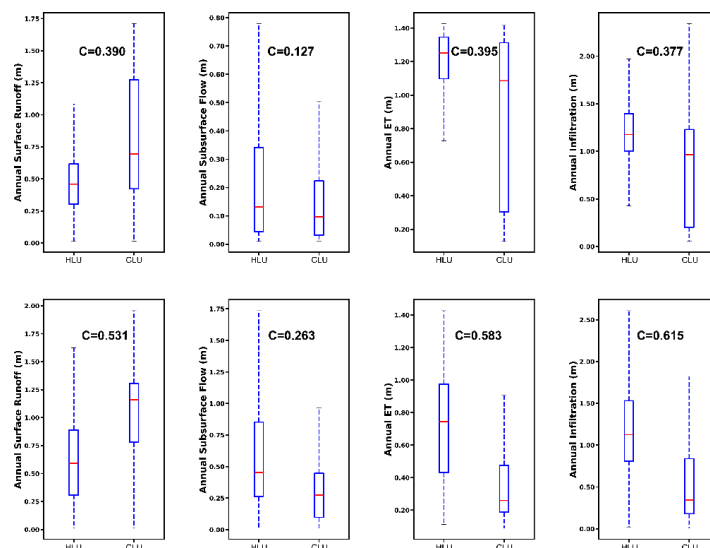
297 **4.2.4 NTRW shows more sensitivity to LULCC**

298 The KS test indicates statistically significant changes in all four hydrological outputs after urbanization, with all p-values
299 below 0.05 (refer to Fig. 8). The results depict an increase in annual surface runoff and reductions in subsurface flow, ET, and
300 infiltration following urbanization. This aligns with findings from Shao et al. (2020), who used a process-based hydrological
301 model to examine the response of surface runoff to LULCC in two adjacent watersheds in Texas, USA. They reported that
302 urbanization leads to increased runoff, a finding consistent with our results.

303 Furthermore, the KS test results reveal relative consistency within each watershed for surface runoff, ET, and infiltration
304 values. Specifically, in the NTRW, the KS values for surface runoff, ET, and infiltration are recorded at 0.39, 0.395, and 0.377,
305 respectively. The corresponding values in the BJRW are 0.531, 0.583, and 0.615. However, subsurface flow shows lower KS
306 values of 0.127 in the NTRW and 0.263 in the BJRW, suggesting that urbanization has a less impact on the annual subsurface
307 flow process.

308 This minimal impact on subsurface water flow suggests that the slower dynamics of subsurface water may buffer the
309 direct effects of urbanization at the annual scale. In the BJRW, where impervious surfaces account for 71% of the land cover
310 change, the response of surface runoff, ET and infiltration is more pronounced (with KS values ranging from 0.531 to 0.615)
311 compared to the NTRW, where impervious surfaces make up 37% of the change (with KS values ranging from 0.377 to 0.395).

312 It is noteworthy that in the BJRW, the KS values for surface runoff, ET, and infiltration are slightly lower than the
313 percentage increase in impervious surfaces. This suggests that the flatter watershed may possess a natural ability to mitigate
314 the effects of LULCC. This observation is supported by Zhou et al. (2015), who noted that flatter terrains tend to absorb
315 changes more effectively due to prolonged water-soil contact times, which enhance infiltration and storage capacities. This
316 capacity may help mitigate the more severe hydrological alterations typically associated with extensive urbanization.



