Title:

Simulating Spatial and Temporal Dynamics of Soil Moisture and Gully Flow Using Improved Grid-Xinanjiang Model with a Prior Parameter Estimates

Running head:

Spatial and Temporal Dynamics of Soil Moisture and Gully Flow

Key words:

Gullies; Improved Grid-Xinanjiang model; Priori parameters estimation; Global Digital Soil Mapping System; Tunxi watershed

Authors' name:

Bingxing Tong[1], Zhijia Li[1], Cheng Yao[1*], Moyang Liu[2], Junfu Gong[1]

Corresponding Author:

Cheng Yao, yaocheng@hhu.edu.cn

Authors' institutions:

[1] College of Hydrology and Water Resources, Hohai University, Nanjing, 210098, China

[2] Fenner School of Environment & Society, Australian National University, Canberra, ACT 0200, Australia

Acknowledgments:

This study was supported by the National Natural Science Foundation of China (Grant No. 52079035), the Fundamental Research Funds for the Central Universities (Grant No. B200203052), and the Postgraduate Research & Practice Innovation Program of Jiangsu Province (KYCX20_0466).

Simulating Spatial and Temporal Dynamics of Soil Moisture and Gully Flow Using Improved Grid-Xinanjiang Model with a Prior Parameter Estimates

Abstract: To systematically generalize the influence of gullies on floods, a distributed model named Improved Grid-Xinanjiang (GXAJ), and a priori parameters estimation scheme based on the Global Digital Soil Mapping System (SoilGrids) are proposed. Within a watershed divided into a series of orthogonal cells, shallow furrows and trenches inside the cells are conceptualized as primary gullies, in which water movement is simulated by kinematic wave equation considering the gullies density, and well-developed grooves between cells are considered as main gullies, where water moves as a kinematic wave and enters the rivers. The simulation of 27 flood events in the Tunxi watershed of Anhui Province from 2008 to 2017 was implemented, and the simulation results were compared with that of Xinanjiang model (XAJ). The relative runoff volume error and flood peak error of the GXAJ model and XAJ model are 8.4% and 10.7%, 8.9% and 12.1%, respectively. The GXAJ model outperforms in the simulation of flood peak, and is capable of producing the dynamics of soil water and gullies flow. The spatial characteristics and the sensitivity of parameters, free storage capacity and gullies density, at various phases, that is, initial, rise, peak, fall and tail, have been analyzed. The value of free storage capacity decreases and then increases with the increase of altitude and distance from the river. The gullies density in the bank and ridge area is greater than that in the middle of the slope segment. Sensitivity analysis shows that gullies density has the noticeable influence on the relative runoff volume error and Nash-Sutcliffe coefficient in the rise phase, while free water storage capacity has a significant effect on the relative runoff volume error during the flood rise phase and Nash-Sutcliffe coefficient in peak phase, respectively.

Keywords: Gullies; Improved Grid-Xinanjiang model; Priori parameters estimation; Global Digital Soil Mapping System; Tunxi watershed

1 INTRODUCTION

The gullies have a significant impact on the rainfall-runoff process of watersheds (Lai, Chen, Wang, Yu & Bai, 2020; Kirkby, 1978). According to the development degree from low to high, the gullies on the slope can be generally classified as shallow furrows, trenches and well-developed grooves. By the gullies, the runoff on the hillside may converge and move quickly, forming a steeply rising flash flood that threatens the lives and property of people living near the river (Mcclean, Dawson, & Kilsby, 2020; Liang, Li, Yuan, & Liao, 2019). Gullies are shaped by the interaction between hydrodynamic factors and soils during slope erosion. The hydraulic characteristics of a river are influenced by the gullies morphology, which in turn affects the erodibility and stability of the soil. The erosive power of the flow increases continuously with the convergence of the sheet flow on slope surface. When the erosive power exceeds the stabilizing capacity of the soil surface particles, soil erosion occurs and primary shallow furrows are formed, which interconnect and contribute to the creation of higher level gullies (Garbrecht, & Martz, 1997; Wang, Xu, Wang, & Wu, 2020; Martz, & Garbrecht, 1995).

However, it is difficult to systematically quantify and generalize the gullies' ability to regulate flow compared to the river network. On the one hand, despite the implementation of field surveys and remote sensing image classification techniques, it is almost impossible for gullies to be accurately identified (Zeng, Xu, & Wan, 2020; Thieken, Lücke, Diekkrüger, & Richter, 1999). On the other hand, influenced by the diverse topography and variation of rainfall, the flow in the gullies changes rapidly during the rainfall-runoff process, making it difficult to collect sufficient observation records (Zhang et al, 2019; Montgomery, 2010). Therefore, there are several confluence methods for simulating river flow movement, but few studies on water flow in slope gullies (Fraga, Cea, & Puertas, 2019; Daniel, Guo, & John, 2020).

Simulation of rainfall-runoff process, a subject that has been intensively studied in the last decades, starts from the adoption of empirical methods (Xia, Wang, Gan, 2019; Kuo et al, 1999). The second stage is mainly characterized by the application of conceptual hydrological models after the 1970s, such as the Sacramento model (SAC) (Sorooshian, Duan, & Gupta, 1993; Gupta, Sorooshian, & Yapo, 1999; Najafi, Moradkhani, & Jung, 2011; Gupta, Wagener, & Liu, 2008). In the third stage since the 21st century, the application of distributed hydrological models such as the remote sensing-based WRF-Hydro model, and coupled atmospheric-hydrological modeling systems have further contributed to the development of flood simulation and prediction (Koren, Reed, & Smith, 2004; Reed, 2004; Ajami, Newsha, Duan, Gao, Sorooshian, & Soroosh, 2006; Abbaszadeh, Gavahi, & Moradkhani, 2020). In August 2016, the WRF-Hydro-core National Water Model has been used to support distributed runoff simulations for approximately 2.7×10^6 rivers across the United States at a resolution of 250 meters per hour (Xiang, Vivoni, Gochis, & Mascaro, 2017; Zhang, Lin, Gao, & Fang, 2020; Lahmers, Gupta, Castro, Gochis, & Hazenberg, 2019; Viterbo, Mahoney, Read, Salas, & Cifelli, 2020; HaNSCn, Shiva, Mcdonald, & Nabors, 2019). In China, the Xinanjiang model (XAJ) proposed by Zhao Renjun in the 1970s was widely adopted (Zhao, 1984; Wang, & Zhao, 1989; Li, Liang, Kan & Zhang, 2016). Based on the statistical analysis of the rainfall-runoff relationship in the Xinanjiang watershed, the saturated-excess runoff mechanism was adopted in the XAJ model to achieve reasonable floods simulation. The Grid-Xinanjiang model (GXM), that is, a distributed version of the well-known XAJ model has also been proposed based on discrete geophysical data (Yao, Li, Bao, & Yu, 2009; Bao, et al, 2011; Li, et al, 2017). However, the effect of hillside gullies on flood has not been addressed in the GXM, especially in mountainous areas of China, where flash flood simulations are limited by poor topographic measurements and hydrological observations (Liang, Lu, Chen, Liu & Lin, 2020; Yao, Li, Yu, & Zhang, 2012).

Therefore, reasonably quantifying the influence of gullies on floods based on topographic characteristics of study area, developing appropriate model structure and algorithm, and realizing the prior estimation of spatial parameters that can support operational flood simulation have become critical issues discussed in this study. Based on the systematic generalization of hillside gullies, an improved distributed model named Improved Grid-Xinanjiang (GXAJ). Limited by the data observation level at that time, the GXM model was mainly based on the approximate soil and vegetation classification and the empirical table recording the corresponding hydrological property values for each classification to estimate the main parameters such as free water storage capacity and filed capacity. Although this approach can meet the driving requirements of distributed models, it is difficult to achieve a fine-grained quantitative description of the spatial characteristics of parameters. Further, a priori parameters estimation scheme based on the Global Digital Soil Mapping System (SoilGrids) (Sun, Wang, Hui, Jing, & Feng, 2020; Grunwald, Thompson, & Boettinger, 2011; Tomislav et al, 2017) are proposed in this study. Within a watershed divided into a series of orthogonal cells, shallow furrows and trenches inside the cells are conceptualized as primary gullies, in which water movement is simulated by kinematic wave equation considering the gullies density, and well-developed gullies between cells are considered as main gullies, where water moves as a kinematic wave and enters the rivers. The simulation of 27 flood events in the Tunxi watershed of Anhui Province from 2008 to 2017 was implemented, and the simulation results were compared with that of Xinanjiang model (XAJ) and measurement. Quantitative analyses of the sensitivity and spatial characteristics of the parameters, free water storage capacity and gullies density are emphasized. In addition, the dynamics of watershed-scale free water content and gullies flow during rainfall-runoff process are presented.

