Development of a hydrological response index to represent TOPMODEL parameters

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Abstract This paper proposes an approach of constructing a hydrological response index (HRI) for description of influences of the catchment's characteristics on hydrological simulations. HRI is composed of the topographic index of TOPMODEL and curve number (CN) of the SCS model, and can be computed from characteristics of topography and land surface components by using GIS and remote sensing techniques. Hydrological simulation is based on TOPMODEL and the parameters are calibrated. The relationship between HRI and the model's key parameters was analysed on the basis of calibration results from 32 hydrological response units (HRU) that were derived from HRI. The study results show that correlation coefficients between HRI and the parameters m and $\ln T_0$ are 0.88 and 0.85, respectively. Furthermore, a good relationship between SR_0 and NDVI by using Landsat data is also found. The validation of model parameters was carried out using those parameters. The validation results show that the correlation coefficient between observed and simulated stream discharges is 0.84. These results indicate that the proposed index can be used to represent the model parameters in the study region.

Key words parameter regionalisation; hydrological response index; regression analysis; validation; Landsat data

INTRODUCTION

Hydrological modelling has always played an important role in the fine management of water resources within catchments. River flow simulation is an effective method for water resource planning, pollution control and conservation. The model parameters are usually calibrated with observed data in order to obtain a good fit between observed and simulated outputs. However, hydrological data are always short in parts of the world. In data-sparse regions, the establishment of a relationship between a catchment's characteristics and the model parameters is a crucial issue to reduce uncertainty in hydrological prediction and to improve water resources management strategies. A number of methods have previously been applied to modelling ungauged basins. Bastola *et al*. (2008) has reviewed three ways: the methods based on spatial proximity, physical reasoning, and statistical approaches. Within them, the statistical method that links model parameters to basin attributes may be a widely used approach. The basic methodology is to optimize model parameters for a large number of gauged catchments and to derive the statistical (e.g. regression, ANN, etc.; Kling & Nachtnebel, 2009) relationship between model parameters and catchment attributes. These relationships can then be used to derive the parameter set for the ungauged basin. A variety of regionalization approaches has been developed and tested ever since, with a varying degree of success (Heuvelmans *et al.*, 2005). In this relationship, the watershed characteristics generally use the individual variable (such as average basin slope, shape factor, elevation, area, wetness index and vegetation cover, land-use/cover, etc.) or their linear combination for expressing the model parameter (Berger & Entekhabi, 2001; Sefton & Howarth, 1998; Jin *et al.*, 2008; Kling & Nachtnebel, 2009). However, the individual variable can not completely describe the model parameter and the combination of these variables loses their physical meaning. The description of these catchment characteristics needs to divide into the HRU in order to reduce the spatial heterogeneity of the characteristics and to illuminate hydrological processes.

This paper discusses the regionalisation of the main controlling parameters of the TOPMODEL for the Luo River basin of China, with an area of about 12 000 km^2. The aim is to present an approach of constructing a hydrological response index (HRI) to describe influences of the spatial distribution of the basin characteristics on hydrological simulations. Specific objectives are: (1) to search for a way to construct an integration describer, (2) to assess the ability of the describer for regionalising the main controlling parameters of TOPMODEL.

STUDY AREA AND DATA

Study area

The study area is Luo River watershed, with 8 discharge and 68 rainfall stations (Fig. 1(a)), a semi-arid region of China. Average annual rainfall amounts to 720 mm and evaporation, 960 mm; 65% of annual precipitation is concentrated in 6–9 months with shorter and more intensive storms. There is a wide variation in topographical, pedological, and land use characteristics (Fig. 1(b), (c)). The southern, east and west part are surrounded by high mountains with good cover of forest and grassland. The north is a plain with agriculture, towns and cities. Agriculture is the dominant land use but rapid urbanization has occurred in the past decade. The middle of the whole basin is covered with fine-textured clay, and sand soil is distributed over mountain tops and valleys with a higher infiltration capacity. The land-use change during the 1980–2000s has been investigated using remote sensing imagery (Fig. 1(d), Table 1).

Table 1 Detection of land-use changes of the study area (%).

	Farmland	Forest	Grassland	Built-up	Water	Unused land	Total
1980s	25.85	25.75	40.76	0.27	1.02	6.35	100
1990s	27.49	28.50	34.01	1.42	1.87	6.71	100
2000s	26.33	31.67	28.86	3.97	2.33	6.84	100

Data

Hydrological observation data from the 1980s to 2000s are used to calibrate model parameters and to validate the results. A digital map of soil texture was obtained from Beijing Institute of Geographical Research. Land-use maps have been extracted using Landsat data acquired in 1980, 1990 and 2001. Both maps were used to calculate the SCS model curve number (CN). DEM data were obtained from NASA, USA, with a resolution of 30 m, which was used to construct the sub-basins of the study area and to calculate the topographic index of TOPMODEL.