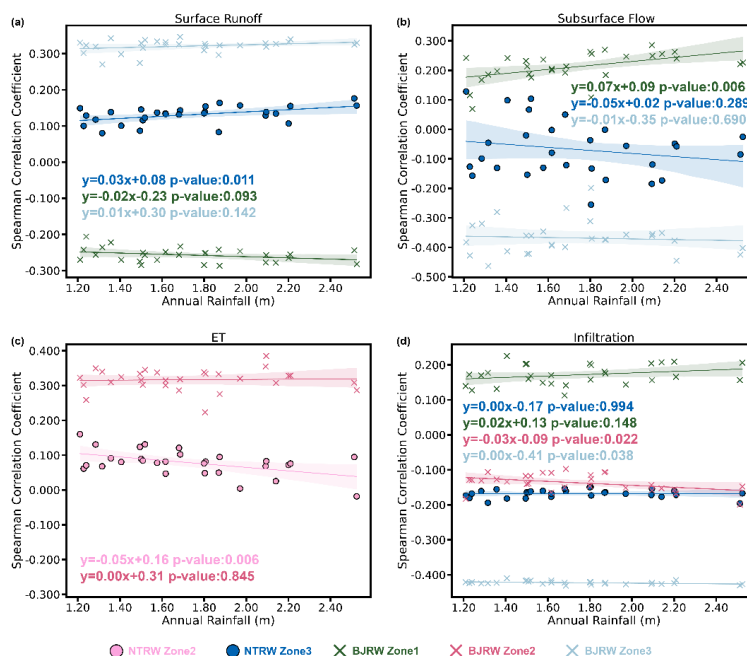
317

318 **Figure 8.** Box plots delineating the impacts of LULCC on the four annual outputs across all meshes within each watershed. The comparison
319 contrasts the outcomes under the HLU and CLU patterns. The top row displays the results of NTRW, while the second row displays the
320 results of BJRW. KS test values (C) are annotated, all p-values are less than 0.05.

321 4.3 Variations with different annual rainfall amounts

322 4.3.1 Rainfall intensifies subsurface flow-slope relationship in BJRW's lower zone

323 Figure 9 presents scatterplots and regression equations that analyze the correlation between annual precipitation and Spearman
324 statistic values from 1993 to 2021, highlighting outcomes that are statistically significant ($p\text{-value} \leq 0.05$), as identified in Sect.
325 4.2.2. The analysis shows minimal changes in Spearman statistic values across most study areas; however, a notable variation
326 was observed in subsurface flow within Zone 1 of the BJRW, where a coefficient of 0.07 indicates that each 100 mm increase
327 in annual precipitation enhances the correlation between slope and subsurface flow by 0.007. This change corresponds to a
328 shift in the Spearman coefficient from 0.174 to 0.258 as annual rainfall increases from 1200 mm to 2400 mm. This observation
329 is supported by findings from Zhang et al. (2022a), who reported that under scenarios of higher precipitation and greater
330 hydraulic conductivity, the extent and permeation depth of the saturated zones beneath mountains exhibit a stronger correlation
331 with the terrain. This effect is likely due to increased precipitation levels raising the water table at lower elevations, thus
332 enhancing the relationship between slope and subsurface flow.

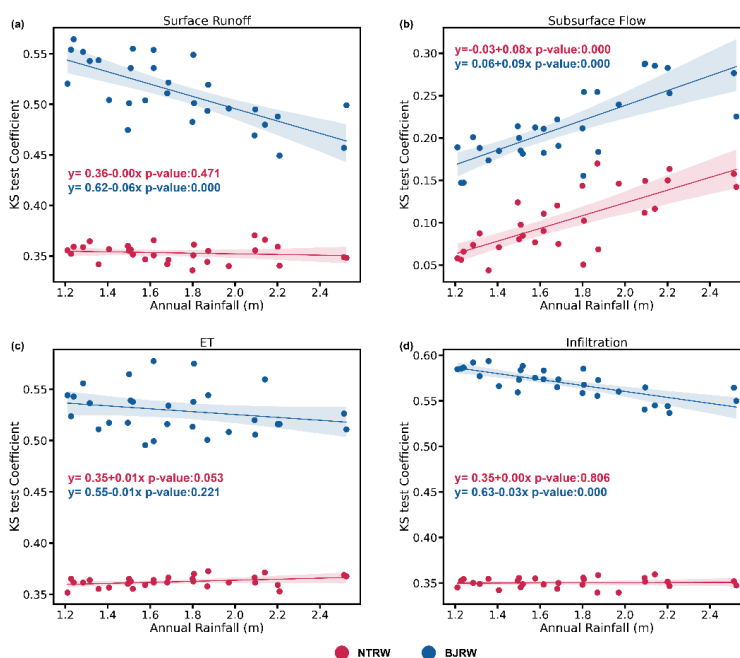


333

334 **Figure 9.** Scatter plots of Spearman statistic values of slope and four model outputs under 29 years of different annual rainfall amounts, with
 335 simple regression equations and shade area showing the 95% confident interval.