2 THE IMPROVED GRID-XINANJIANG MODEL

The Grid-Xinanjiang model (GXM), that is, a distributed version of the well-known XAJ model, has also been proposed by Yao etc. In GXM model, the watershed is discretized into a series of orthogonal cells where runoff generation using saturated-excess mechanism are implemented, the flow direction of each cell is identified with the Digital Elevation Model (DEM) to obtain the confluence sequence of the runoff. A series of cases where water balance has been achieved demonstrated the stability of the distributed structure, therefore it was retained in the upgrade of the Grid-Xinanjiang model. Furthermore, the effect of gullies on floods has been systematically generalized contributing to Improved Grid-Xinanjiang (GXAJ) developed in this study. Specifically, the gullies have been generalized into shallow furrows, trenches and well-developed grooves according to the level of development. The shallow furrows and trenches inside cells are conceptualized as primary gullies, and the well-developed grooves between cells are considered as the main gullies. The runoff generated in the cell would first enters the primary gullies using the kinetic wave equation considering the gullies density, and then flows through multiple cells in the main gullies. Finally, gullies flow enters river and reaches the outlet of watershed after the Muskingum-Cunge confluence evolution. The rainfall-runoff process in the slope cells is divided into four parts: the saturation-excess runoff generation, the runoff flows into the primary gullies on the slope, flow movement in primary gullies and flow movement through multiple cells in main gullies. Gullies flow from cells near bank would be discharged into river, then participate in river routing to reaches the outlet of watershed, forming flood hydrograph (Figure 1).

2.1 Runoff generation and overland flow within cells

With the triplex evaporation and saturation-excess runoff mechanism, process of evaporation, dynamic change of soil moisture and runoff generation in each cell has been simulated. In evaporation and runoff generation, the soil is stratified into three layers named upper, lower and bottom. Water in soil is divided into free water and tension water depending on whether it can flow freely by gravity or not. The rainfall would first infiltrate into the soil to meet the tension water deficiency. After the tension reservoir is full, water would flow out from the side and bottom of the upper soil layer, respectively, and turn into interflow and groundwater. When the upper layer of soil moisture has been saturated, the excess water flows over the sloping surface as overland runoff. If the time required for various runoff to flow through the slope surface exceeds the time step used in the model, only a portion of the generated runoff is able to enter gullies and further participate in the convergence routing. It can be argued that the slope surface has a moderating effect, which is quantified in this study by the linear reservoir technique.

$$R_1 = R_0 \times \gamma + InR \times (1-\gamma) \qquad (1)$$

where R_1 is the runoff entering gullies at present period, R_0 is the outflow from the soil to gullies in the last period, InR is the runoff generated in present period, γ is the coefficient of linear reservoir.

2.2 Flow movement in primary gullies

Shallow furrows and trenches, the important paths for flow within cells, are generalized as primary gullies, in which the water movement is modeled by kinematic wave equation considering the gullies density (D).

$$\frac{\partial A}{\partial t} + \frac{1}{D}\frac{\partial Q}{\partial x} = 0 \qquad (2)$$

$$S_f = S_o \qquad (3)$$

where A is the cross section area, Q is the discharge in primary gullies, and *t* and *x* refer to the time and space items, respectively. S_f is the hydraulic gradient, S_o is the bottom slope of primary gullies.

In combination with the kinematic wave equation and the hydraulic characteristics of the main gullies (e.g. wetted perimeter, roughness, etc.), the differential format is used to perform numerical calculations for water flow simulation.

$$\sigma\beta Q^{\beta-1}\frac{\partial Q}{\partial t} + \frac{1}{D}\frac{\partial Q}{\partial x} = 0 \qquad (4)$$

$$A = \sigma Q^{\beta}, \sigma = \left[\frac{n P^{2/3}}{\sqrt{S_f}}\right]^{3/5}, \beta = 3/5 \qquad (5)$$

$$Q_{i+1}^{j+1} = \frac{\left[\sigma\beta\left(\frac{Q_{i+1}^{j} + Q_{i}^{j+1}}{2}\right)^{\beta-1} Q_{i+1}^{j} + \frac{\Delta t}{D\Delta x} Q_{i}^{j+1}\right]}{\left[\sigma\beta\left(\frac{Q_{i+1}^{j} + Q_{i}^{j+1}}{2}\right)^{\beta-1} + \frac{\Delta t}{D\Delta x}\right]} \qquad (6)$$

where P is the wetted perimeter, n is the roughness, σ and β are the coefficients of equation, i and j are the space and time index, respectively, and Δx and Δt are the space and time step, respectively.

2.3 Flow movement in main gullies and water exchange mechanism between cells

The well-developed grooves are used as the main gullies to achieve the flow of water between cells. The motion of the water flow in the main gullies can be numerically simulated using the kinematic wave equation of motion combined with Manning's formula.

$$\frac{\partial A}{\partial t}+\frac{\partial Q}{\partial x}=q \tag{7}$$

$$S_f=S_g \tag{8}$$

$$Q_{i+1}^{j+1}=\frac{\left[\alpha\beta\left(\frac{Q_{i+1}^{j}+Q_{i}^{j+1}}{2}\right)^{\beta-1}Q_{i+1}^{j}+\frac{\Delta t}{\Delta x}Q_{i}^{j+1}+\frac{q_{i+1}^{j}+q_{i}^{j+1}}{2}\right]}{\left[\alpha\beta\left(\frac{Q_{i+1}^{j}+Q_{i}^{j+1}}{2}\right)^{\beta-1}+\frac{\Delta t}{\Delta x}\right]} \tag{9}$$

where S_g is the slope of the main gully, and q is the lateral inflow.

When simulating the water movement, the possible hydraulic connection between adjacent cells should be considered. In this study, after the cell receives the incoming water from the uphill section, the outflow is generated only when the tension water deficit is satisfied.

2.4 River flood routing

Compared with gullies, water flow movement in rivers is more stable. To reflect the influence of geographical factors such as section width, slope, and roughness on water flow, the Muskingum-Cunge method has been utilized for water movement simulation in the river.

$$Q_{out,t}=C_0\times Q_{¿,t-1}+C_1\times Q_{¿,t}+C_2\times Q_{out,t-1} \tag{10}$$

$$X=0.5\left(1-\frac{Q}{BS_fC_k\Delta x}\right),\quad K=\frac{\Delta x}{C},C=\frac{C_k\Delta t}{\Delta x} \tag{11}$$

$$C_0=\frac{KX+0.5\Delta t}{K(1-X)+0.5\Delta t},C_1=\frac{0.5\Delta t-KX}{K(1-X)+0.5\Delta t},C_2=\frac{K(1-X)-0.5\Delta t}{K(1-x)+0.5\Delta t} \tag{12}$$

where: C_0, C_1 and C_2 are formula coefficients, $Q_{out,t}$ is the outflow at present period,

$Q_{in,t-1}$, is the inflow at the previous period, $Q_{in,t}$ is the inflow at present period, and $Q_{out,t-1}$ is the outflow at the previous period, X is the coefficient of Muskingum-Cunge method, being inverse correlate with the downstream congestion on the upstream flow, K is the slope of the storage-discharge relationship, B is the width of the river cross, C_k is the velocity of flood wave, and C is the average flow velocity.