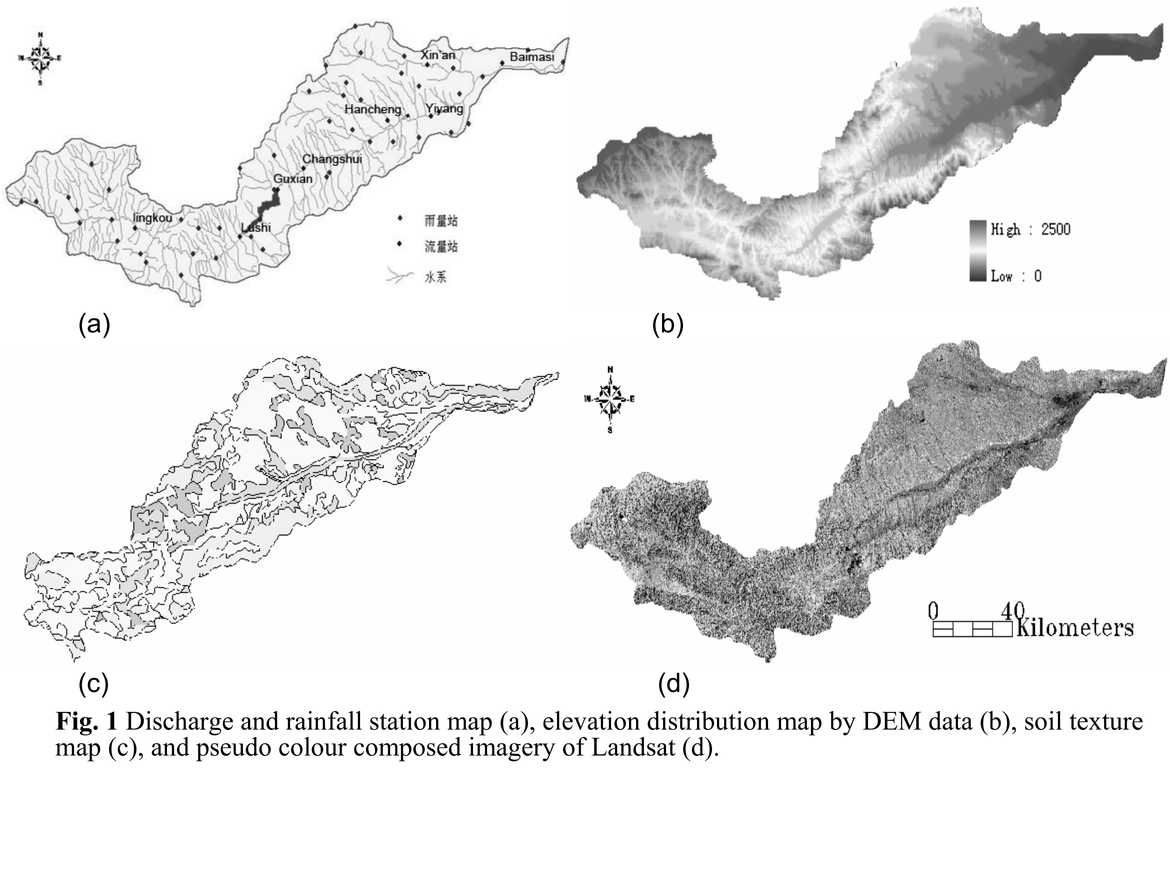

Fig. 1 Discharge and rainfall station map (a), elevation distribution map by DEM data (b), soil texture map (c), and pseudo colour composed imagery of Landsat (d).

METHOD

Construction and analysis of HRI

The catchment's characteristics decide the response of the underlying surface to precipitation input, which can be described in two ways: the morphological structure and the material composition in a basin. TOPMODEL uses the topographic index to reflect the spatial distribution of slope and water deficit in a basin. However, the model considers less about the material composing a unit. Besides, the model does not supply the method of the division and description of HRU, so it is difficult to build the relationship between model parameters and attributions in HRU. Therefore, the development of an integrated index to HRU is a crucial issue to reduce uncertainty in hydrological prediction in data-sparse regions. It is not only a quantitative describer for HRU, but also can provide methods for the extraction of HRU and the transformation derived parameters for HRU in ungauged regions.