336 4.3.2 Rainfall intensifies the changes in groundwater caused by LULCC

337 Figure 10 presents scatter plots correlating KS test values for four hydrological outputs with 29 years of annual rainfall data,
 338 evaluating how the impacts of LULCC vary under different precipitation intensities. Our analysis highlights significant
 339 variability in the effects of LULCC across various annual rainfall amounts in the BJRW. Here, surface runoff and infiltration
 340 exhibit reduced variations before and after urbanization as annual rainfall increases, whereas variations in subsurface flow
 341 intensify. In the NTRW, significant changes are primarily observed in annual subsurface flow, which also shows increased
 342 variation with higher levels of annual precipitation. In scenarios where all surfaces are pervious, an increase in annual rainfall
 343 leads to gradually saturated soil moisture, thereby enhancing surface runoff and reducing water infiltration. This behavior
 344 mirrors observations on impervious surfaces. However, in environments predominantly composed of impervious surfaces,
 345 surface water cannot effectively infiltrate to form groundwater. This leads to a poor connectivity in saturated zones, thereby
 346 impeding the formation of subsurface flow. As annual rainfall increases, the differences in subsurface flow between land use
 347 patterns become more pronounced.



348

349 **Figure 10.** Scatter plots of KS test coefficients of LULCC and four model outputs under 29 years of different annual rainfall scenarios, with
350 simple regression equations and shade area showing the 95% confident interval.

351 4.4 Limitations and future work

352 Our study provides valuable insights into the effects of topography and LULCC on hydrological processes across various
353 spatiotemporal scales in different watersheds. Although the hydrological model used was comprehensively calibrated using
354 observational data and demonstrated accurate predictive capabilities, several limitations warrant consideration. Firstly, the
355 calibration of the model parameters was conducted manually using local data, which may not encompass the optimal parameter
356 sets unidentified in this study. Furthermore, the inherent uncertainties associated with the monitoring data and the model
357 structure were not thoroughly evaluated. Due to the complexity of ISSHMs and the significant amount of time required to
358 thoroughly assess all uncertainties, such evaluations remain challenging but are necessary for advancing the field. Secondly,
359 our study area is located in a subtropical humid region characterized by frequent rainfall and consistently moist soils. This
360 geographical specificity may limit the generalizability of our findings to regions with different climatic conditions. Thirdly,
361 the rainfall data utilized in this study only encompassed the typical range of precipitation for the region; extreme rainfall events,
362 which may induce unique hydrological responses, were not investigated. The impact of such extreme conditions remains to be
363 explored in future studies.



364 5 Conclusions

365 Utilizing the ISSHM model, SHUD, this study explored the effects of topographical slope and urbanization-induced LULCC
366 on surface runoff, subsurface flow, ET, and infiltration across various spatiotemporal conditions in two neighboring subtropical
367 watersheds. In conclusion, this study confirms the complex and variable effects of topography and LULCC on hydrological
368 processes across various watersheds, spatial locations within watersheds, and temporal scales. On a daily scale, slope is found
369 to correlate with subsurface flow. However, on an annual scale, slope correlates with all hydrological processes, with the
370 strongest correlation observed in mountainous regions. In flatter watersheds, prolonged soil-water interactions enhance
371 infiltration and influence water redistribution, thus increasing the correlation between slope and surface runoff and subsurface
372 flow, especially as annual precipitation increases. Our findings suggest that urbanization significantly increases surface runoff
373 while decreasing infiltration and ET, with minimal impact on subsurface flow. Furthermore, watersheds with steeper slopes
374 show a more pronounced response to urbanization, whereas those with gentler slopes mitigate the effects of LULCC on
375 increased surface runoff. This phenomenon can be described as a buffering effect of gently sloping watersheds. However, this
376 buffering effect diminishes as annual rainfall increases. This study underscores the need for hydrologic management strategies
377 tailored to the specific topography and LULCC characteristics of each watershed. A comprehensive understanding of these
378 factors is crucial for developing effective water resource management approaches that support sustainable development in
379 these areas.

380 Appendix A: SHUD hydrological processes formulas

381 The comprehensive exposition of the governing equations for the SHUD is provided in Shu et al. (2020). Here, the emphasis
382 is placed on expounding the equations that are relevant to the processes addressed in this study.