3 PARAMETERIZATION SCHEME

The main parameters of GXAJ model are shown in Table 1:

Free and tension water storage capacities indicated by SM and WM, respectively, are key parameters for runoff generation in the saturation-excess mechanism. Flow generally occurs only after the moisture exceeds the field capacity of soil, so the amount of water that the soil could hold between the field capacity and the wilting point (the lowest possible moisture content of the soil in natural conditions) is the tension water storage capacities WM. The generation of surface runoff means that the soil is saturated, and the amount of water needed to saturate the soil from its field capacity is the free water storage capacity SM. Parameters KI and KG are used to classify runoff components, representing the ratio of the water flowing from the soil sides and the bottom to the amount of water that can flow freely by gravity in the soil during the calculation period, respectively. CI and CG are the coefficient of linear reservoir mentioned in section 2.1 for interflow and groundwater, respectively. Gullies density describes the spatial characteristics of the gullies and indicating the ratio of the total length of gullies to the area of the watershed. Manning roughness, expressed as Mn, reflects a comprehensive dimensionless number that affects the resistance to water flow.

A priori estimation scheme named GeoPara (Figure 2) was proposed for the spatial parameters of the GXAJ model by combining the soil data provided by the Global Digital Soil Mapping System (SoilGrids). Soil hydrological properties including saturated capacity (θ_s), field capacity (θ_f), wilting point (θ_{wp}) and saturated hydraulic conductivity (KS) have been obtained based on the characteristic of underlying surface such as soil texture, and then these properties were utilized to estimate the WM, SM, KI, KG, CI and CG of the GXAJ model. Furthermore, gradient, width and Manning roughness have been extracted from the Digital Elevation Model for flow movement simulation in channel system consisted of rivers and gullies (Mohammad & Seyed, 2019; Diaz, 2005). For gullies density D, it can be estimated by combining the distance to the gullies and the infiltration capacity of the soil based on Langbein's topographic survey (Langbein, 1947) and Horton's theoretical analysis (Horton, 1936).

3.1 Hydrological properties of soil

The change range of soil moisture gradually decreased in the deeper layer, according to which the soil can be roughly divided into active and stable layers from top to bottom (Wang, Fu, Zhang, & Xu, 2019). Soil active layer plays an important role in rainfall-runoff processes, but are difficult to accurately identify and measure at the watershed scale (Levia, & Frost, 2003; Haney, SeNSCman, Hons, & Zuberer, 2000). Fortunately, water is one of the most active variables in nature and it influences the evolution and fertility of the soil, so that, in general, the organic matter content of the active layer is higher than at the bottom of the soil (Saxton, & Rawls, 2006; Kim, 2017), which could provide a reference for soil stratification.

Based on the content of organic matter at the depth of 5, 15, 30, 60, 100 and 200 cm from the surface provided by SoilGrids, the change trend could be obtained that would contribute to the vertical stratification of the soil and the estimation of the thickness of the spatially active layer (Figure 3).

$$L_h = T_{Min} + (T_{Max} - T_{Min}) \times \left(\frac{L_a}{T_M} \right) \tag{13}$$

where L_h is the thickness of the active soil layer. T_{min} and T_{max} are the minimum and maximum thickness of the active soil layer, respectively, which can be estimated by the ratio of organic matter content to total organic matter within a given soil layer. As shown in Figure 2, α and β indicate two given layers. The values of α and β could be obtained from the field survey and operational experience of underlying surface characteristics generalization in rainfall-runoff process simulation in the watershed. L_a is the thickness of the soil aeration zone, and T_M is maximum soil thickness of watershed, referring to SoilGrids.

Using experimental formula given by USDA-ARS Hydrology and Remote Sensing Laboratory (Saxton, & Rawls, 2006), the hydrological characteristics of soil including saturated capacity (θ_s), field capacity (θ_f), wilting point (θ_{wp}) and saturated hydraulic conductivity (KS) have been estimated based on soil texture data (silt, clay, sand and organic matter content) provided by SoilGrids.

$$\begin{cases} \theta_\gamma = -0.024 \times Ratio_S + 0.487 \times Ratio_C + 0.006 \times Ratio_{Om} + 0.005 \times Ratio_S \times Ratio_{Om} \\ \quad - 0.013 \times Ratio_C \times Ratio_{Om} + 0.068 \times Ratio_S \times Ratio_C + 0.031 \\ \theta_\wp = \theta_\gamma + (0.14 \times \theta_\gamma - 0.02) \end{cases} \tag{14}$$

$$\begin{cases} \theta_\varepsilon = 0.278 \times Ratio_S + 0.034 \times Ratio_C + 0.022 \times Ratio_{Om} - 0.018 \times S \times Ratio_{Om} \\ \quad - 0.027 \times Ratio_C \times Ratio_{Om} - 0.584 \times Ratio_S \times Ratio_C + 0.078 \\ \theta_\sigma = \theta_\varepsilon + (0.636 \times \theta_\varepsilon - 0.107) \end{cases} \tag{15}$$

$$\begin{cases} \theta_\mu = -0.251 \times Ratio_S + 0.195 \times Ratio_C + 0.011 \times Ratio_{Om} + 0.006 \times Ratio_S \times Ratio_{Om} \\ \quad - 0.027 \times Ratio_C \times om + 0.452 \times Ratio_S \times Ratio_C + 0.299 \\ \theta_\tau = \theta_\mu + 1.283 \times \theta_\mu^2 - 0.374 \times \theta_\mu - 0.015 \\ \theta_s = \theta_\tau + \theta_\sigma - 0.097 \times Ratio_S + 0.043 \end{cases} \tag{16}$$

$$\begin{cases} \theta_f = 1 - ((1 - \theta_s) \times 1.2) \\ R = (\log \theta_\tau - \log \theta_\gamma) / (\log 1500 - \log 33) \\ Ks = 1930 \times (\theta_s - \theta_\tau)^{(3-R)} \end{cases} \tag{17}$$

where $Ratio_s$, $Ratio_c$ and $Ratio_{om}$ are sand, clay and organic matter content in weight, respectively; θ_γ, θ_ε, θ_σ, θ_μ, θ_τ and R are intermediate variables.

3.2 Spatial parameters

In addition to the hydrological characteristics of the soil, the parameters SM and WM, which quantify the water storage capacity, are also related to the layer thickness (Equation 18). It should be noted that due to the stratification of the soil, the value of the tension water storage capacity of each soil layer also needs to be considered separately. According to saturation-excess runoff mechanism, the value of the parameter WM is the sum of the tension water storage capacity of the upper soil layer (WUM), i.e. the active layer in this study, and the rest of the soil layers, including the lower (WLM) and deep layers (WDM). The ratio of WUM to WM could be estimated by the ratio of active layer to soil vadose zone. WDM that has tiny impact on hourly floods could be distinguished from WM by operation experience, of which the value is about 40 to 50% of WM, generally. Parameters KI and KG, gullies capacity of soil water, which are affected by terrain slope (Equation 19). CI and CG are the quantization of runoff regression, which are closely related to the length and gradient of slope segments (Equation 20).

$$\begin{cases} SM = L_h \times \left(\theta_s - \theta_f\right) \\ WM = L_a \times \left(\theta_f - \theta_{\wp}\right) \end{cases} \tag{18}$$

$$\begin{cases} KI = \dfrac{2 \times KS_u \times S_{oc}}{\left(\theta_s - \theta_f\right) \times L_{hill}} \\ KG = \dfrac{2 \times KS_m \times S_{oc}}{\left(\theta_s - \theta_f\right) \times L_{hill}} \end{cases} \tag{19}$$

$$\begin{cases} CI = e^{\left(-1/tthi\right)} \\ CG = e^{\left(-1/tthg\right)} \end{cases} \tag{20}$$

where S_{oc} is the terrain slope, KS_u and KS_m are the saturated hydraulic conductivity of upper and lower layer of soil, L_{hill} is the length of slope segments, tthi and tthg are time required for interflow and groundwater flow through slope segments, estimated on the basis of L_{hill}, S_{oc}, KS_u and KS_m ($tthi = \dfrac{L_{hill}}{KS_u \times slp}, tthg = \dfrac{L_{hill}}{KS_m \times slp}$).

3.3 River width

The upstream gullies area and slope origin moment, the two main factors of the proposed river width model (GeoRW), are used to quantify the trend and terrain factor for describing the variation of river width from upstream to downstream. The trend factor RW_a and terrain factor RW_s are expressed on the basis of upstream gullies area and slope origin moment, respectively.

$$B = \delta \times RW_{te} + \mu \tag{21}$$

$$RW_{te} = RW_a \times RW_s \tag{22}$$

$$\begin{cases} RW_a = 1 - \dfrac{\sqrt{MaxH} - \sqrt{H}}{\sqrt{MaxH} - \sqrt{T}} \\ RW_s = 1 - \dfrac{S_{mean}}{MaxS} \end{cases} \tag{23}$$

where B is the river width, δ is the proportional coefficient of the river width model, μ is the basic river width, RW_s is the slope factor, RW_a is the confluence accumulation factor, MaxH is the maximum value of the cumulative confluence, that is, the cumulative confluence at the outlet of the watershed, H is the cumulative confluence in the river cell, T is the cumulative confluence threshold when the river network is extracted, and S_{mean} is centered on the river cell unit, taking (B_{max}×1.414)/2 as the first-order origin distance of the slope within the radius, B_{max} is the width of the widest channel section. MaxS is the maximum value of the first-order origin distance of the slope. δ and μ can be estimated from a small number of sample river sections in satellite images (Tong, Li, Wang, Yao, & He, 2020; Horritt, & Bates, 2001). The bottom slope of the river section is obtained from the ratio between the elevation difference between the upper and lower reaches and the length of the river section, and the slope is approximated by S_{mean}.

3.4 Gullies density

In 1939 and 1940, Langbein and his colleagues, have conducted a large number of topographic surveys on 340 watersheds in the northeastern United States with the assistance of the Engineering Projects Administration of the Federal Bureau of Engineering (Langbein, 1947). Benson and Horton analyzed the gullies density on this basis and believed that the runoff moves and converges on the slope (Benson, 1959; Horton, 1936). When the erosivity of the water flow exceeds the erosion resistance of the soil surface, the gullies would be generated and continue to develop.

The distance from the dividing line to the point where the erosion force equals the erosion resistance is called the "critical distance", and the surface zone within the critical distance is called the "non-erosion zone". One of the most important factors in determining the width of a non-eroded zone is the infiltration capacity of the soil. Specifically, the greater the infiltration capacity, the smaller the surface runoff. As the infiltration capacity increases, the critical distance also increases since a larger slope segments length is required to accumulate surface water flow of sufficient depth and speed to begin erosion. When the infiltration capacity decreases, the surface water flow will gradually increase correspondingly. The increase in the density of gullies will provide a more efficient way to transport water from the surface. The formula 24 and 25 quantified this relationship that the permeability is inversely proportional to the square of the gullies density, and this relationship is more obvious as it is closer to the river (Jacob, 1944; Gardiner, 2010).

Considering the saturation-excess runoff mechanism, this study does not focus on the process of soil infiltration capacity change with soil moisture. The saturated hydraulic conductivity of soil, that is, the infiltration capacity when soil is saturated, is used to quantify the rate of rainfall infiltration. The distance of each cell from gullies can be extracted from Digital Elevation Model. Based on the work mentioned above, the spatial distribution of gullies density could be estimated to support numerical simulation of flow movement.

$$h=\sqrt{h_0^2+2\frac{w}{Ks}\left(L_0 x-\frac{x^2}{2}\right)} \tag{24}$$

$$D^2=\frac{w}{8hKs} \tag{25}$$

where h is the elevation of the water table at any point distance from the draining stream (x). h_0 is the elevation of the draining stream, L_0 is the distance from the stream to the ground-water divide. w is rate of accretion to the water table.

4 MODEL APPLICATION CASE

4.1 Study area and data

The proposed GXAJ model was tested for Tunxi watershed of 2670 km^2 drainage area with 11 rain gauges is located in a mountainous region with elevation ranging from 122m above sea level at the outlet to 1619m in Anhui province, China. The longest river in the watershed flows eastward to reach the outlet of watershed where the hydrological station named Tunxi is located. The long-term average annual rainfall, pan evaporation and runoff from 2007 to 2018 are 2119 mm, 770mm and 1349mm, respectively. Due to the dominance of monsoon climate, more than 60% of annual rainfall occurs during May to September (flood season). The vegetation mainly consists of evergreen coniferous forests, deciduous broad-leaved forests, mixed forests, woodlands, woodland grasslands and pasture. The rainfall and discharge records of 27 flood events from the data collection network of Tunxi watershed were used to evaluate the GXAJ model's performance incorporating spatial parameters estimation mechanism (GeoPara). The spatial distribution of rainfall was obtained from interpolating the rainfall data from the 11 rain gauges (Figure 4a) using the inverse distance squared procedure.

With the development of remote sensing analysis and geophysical observation technical at watershed scale, a new version of Global Digital Soil Mapping System (SoilGrids250m^{TM} V2.0, abbreviated as SoilGrids), which reflects the spatial characteristics of the subsurface, such as soil texture, has been online and applied in summer 2020 (Batjes, Ribeiro, & Oostrum, 2020). SoilGrids provides global predictions for standard numeric soil properties (organic carbon, bulk density, Cation Exchange Capacity (CEC), pH, soil texture fractions and coarse fragments) at seven standard depths (0, 5, 15, 30, 60, 100 and 200 cm) at 250m resolution, in addition to predictions of soil depth based on ca. 230,000 soil profiles data (WoSIS) and environmental layers such as climate, land cover, and topography, etc. Compared with the original version, SoilGrids V2.0 further improves the credibility and quantity of soil profile data, and could basically be used as a reliable source of soil data in mountainous areas where topographic measurements are lacking. Another data that can be easily obtained in mountainous areas is the Digital Elevation Model (DEM) with 90 m spatial resolution measured jointly by NASA and NIMA (Sahoo, & Jain, 2018), which is utilized in this study to depict the topography of the watershed (Figure 4).

4.2 Spatial river width estimation

The spatial distribution of the river width has been extracted according to the method in 3.4 is as follows:

From Figure 5, several features of river width variation are obvious. The upstream region of the rivers has steep slopes where rivers are usually narrow with steep banks. Close to the watershed outlet, the gentle slope intermountain zone along with the river makes the branch less constrained by the terrain, the flattened terrain and the intersection of rivers widen the downstream channel. This is the case that wider river reaches are often located at flatter terrain with larger upstream gullies area. The predominant feature is that the river widths tend to increase with upstream gullies area while fluctuate along the channels down to the outlet.

4.3 Spatial parameters estimation

According to the prior parameter estimation method proposed in this study, the spatial distribution of parameters such as SM, WM, KI, KG, CI, CG, and D have been obtained (Figure 6).

5 RESULT AND DISCUSSION

5.1 Flood simulation results

The 27 flood events of Tunxi watershed during 2008 to 2017 were used to evaluate the performance of GXAJ model with spatial parameters estimation mechanism (GeoPara). Four indexes of relative runoff volume error (RRE, %), relative peak discharge error (RPE, %), peak time error (PTE, h) and Nash-Sutcliffe coefficient (NSC) were utilized to analyze the simulation results of GXAJ model, which were compared with that of XAJ model (Figure 7).

$$RRE=\frac{R_{¿}-R_{obs}}{R_{obs}}\times 100\,\% \tag{26}$$

$$RPE=\frac{Q_{simp}-Q_{obsp}}{Q_{obsp}}\times 100\,\% \tag{27}$$

$$PTE=T_{simp}-T_{obsp} \tag{28}$$

$$NSC=1-\frac{\sum_{t=0}^{t=n}\left(Q_{¿}^{t}-Q_{obs}^{t}\right)^{2}}{\sum_{t=1}^{t=n}\left(Q_{obs}^{t}-\overline{Q_{obs}}\right)^{2}} \tag{29}$$

where Q^t_{sim} and Q^t_{obs} are simulated and measured discharge at time *t*, respectively. Q_{simp} and Q_{obsp} are simulated and measured flood peaks, respectively. T_{simp} and T_{obsp} are simulated and measured flood peak time, respectively.

From the simulation results, the relative runoff volume error and flood peak error of the GXAJ model are 8.4% and 10.7%, and the relative runoff volume error and flood peak error of the XAJ model are 8.9% and 12.1%. The NSC and PTE of the GXAJ model and the XAJ model are 0.85 and 0.88, 2.1h and 1.6h, respectively.