383 - *Infiltration*. SHUD adopts the Richards equation like most ISSHMs adopted to describe the infiltration process. While there
384 are no general analytical solutions to the Richards equation, SHUD adopted the Green-Ampt infiltration equation (Eq. (A1)),
385 which allows a simple form of Darcy's law to be used to calculate the infiltration rate q_i [LT^{-1}],

$$386 \quad q_i = K_i \left(1 + \frac{h_s}{D_{inf}} \right) \quad (A1)$$

387 where h_s [LT^{-1}] is the ponding water height plus precipitation, D_{inf} [L] is the infiltration depth representing the top soil layer,
388 K_i [LT^{-1}] is the effective infiltration conductivity, and it is a function of soil saturation ratio, soil properties, and h_s . The Green-
389 Ampt method assumes that the infiltrating wetting front forms a sharp jump from a constant initial moisture content ahead of
390 the front to saturation at the front.



391 -*Evapotranspiration*. Potential evapotranspiration (PET) is computed using the Penman-Monteith equation (Eq. (A2)), while
392 actual evapotranspiration (AET) is derived by multiplying PET with a soil moisture stress coefficient, determined by soil
393 moisture content and groundwater table depth.

$$394 \quad \lambda E = \frac{\Delta_e H + \rho_a c_p (e_s(T_z) - e_z) / r_a}{\Delta_e + \gamma (1 + r_c / r_a)}, \quad (\text{A2})$$

395 where $\lambda (=2.4710^6, \text{Jkg}^{-1})$ is the latent heat of evaporation, $E [\text{LT}^{-1}]$ is the PET rate, Δ_e is the slope of the saturation vapor
396 pressure versus temperature curve, H is total available energy, ρ_a is the density of the air, c_p is the specific heat capacity of the
397 air, $e_s(T_z)$ is the saturated vapor pressure at the height of z , e_z is the vapor pressure at the height of z , r_a and r_c are the two
398 resistance coefficients, γ is the psychrometric constant.

399 - *Surface runoff*. The kinematic wave equation (Eq. (A3)) is used to approximate the surface runoff in the SHUD,

$$400 \quad \frac{\partial h}{\partial t} = -\frac{\partial(vh)}{\partial x} - \frac{\partial(vh)}{\partial y} + r, \quad (\text{A3})$$

401 where $h [\text{L}]$ represents the average depth of flow, $v [\text{LT}^{-1}]$ is the flow velocity, and $r [\text{LT}^{-1}]$ is a rate of addition or loss of water
402 caused by precipitation, infiltration and evaporation. The relationship between v and h is represented by the Manning equation
403 (Eq. (A4)),

$$404 \quad v = -\frac{S_0^{1/2} h^{2/3}}{n}, \quad (\text{A4})$$

405 where $S_0 [-]$ is the surface slope, $n [\text{TL}^{-1/3}]$ is the Manning roughness.

406 - *Subsurface flows*. The SHUD applies the Richards equation (Eq. (A5)) to describe both saturated and unsaturated flows, and
407 the water density is assumed to be constant,

$$408 \quad \frac{\partial \theta}{\partial t} = \frac{\partial}{\partial x} \left[K_x(\theta) \frac{\partial \Phi}{\partial x} \right] + \frac{\partial}{\partial y} \left[K_y(\theta) \frac{\partial \Phi}{\partial y} \right] + \frac{\partial}{\partial z} \left[K_z(\theta) \frac{\partial \Phi}{\partial z} \right], \quad (\text{A5})$$

409 where $\theta [-]$ is volumetric moisture content, $K_x(\theta) [\text{LT}^{-1}]$, $K_y(\theta) [\text{LT}^{-1}]$, and $K_z(\theta) [\text{LT}^{-1}]$ indicate hydraulic conductivity
410 depends on direction and is treated as a function of θ , $\Phi [\text{L}]$ is the total potential ($\Phi = \psi + z$ where $\psi [\text{L}]$ is the capillary
411 potential and z is the elevation above the datum). The SHUD utilizes the van Genuchten functions to solve the relationship for
412 soil moisture content, capillary potential, and hydraulic conductivity.