For further refined analysis of simulation results, the flood has been divided into five phases, namely initial, rise, peak, fall and tail phase (Figure 8a). Taking the No.2013042810 flood as an example, the flood process is considered as a function of time (q=f(T)), and then the first order derivative of the function is calculated ($Q'=\partial f(T)/\partial T$). The appropriate period δ (δ = 3h) is adopted to smooth the derivative process to obtain the mean linear Q'_{ave} reflecting the changing trend of Q'. As can be seen in Figure 8a, the mean linear Q'_{ave} shows significant increasing from point A, achieving the highest value at point B. After then, Q'_{ave} sharply decreased to the lowest point C. Finally, the line gradually returns to its original position at point D. Therefore, the flooding can be divided according to these points described above.

According to Figure 8, the GXAJ model, which considers the influence of gullies, can reasonably simulate the characteristics of flood fluctuations, especially during the rise phase. The flood simulated by the GXAJ model starts to rise at point A on the horizontal axis, leaping from 53 m^3/s to 94 m^3/s, which is basically close to the measured change from 54 m^3/s to 101 m^3/s. In the rise phase, although the simulated results are somewhat larger compared to the measured data, with RRE of about 24%, the rising trend is reasonably simulated, which has been illustrated by NSC of 0.71. The RRE is significantly reduced to 7.5% in the critical stage of the flood simulation, that is, the peak phase. Meanwhile, an appropriate process simulation was achieved, resulting in NSC of 0.98. In the first half of the fall phase, the simulation results remain fine, but in the second half of the fall phase, noticeable simulation errors start to appear, bringing the RRE to 35%. During the rise phase, as the intensity of rainfall increases, gullies on the slope can provide an efficient pathway of water conveyance, enabling a rapid rise in discharge in the river and watershed outlet. At the beginning of the flood fall, although the rainfall has stopped, there is still water flow in the river, which is conducive to the rapid transportation of the remaining water on the slope. The reduction in flow would result in a gradual decline in velocity, making the tail end of the flood recede at a lower rate.

5.2 Rationality analysis of parameters

The rationality of spatial distribution of parameters is one of the critical issues to ensure the dynamic simulation of hydrological factors such as soil moisture and water flow by the model (Tong, Li, Yao, & Huang, 2018; Kim, Lee, Kim, & Choi, 2016). The correlation between parameters including free storage capacity (SM) and gullies density (D) with factors such as elevation and distance from the river was further explored. Given that the undulating topography is concentrated in the southwestern part of the watershed, a focus area of alternating valleys and ridges was set there, which is indicated by the red boxes in Figure 9 and Figure 11 . The quantitative relationships between parameters such as SM and D and geographic elements including elevation (DEM) and distance from river (Dis) in the focus area are shown in Figure 10 and Figure 12.

Figure 9 and Figure 10 show that the value of SM first decreases and then increases with longer distance from the river and higher elevation. In the bank area located at the bottom of the valley, the soil layer containing sediment is thick, and has a high water storage capacity. In the slope section far from the river, erosion caused a thin soil layer with a small organic matter content and SM value. However, along the mountain ridge with high altitude, the value of SM increases with the thicker soil and larger organic matter content. Therefore, in the area of focus, the SM values of bank and mountain ridges are larger than that of the middle of the slope segments.

As can be seen from Figure 11 and Figure 12, the gullies density D values near the ridges are smaller than that of the areas along the river. The rainfall can enter into soil easily due to strong infiltration capacity of thick leaf litter and humus layer along mountain ridges. Specifically, the greater the infiltration capacity, the less surface runoff contributes to soil erosion. Thus, a longer critical distance is required to accumulate the flow needed to form the gullies, which implies lower gullies density. Close to the river, the proportion of fine sediment gradually increases and the infiltration capacity decreases, contributing to the generation of surface runoff. Moreover, the runoff carrying sediment from the upper slopes is discharged into the river through the bank area. These factors mentioned above promote the phenomenon that gullies density values increase with shorter distances from the river, which is consistent with the views on the spatial characteristics of gullies proposed by Horton and Benson et al. (Benson, 1959; Horton, 1936; Raphaël, Paolo, Giulia, Parlange, & Andrea, 2016; Godsey, & James, 2015).

5.3 Parameters sensitivity

The sensitivities of SM and D in various flood phases are analyzed, which could inform the need for dynamic adjustment of parameters in further potential real-time forecasting and facilitate fine simulation of rainfall-runoff processes. First, the main parameters of the GXAJ model for the Tunxi watershed were prior estimated based on data on soil texture and topography. Then, the parameters SM and D varied in the range of 0-30 and 0.1-15 in step of 0.1, respectively, to participate in the simulation of

No.2013042810 flood. The results are statistically evaluated by RRE, RPE, PTE and NSC. Furthermore, the NSC and RRE are utilized to quantify the influence of parameters SM and D on the rise, peak, fall and tail phases, respectively (Figure 13 and Figure 14).

According to Figure 15 , in various phases of the flood process, for SM and D, the differences may lead to the largest variations in RRE in the rise phase, followed by fall, peak and tail phase, successively. The sensitivity of SM is obvious in the rise phase, but not in the rest of the phases. Parameter D has significant effect on the rise phase of the flood, and the effect on the fall phase can also be identified. Both parameters SM and D can have a large impact on the RRE during the flooding phase, where the RRE is more likely to vary with the change of D. From Figure 15 , D have strong impact on NSC in the rise phase and a slight effect in the flood peak phase. On the contrary, the parameter SM has a significantly influence on the flood peak, but tiny influence on the flood rise, fall and tail. It can be concluded that D has the noticeable influence on the RRE and NSC during the rise phase, while SM has a significant effect on the RRE in the flood rise phase and NSC during peak phase, respectively.

5.4 Dynamic change of soil moisture and channel flow

In addition to the hydrograph in the river, the GXAJ model can be used to reasonably simulate the spatial dynamics of free water content and channel flow at the watershed scale, which is one of capabilities beyond XAJ model. Taking the No.2013042810 flood as an example, the soil free water content simulated by GXAJ model have been illustrated at the time of 35h, 45h, 55h, 65h ,75h and 85h (Figure 16). It can be seen that the free water content of soil is low before the occurrence of rainfall. Following the rainfall, free water content increases gradually and reaches saturation state before the flood peak appears. After the rainfall stop, the free water content decreases and finally stabilizes in a certain point which is slightly higher than that at the rainfall occurrence.

Compared to soil water content, flow in gullies change more rapidly and are hardly graphed. The continuous heavy rainfall would cause the streams in the gullies to resemble the flow in the primary river, instead of the original trickle on the slope. In the rainfall-runoff process, the distance between the cell where this phenomenon occurs and the river changes dynamically, so that the flow in the gullies keeps extending towards the uphill during the rise of the flood and dissipates towards the downhill when the flood falls. For graphing dynamic change of gullies flow appropriately, the flow index μ was utilized to tell the cell in which gullies flow is strong or not. Specifically, the cell where the gully is located is highlighted (Figure 17) when the gullies flow exceeds μ, the value of which is influenced by climate and topography. In the case of sufficient rainfall and steeper slopes in the watershed, the water flows are more likely to converge to promote the formation of channels. Therefore, based on the hourly rainfall data of Tunxi watershed in the flood season from 2008 to 2017, the runoff generated in each cell have been calculated to determine flow index μ with the consideration of terrain slope.

$$\mu = \frac{1}{K} \sum_{k=1}^{K} \sum_{b=1}^{NS} \left(R_{k,b} \times S_{k,b} \right) = \sum_{g=1}^{GS} \left(R_g \times S_g \right) \quad (30)$$

where NS is the quantity of cells converging to the source points of river system, b is the index of cells converging to the source points, from 1 to NS; K is the quantity of source points in the river system, and k is the index of source points, from 1 to K. $S_{k,b}$ and $R_{k,b}$ are respectively the slope and runoff of the cell numbered b. GS is the quantity of cells converging to the highlighted cell during rainfall-runoff process.

6 CONCLUSION

The gullies system composed of shallow furrows, trenches and well-developed grooves has been systematically generalized in Improved Distributed Grid-Xinanjiang model (GXAJ). Within the watershed divided into a series of orthogonal cells, the shallow furrows and trenches inside cells are conceptualized as primary gullies, and the well-developed grooves between cells are considered as the main gullies. The runoff generated in the cell would first enters the primary gullies using the kinetic wave equation considering the gullies density, and then flows through multiple cells in the main gullies to enters river. Based on the soil data provided by the Global Digital Soil Mapping System (SoilGrids), a parameter estimation scheme (GeoPara) has been proposed to support the simulation of 27 flood events in the Tunxi watershed of Anhui Province by GXAJ model, of which the simulation results were compared with that of XAJ model and measurement. According to the statistical analysis, the error level of peak error and Nash-Sutcliffe coefficient (NSC) of GXAJ model and XAJ model are 10.7% and 12.1%, 0.85 and 0.88, respectively. For further refined analysis of simulation results, the flood has been divided into five phases, namely initial, rise, peak, fall and tail phases. Specifically, although the GXAJ model overestimates the discharge by 24% in the flood rise phase, the rising trend is reasonably simulated with the NSC of 0.71. Meanwhile, the simulation results of GXAJ model considering the influence of gullies are basically consistent with the measurement in flood peak phase, illustrated by RRE of 7.5% and NSC of 0.98. It can be considered that The GXAJ model enables a reasonable simulation of floods, especially the flood peak.

Sensitivity analysis of the free water storage capacity SM and gullies density D are conducted in various flood phases. For SM and D, the differences may lead to the largest variations in RRE in the rise phase, followed by fall, peak and tail phase, successively. It can be concluded that D has the noticeable influence on the RRE and NSC during the rise phase, while SM has a significant effect on the RRE in the flood rise phase and NSC during peak phase, respectively. In addition to the hydrograph, spatial dynamics of free water content and channel flow at the watershed scale could be simulated reasonably by GXAJ model. It can be seen that the free water content of soil is low before the occurrence of rainfall. Following the rainfall, free water content increases gradually and reaches saturation state before the flood peak appears. After the rainfall stop, the free water content decreases and finally stabilizes in a certain point which is slightly higher than that at the rainfall occurrence. Compared with the soil water content, the flow in gullies changes rapidly, extending towards the uphill during the rise of the flood and dissipates towards the downhill when the flood falls.

DATA AVAILABILITY STATEMENT

The data collected from the gauging stations including rainfall and streamflow are available on request from the corresponding author, which are not publicly available due to privacy or ethical restrictions. The soil data from Global Digital Soil Mapping System are openly available at https://doi.org/10.1371/journal.pone.0169748 (Tomislav et al, 2017). The high-resolution terrain data used in this study are openly available at https://doi.org/10.1016/j.cageo.2017.10.001 (Sahoo, R., & Jain, V. 2018).

REFERENCES

Abbaszadeh, P., Gavahi, K., & Moradkhani, H. (2020). Multivariate remotely seNSCd and in-situ data assimilation for enhancing community WRF-Hydro model forecasting. *Advances in Water Resources*, 145, 103721.
https://doi.org/10.1016/j.advwatres.2020.103721.

Ajami, Newsha, K., Duan, Q., Gao, X., Sorooshian, & Soroosh. (2006). Multimodel combination techniques for analysis of hydrological simulations: application to distributed model intercomparison project results. *Journal of Hydrometeorology*, 7, 755-768.
https://doi.org/10.2307/2060650.

Bao, H.J., Zhao, L.N., He, Y., Li, Z.J., Wetterhall, F., Cloke, H. L. …. Manful, D. (2011). Coupling eNSCmble weather predictions based on TIGGE database with Grid-Xinanjiang model for flood forecast. *Advances in Geosciences*, 29(30), 61-67. https://doi.org/10.5194/adgeo-29-61-2011.

Batjes, N. H., Ribeiro, E., & Oostrum, A. V. (2020). Standardised soil profile data to support global mapping and modelling (WoSIS snapshot 2019). *Earth System Science Data*, 12, 299-320.
https://doi.org/10.5194/essd-12-299-2020.

Benson, M. A. (1959). Channel-Slope Factor in Flood-Frequency Analysis. *Journal of the Hydraulics Division*, 85(1), 1-9.

Daniel, B. W., Guo, Y., & John, F. E. (2020). Six decades of rainfall and flood frequency analysis using stochastic storm transposition: Review, progress, and prospects. *Journal of Hydrology*, 585, 124816. https://doi.org/10.1016/j.jhydrol.2020.124816.

Diaz, R. G. Analysis of Manning coefficient for small-depth flows on vegetated beds. (2005). *Hydrological Processes*, 19(16), 3221-3233. https://doi.org/10.1002/hyp.5820.

Fraga, I., Cea, L., & Puertas, J. (2019). Effect of rainfall uncertainty on the performance of physically based rainfall-runoff models. *Hydrological Processes*, 33, 160-173. https://doi.org/10.1002/hyp.13319.

Garbrecht, J., & Martz, L. W. (1997). The assignment of gullies direction over flat surfaces in raster Digital Elevation Models. *Journal of Hydrology*, 193(4), 204-213. https://doi.org/10.1016/S0022-1694(96)03138-1.

Gardiner, V. (2010). Estimation of gullies density from topological variables. *Water Resources Research*, 15(4), 909-917. https://doi.org/10.1029/wr015i004p00909

Godsey, S. E., & James, W. K. (2015). Dynamic, discontinuous stream networks: hydrologically driven variations in active gullies density, flowing channels and stream order. *Hydrological Processes*, 28(23), 5791-5803. https://doi.org/10.1002/hyp.10310.

Grunwald, S., Thompson, J. A., & Boettinger, J. L. (2011). Digital soil mapping and modeling at continental scales: Finding solutions for global issues. *Soil Science Society of America Journal*, 75, 1201-1213. https://doi.org/10.2136/sssaj2011.0025.

Gupta, H. V., Sorooshian, S., & Yapo, P. O. (1999). Status of automatic calibration for hydrologic models: comparison with multilevel expert calibration, *Journal of Hydrologic Engineering*, 4(2), 135-143. https://doi.org/10.1061/(ASCE)1084-0699(1999)4:2(135).

Gupta, H.V., Wagener, T., & Liu, Y. (2008), Reconciling theory with observations: elements of a diagnostic approach to model evaluation. *Hydrological Processes*, 22(18), 3802-3813.
https://doi.org/10.1002/hyp.6989

Haney, R. L., SeNSCman, S. A., Hons, F. M., & Zuberer, D. A. (2000). Effect of glyphosate on soil microbial activity and biomass. *Weed Science*, 48(1):89-93. https://doi.org/10.1614/0043-1745(2000)048[0089:EOGOSM]2.0.CO;2.

HaNSCn, C., Shiva, J. S., Mcdonald, S., & Nabors, A. (2019). Assessing retrospective National Water Model streamflow with respect to droughts and low flows in the Colorado River basin. *Journal of the American Water Resources Association*, 55(4). https://doi.org/10.1111/1752-1688.12784.

Horritt, M. S., & Bates, P. D. (2001). Predicting floodplain inundation: raster-based modelling versus the finite-element approach. *Hydrological Processes*, 15, 825-842. https://doi.org/10.1002/hyp.188.

Horton, Robert, E. (1936). Maximum groundwater levels. Eos Transactions American Geophysical Union, 17(2), 344-357.
https://doi.org/10.1029/TR017i002p00344.

Jacob, C. E. (1944). Correlation of ground-water levels and precipitation on Long Island, New York. 25(6), 928-939. https://doi.org/10.1029/TR025i006p00928.

Kim, D., Lee, J., Kim, H. & Choi, M. (2016). Spatial composition of AMSR2 soil moisture products by conditional merging technique with ground soil moisture data. *Stochastic Environmental Research & Risk Assessment*, 30, 2109-2126. https://doi.org/10.1007/s00477-016-1300-0.

Kim, S. B., Jakob, J., Johnson, T., Moghaddam, M., Tsang, L., Colliander, A., …Yueh, S. H. (2017). Surface soil moisture retrieval using the L-band synthetic aperture radar onboard the soil moisture active-passive satellite and evaluation at core validation sites. *IEEE Transactions on Geoscience and Remote Sensing*, 55(4), 1897-1914. https://doi.org/10.1109/TGRS.2016.2631126.

Kirkby, M. J. (1978). Hillslope hydrology. Wiley.
https://doi.org/10.1002/esp.3290070112.