413 **Appendix B: Assessment equations**

414 The Spearman rank correlation method evaluates the strength and monotonic nature of relationships between two variables
415 without relying on assumptions regarding data distribution or residuals. The KS two-sample test compares two samples to



416 determine if they are drawn from the same distribution, without assumptions about the underlying distribution. The KS statistic
 417 is the maximum absolute difference between the CDFs of the two data vectors.

418 For the daily scale analysis, we focused on positive model outputs during rainy days (precipitation ≥ 0.1 mm per day).
 419 We employed matrix \mathbf{D} for each zone (Zone 1 to Zone 3) to assess daily outputs related to slope angle for each grid (Eqs. (B1)
 420 and (B2)).

$$421 \quad \mathbf{D} = \begin{bmatrix} \mathbf{W}_1 \\ \vdots \\ \mathbf{W}_N \end{bmatrix}, \quad (B1)$$

$$422 \quad \mathbf{W}_n = \begin{bmatrix} y_{1n} & p_1 & s_n \\ \vdots & \vdots & \vdots \\ y_{in} & p_i & s_n \end{bmatrix} \quad (B2)$$

423 In matrix \mathbf{D} , each row \mathbf{W}_n ($n=1, 2, \dots, N$) corresponds to the model outputs associated with a specific hydrological process
 424 of the n th grid. Within \mathbf{W}_n , each row represents a rainy day under consideration, with i denoting the total number of rainy days
 425 analyzed. Each row comprises three values: the daily model output y_{kn} ($k=1, 2, \dots, i$), the corresponding rainfall amount p_k
 426 ($k=1, 2, \dots, i$), and the grid's slope angle s_n . Consequently, the Spearman correlation coefficient was computed between the
 427 transpose vectors $\mathbf{y}_{N \times i}^T$ and $\mathbf{s}_{N \times i}^T$.

428 To analyze LULCC effects, vectors \mathbf{H}_d (Eq. (B3)) and \mathbf{C}_d (Eq.(B4)) were generated for each grid under HLU and CLU
 429 patterns, and the KS test value was computed between these two vectors for each grid,

$$430 \quad \mathbf{H}_d = [y_{1|HLU}, y_{2|HLU}, \dots, y_{i|HLU}], \quad (B3)$$

$$431 \quad \mathbf{C}_d = [y_{1|CLU}, y_{2|CLU}, \dots, y_{i|CLU}], \quad (B4)$$

432 where i denotes the total number of rainy days, $y_{k|HLU}$ and $y_{k|CLU}$ ($k=1, 2, \dots, i$) represent the model daily output of this grid
 433 under the HLU pattern and the CLU pattern on the k th rainy day, respectively. We also calculated the absolute difference in
 434 mean values of these two vectors to quantify the magnitude of change between the two land use patterns in terms of their
 435 effects on the model outputs.

436 To evaluate the effects of slope on an annual scale, a new matrix \mathbf{A} is constructed as following Eq. (B5):

$$437 \quad \mathbf{A} = \begin{bmatrix} y_1 & s_1 \\ \vdots & \vdots \\ y_N & s_N \end{bmatrix}, \quad (B5)$$

438 where N represents the number of grids within each zone, y_n and s_n ($n=1, 2, \dots, N$) denote the annual output and slope angle
 439 for the n th grid, respectively. Only grids with annual volumes exceeding 10 mm were considered for surface runoff and
 440 subsurface flow analysis to concentrate on pronounced flows. Subsequently, the Spearman correlation coefficient was
 441 calculated between the transpose vectors \mathbf{y}_N^T and \mathbf{s}_N^T .