Koren, V., Reed, S., & Smith M. (2004). Hydrology laboratory research modeling system (HL-RMS) of the US national weather service. *Journal of Hydrology*, 291, 297-318. https://doi.org/10.1016/j.jhydrol.2003.12.039.

Kuo, W. L., Steenhuis, T. S., Mcculloch, C. E., Mohler, C. L., Weinstein, D. A., Degloria, S. D., & Swaney, D. P. (1999). Effect of grid size on runoff and soil moisture for a variable-source-area hydrology model. *Water Resources Research*, 35(11), 3419–3428. https://doi.org/ 10.1029/1999WR900183.

Lahmers, T. M., Gupta, H., Castro, C. L., Gochis, D. J., & Hazenberg, P. (2019). Enhancing the structure of the WRF-Hydro hydrologic model for semi-arid environments. *Journal of Hydrometeorology*, 20(4), 691–714. https://doi.org/10.1175/JHM-D-18-0064.1.

Lai, C., Chen, X., Wang, Z. L., Yu H.J. & Bai, X. Y. (2020). Flood risk assessment and regionalization from past and future perspectives at basin scale. *Risk Analysis*, 40(7), 1399-1417. https://doi.org/10.1111/risa.13493.

Langbein, W. B. (1947). Topographic characteristics of gullies basins: U.S. Geol. Survey Water-Supply Paper. 968(C), 125-157.

Levia, D. F., & Frost, E. E. (2003) A review and evaluation of stemflow literature in the hydrologic and biogeochemical cycles of forested and agricultural ecosystems. *Journal of Hydrology*, 274, 1-29. https://doi.org/10.1016/S0022-1694(02)00399-2.

Li, Z. J., Liang, K., Kan, G. Y., Li Q. L., Yao, C., & Zhang, K. (2016). A method for deriving the river network flow concentration parameter Cs of the Xin'anjiang model. *Advances in Water Science*, 27(5), 652-661. https://doi.org/10.14042/j.cnki.32.1309.2016.05.002.

Li, Z. J., Yao, C., Zhang, K., Zhu, Y. L., Liu Zhiyu, Li Qiaoling., …, Huang, P. N. (2017). Research and application of the high-resolution rainfall runoff hydrological model in flood forecasting. *Journal of Hohai University (Natural Sciences)*, 45(6), 471-479. https://doi.org/10. 3876/ j. issn. 1000 1980. 2017. 06. 001.

Liang, C., Li, D. Q., Yuan, Z. J., & Liao, Y., S. (2019). Assessing urban flood and drought risks under climate change, China. *Hydrological Processes*, 33(9), 1349-1361. https://doi.org/10.1002/hyp.13405.

Liang, D., Lu, J. Z., Chen, X.L., Liu C., & Lin, J.L. (2020). An investigation of the hydrological influence on the distribution and transition of wetland cover in a complex lake–floodplain system using time-series remote sensing and hydrodynamic simulation. *Journal of Hydrology*, 587, 125038. https://doi.org/10.1016/j.jhydrol.2020.125038.

Martz, L. W., & Garbrecht, J. (1995). Automated recognition of valley lines and gullies networks from grid Digital Elevation Models: a review and a new method-comment. *Journal of Hydrology,* 139(4), 263-293. https://doi.org/10.1016/0022-1694(94)02619-M.

Mcclean, F., Dawson, R., & Kilsby, C. (2020). Implications of using global Digital Elevation Models for flood risk analysis in cities. *Water Resources Research*, 56(10), e2020WR028241. https://doi.org/10.1029/2020WR028241.

Mohammad, A., & Seyed, M. H. (2019). A simple innovative method for calibration of Manning's roughness coefficient in rivers using a similarity concept. *Journal of Hydrology*, 575, 810-823. https://doi.org/10.1016/j.jhydrol.2019.05.083.

Montgomery, D. R., & Dietrich, W. E. (2010). Source areas, gullies density, and channel initiation. *Water Resources Research*, 25(8), 1907-1918. https://doi.org/10.1029/WR025i008p01907

Najafi, M. R., Moradkhani, H., & Jung, I. W. (2011). Assessing the uncertainties of hydrologic model selection in climate change impact studies. *Hydrological Processes*, 25(18), 2814-2826. https://doi.org/10.1002/hyp.8043.

Raphaël, M., Paolo, T., Giulia, S., Parlange, M. B., & Andrea, R. (2016). Field study on gullies densities and rescaled width functions in a high-altitude alpine catchment. *Hydrological Processes*, 30(13), 2138-2152. https://doi.org/10.1002/hyp.10783.

Reed, S., Koren, V., Smith M., Zhang, Z., Moreda, F., Seo, D. J., & Participants, A. D. (2004) Overall distributed model intercomparison project results. *Journal of Hydrology*, 298, 27-60. https://doi.org/10.1016/j.jhydrol.2004.03.031.

Sahoo, R., & Jain, V. (2018). Sensitivity of gullies morphometry based hydrological respoNSC (GIUH) of a river basin to the spatial resolution of DEM data - ScienceDirect. *Computers & Geosciences*, 111, 78-86. https://doi.org/10.1016/j.cageo.2017.10.001.

Saxton, K. E., & Rawls, W. J. (2006). Soil water characteristic estimates by texture and organic matter for hydrologic solutions. *Soil Physics*, 70, 1569-1578. https://doi.org/10.2136/sssaj2005.0117.

Sorooshian, S., Duan, Q., & Gupta, V. K. (1993). Calibration of rainfall-runoff models: Application of global optimization to the Sacramento Soil Moisture Accounting Model. *Water Resources Research*, 29(4), 1185-1194. https://doi.org/10.1029/92wr02617.

Sun, T. T., Wang, Y. G., Hui, D. F., Jing, X., & Feng, W. T. (2020). Vertical distributions of soil microbial biomass carbon: a global dataset. *Data in Brief*, 32: 106147. https://doi.org/10.1016/j.dib.2020.106147.

Thieken, A. H., Lücke, A., Diekkrüger, B., & Richter, O. (1999). Scaling input data by GIS for hydrological modelling. *Hydrological Processes*, 13(4), 611-630. https://doi.org/10.1002/(SICI)1099-1085(199903)13:4<611::AID-HYP758>3.0.CO;2-6/.

Tomislav, H., Jorge, M. D. J., Heuvelink, G. B. M., Maria, R.G., Milan, K., Aleksandar, B., …Bernhard, B. M. (2017). SoilGrids250m: Global gridded soil information based on machine learning. *PLoS One*, 12(2), e0169748. https://doi.org/10.1371/journal.pone.0169748.

Tong, B. X., Li, Z. J., Wang, J. F., Yao, C., & He, M. (2020). Development of topography-based river width estimation model for medium-sized mountainous watersheds. *Journal of hydrologic engineering*, 25, 1-11. https://doi.org/10.1061/(ASCE)HE.1943-5584.0001888

Tong, B. X., Li, Z. J., Yao, C., & Huang, Y. C. (2018). Derivation of the spatial distribution of free water storage capacity based on topographic index. *Water*, 10 (10):1-15. https://doi.org/10.3390/w10101407.

Viterbo, F., Mahoney, K., Read, L, Salas, F., & Cifelli, R. (2020). A multiscale, hydrometeorological forecast evaluation of National Water Model. *Journal of Hydrometeorology*, 21, 475-499. https://doi.org/10.1175/JHM-D-19-0125.1.

Wang, C., Fu, B., Zhang, L., & Xu Z. H. (2019). Soil moisture-plant interactions: an Ecohydrological review. *Journal of Soils & Sediments*, 19, 1-9. https://doi.org/10.1007/s11368-018-2167-0.

Wang, D. F., Xu, H. D., Wang, X. L., & Wu, X. (2020). Statistical analyses of the effect of a gullies tunnel on landslide hydrogeological characteristics. *Hydrological Processes*, 34(1), 2418-2432. https://doi.org/10.1002/hyp.13738.

Wang, P. L., & Zhao, R. J. (1989). Optimazation method of calibration of Xianjing Model (3 Components). *Journal of Hohai University (Natural Science Edition)*, 1989, 04: 65-69. https://doi.org/ CNKI:SUN:HHDX.0.1989-04-009.

Xia, J., Wang, H. Y., Gan, Y. Y., et al. (2019). Research progress in forecasting methods of rainstorm and flood disaster in China. *Torrential Rain and Disasters*, 38(5), 416-421. https://doi.org/ 10.3969/j.issn.1004-9045.

Xiang, T., Vivoni, E. R., Gochis, D. J., & Mascaro, G. (2017). On the diurnal cycle of surface energy fluxes in the North American monsoon region using the WRF-Hydro modeling system. *Journal of Geophysical Research: Atmospheres*, 122, 9024-9049. https://doi.org/10.1002/2017JD026472.

Yao, C., Li, Z. J., Yu, Z. Z., & Zhang, K. (2012). A priori parameter estimates for a distributed, grid-based xinanjiang model using geographically based information. *Journal of Hydrology*, 468(25), 47-62. https://doi.org/10.1016/j.jhydrol.2012.08.025.

Yao, C., Li, Z. J.; Bao, H. J.; & Yu, Z. B. (2009). Application of a Developed Grid-Xinanjiang Model to Chinese Watersheds for Flood Forecasting Purpose. *Journal of Hydrologic Engineering*, 14(9), 923-934. https://doi.org/10.1061/(ASCE)HE.1943-5584.0000067

Zeng, Z. Y., Xu, J. J., & Wan, Y. Q. (2020). Advances in flood risk identification and dynamic modelling based on remote sensing spatial information. *Advances in Water Science*, 31(3), 463-472. https://doi.org/10.14042/j.cnki.32.1309.2020.03.016

Zhang, G.T., Cui, P., Yin Y. Z., Wen, J., Wang, H., Yan, Y., … Wang, J. (2019). Real-time monitoring and estimation of the discharge of flash floods in a steep mountain catchment. *Hydrological Processes*, 33(25), 3195-3212. https://doi.org/10.1002/ hyp. 13551.

Zhang, J. Q., Lin, P. R., Gao, S. & Fang, Z. (2020). Understanding the re-infiltration process to simulating streamflow in north central Texas using the WRF-Hydro modeling system. *Journal of Hydrology*, 587, 124902. https://doi.org/10.1016/j.jhydrol.2020.124902.

Zhao, R. J. (1984). Watershed hydrological simulation: Xinanjiang model and Shanbei model. Beijing: Water Resources and Electric Power Press.

TABLES

Table 1 Main parameters of GXAJ model

parameter	meaning	unit	parameter	meaning	unit
SM	free water storage capacity	mm	*CI*	regression coefficient of interflow	-
WM	tension water storage capacity	mm	*CG*	regression coefficient of groundwater	-
KI	outflow coefficient of	mm	*D*	gullies density	km^{-1}

KG	interflow outflow coefficient of groundwater	mm	*Mn*	Manning roughness	-

FIGURE LEGENDS

FIGURE 1. Schematic of water movement. The watershed has been divided into a series of orthogonal cells where the overland flow occurs during rainfall. Shallow furrows and trenches inside the cells are conceptualized as primary gullies, in which water movement is simulated by kinematic wave equation considering the gullies density, and well-developed grooves between cells are considered as main gullies where water moves as a kinematic wave and enters the river to participate in flood routing.

FIGURE 2. Flowcharts of parameter estimation. Input data, topographic characteristics and parameters are colored in green, orange and blue respectively.

FIGURE 3. Vertical distribution of organic matter has been shown schematically. α and β are ratio of the organic matter content within the possible thinnest and thickest layer to the total organic matter, respectively, which could be obtained according to the field survey and operational experience of underlying surface characteristics generalization in rainfall-runoff process simulation in the watershed.

FIGURE 4. Observation stations and geographical data of Tunxi watershed. The digital elevation and observation station network is shown in (a), from west to east, the rainfall stations are Zuo Long, Cheng cun, Da liang, Qian xian, Shang xikou, Yan qian, Ru cun, Xiu ning, Wu cheng, Tunxi and Shi men in order. The hydrological station Tunxi is located at the outlet of the watershed. (b) Thickness of the soil aeration zone. Mass fraction of Sand, Silt and Clay have been shown in (c), (d) and (e), respectively. (f) Organic matter in dg/kg^{-1}.

FIGURE 5. Spatial distribution of river widths and terrain slope within Tunxi watershed. Considering the difficulty of showing narrow rivers with lines on a small-scale cell map, the cells through which the river flows are converted into points whose size can be used to quantify the river width. To make the legend length appropriate, the size of the points are divided into five sections: 12-20, 20-40, 40-60, 65-90 and

90-147 meters. Areas with low slope are marked in green and those with high slope are in red.

FIGURE 6. Spatial parameters of Tunxi watershed. (a) Free water storage capacity, SM. (b) Sum of tension water capacity in upper, lower and deep layers. (c) The distribution of WUM, and the ratio of WUM to WM can be roughly estimated from the ratio of active layer to soil vadose zone. (d) Based on operational experience, the value of WDM that has little effect on hourly-scale flooding is generally about 40 to 50% of WM, and thus can be distinguished from WM. (e) Outflow coefficient of interflow, KI. (f) Outflow coefficient of groundwater, KG. (g) Regression coefficient of interflow, CI. (h) Regression coefficient of groundwater, CG. (i) Gullies density, D.

FIGURE 7. Flood simulation results. The results of the GXAJ model and the XAJ model are shown on the horizontal and vertical axes, respectively, with a 45-degree angle divider for visual comparison. For error metrics such as RRE, RPE, and PTE, the points on the left side of the dividing line indicate that the GXAJ model performs better than the XAJ model. For NSC, the conclusion is reversed.

FIGURE 8. Various phases of No.2013042810 flood. (a) The flood process is colored in blue. The first order derivative of the flood process is Q', being represented by the black line. The red line Q'_{ave} is the result of smoothing the black line and is mainly used to reflect the trend of Q'. The Q'_{ave} shows significant increasing from point A, achieving the highest value at point B. After then, Q'_{ave} sharply decreased to the lowest point C. Finally, the line gradually returns to its original position at point D. With reference to these points mentioned, the flood can be divided into initial, rise, peak, fall and tail phase phases. (b) The measured results and GXAJ model simulations for flood 2013042810 are shown by black and red lines, respectively. The inverse scale on the right vertical axis is used to quantify the precipitation, which is represented by the blue bar.

FIGURE 9. Spatial analysis of SM. (a) Digital elevation the Tunxi watershed. (b) is an enlargement of the area in the red box of (a). (c) shows the spatial distribution of free storage capacity. (d) is also a zoomed-in view of a local area, similar to (b), with

the purpose of presenting the distribution of SM parameters among multiple tributaries.

FIGURE 10. Rationality analysis of SM. (a) The correlation between free water storage capacity and elevation. (b) The correlation between free water storage capacity and distance from river.

FIGURE 11. Spatial analysis of D. (a) The distance from the river within the Tunxi watershed has been shown. The area in the red box is enlarged in (b). (c) is a map of the spatial distribution of gullies density, and (d) is a zoomed-in view of the area in the red box of (c). Rivers have been labeled to visualize the distance to the river in any cell.

FIGURE 12. Rationality analysis of D. (a) The correlation between gullies density and elevation. (b) The correlation between gullies density and distance from river.

FIGURE 13. Sensitivity of SM at various flood phases. The change of RRE, RPE, PTE and NSC with parameter SM of the whole process of flood have been shown in first row. The following rows have revealed the change of RRE and NSC with SM in rise, peak, fall and tail phases, respectively.

FIGURE 14. Sensitivity of D at various flood phases. RRE, RPE, PTE and NSC of the whole process of flood have been shown in first row. The following rows have revealed the change of RRE and NSC with gullies density in rise, peak, fall and tail phases, respectively.

FIGURE 15. Parameter sensitivity analysis. (a) Variations in RRE with changes in D and SM during the rise, peak, fall, and tail phases, respectively. (b) Variance of NSC with changes in D and SM during the rise, peak, fall, and tail phases, respectively.

FIGURE 16. Dynamic change of soil free water content, simulated by GXAJ model at the time of 35h, 45h, 55h, 65h, 75h and 85h.

FIGURE 17. Dynamic change of flow in channel system consisted of rivers and gullies, simulated by GXAJ model at the time of 35h, 45h, 55h, 65h, 75h and 85h