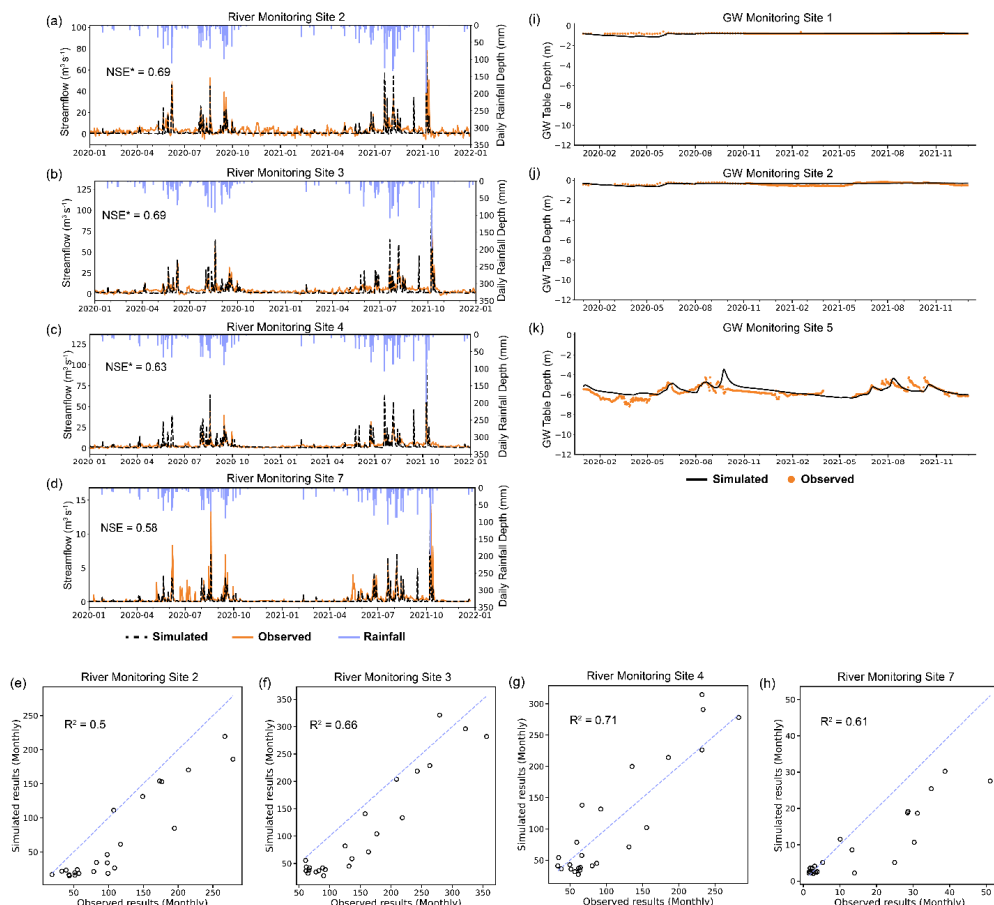
442 The KS test was also applied at the annual scale to compare model outputs between HLU and CLU patterns across the
 443 entire subbasin range. Vectors H_y (Eq. (B6)) and C_y (Eq. (B7)) represent the annual model outputs under the HLU pattern and
 444 the CLU pattern, respectively.

$$445 \quad H_y = [y_{1|HLU}, y_{2|HLU}, \dots, y_{j|HLU}], \quad (B6)$$

$$446 \quad C_y = [y_{1|CLU}, y_{2|CLU}, \dots, y_{j|CLU}], \quad (B7)$$

447 Here z denotes the number of grids across each subbasin, $y_{k|HLU}$ and $y_{k|CLU}$ ($k=1, 2, \dots, z$) represent the model annual
 448 output of the k th grid under the HLU pattern and the CLU pattern, respectively. Then the KS test was carried out between these
 449 two vectors.

450 **Appendix C: Supplementary calibration results**



451
 452 **Figure C1.** Other sites calibration results across daily river discharge (a)–(d), and monthly river discharge (e)–(h), and groundwater table
 453 depth (i)–(k).



454 **Table C1.** Spearman coefficients between infiltration and subsurface flow.

	Zone 1	Zone 2	Zone 3
Daily scale			
NTRW	-	-	0.20
BJRW	0.19	-	-
Annual scale			
NTRW	0.67	0.68	0.72
BJRW	0.82	0.66	0.77

455

456 *Code and data availability.* The source code of the SHUD model can be downloaded from [https://github.com/SHUD-](https://github.com/SHUD-System/SHUD)
457 [System/SHUD](https://github.com/SHUD-System/SHUD). The model spatial input data are freely available from the described source listed in Table 1. The
458 meteorological data and monitoring data in this study can be obtained upon request.

459

460 *Author contributions.* HL contributed to methodology, validation, visualization, writing of the original draft and editing. HY
461 contributed to data collection, reviewing and editing the original draft. MG contributed to conceptualization, supervision,
462 methodology, writing, reviewing and editing the original draft.

463

464 *Competing interests.* The authors declare that they have no conflicts of interest.

465

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