(1) Topographic index calculation In TOPMODEL, the topographic index is used to reflect the wetness status of the point or grid for a long time. Also, it can describe the dynamic condition of flow on the slope. Using the improved multi-flow route method to calculate topographic index (Quinn, 1994), the formulation is as follows and the spatial distribution of the index is as in Fig. 2(a):

$$\ln(\alpha / \tan \beta) = \ln[A / \sum_{j=1}^{n} (L_j \times \tan \beta_j)] + \ln(\sum_{j=1}^{n} L_j / \sum_{i=1}^{m} K_i) \quad (1)$$

(2) CN value In the SCS model, the CN value is used to assess the amount of water that enters the soil profile or yields flow. The value is influenced in many ways; soil texture and land-use/cover may be the two dominant factors. Using the two data sets and hydrological data, the CN value can be calculated with the SCS model (Ragan, 1980). The result is shown in Fig. 2(b).

(3) Hydrological response index (HRI) construction From the basic physical meaning of the topographic index (*TI*) and *CN*, *HRI* can be constructed with their multiplication as follows:

$$HRI = (TI \times CN)^{\alpha} \quad (2)$$

where α is an empirical parameter which may be related to climate conditions. In this paper α is 0.5. The hydrological response index distribution is shown in Fig. 3.

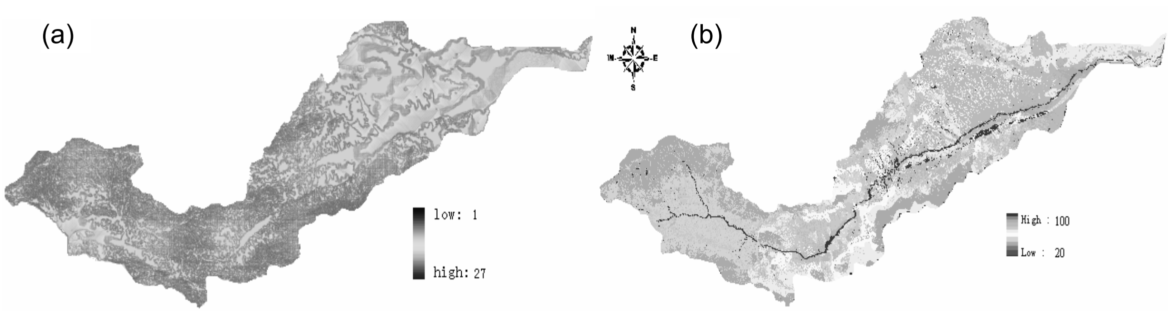

Fig. 2 (a) Topographic index distribution. (b) CN value distribution in 2000.

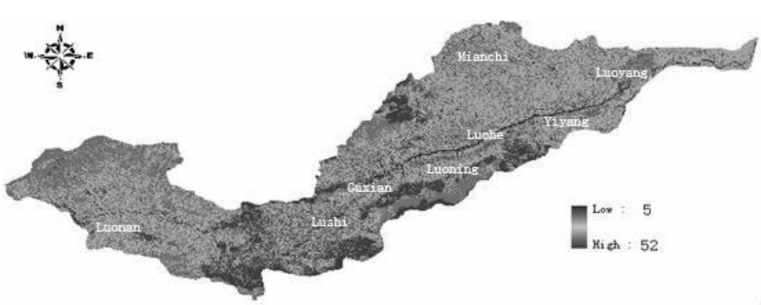

Fig. 3 Hydrological response distribution in Luo River in 2000.

Physical explanation of HRI The HRI is a non-dimensional index. The combination of *TI* and *CN* has some physical meaning. From Fig. 3, HRI distribution is close to the topography and land cover. The urban region has a higher value of HRI and mountain with forest cover has a lower value. The relationship between HRI and some geographical parameters that are derived using Landsat data is shown in Fig. 4; it can be seen that the dominant parameters of HRU have better correlation coefficients with HRI. The highest coefficient appears in HRI with NDVI. The lower coefficient is HRI with evapotranspiration ($R^2 = 0.56$). The albedo and temperature that denote the surface energy in the HRU have a positive correlation. The statistical relationship suggests that HRI may reflect the capacity of the water storage or produce runoff. The results indicate that HRI not only maintains the primary meaning of the two indices, but also exploits their connotation in describing the surface characters and the probability of the HRI producing runoff.

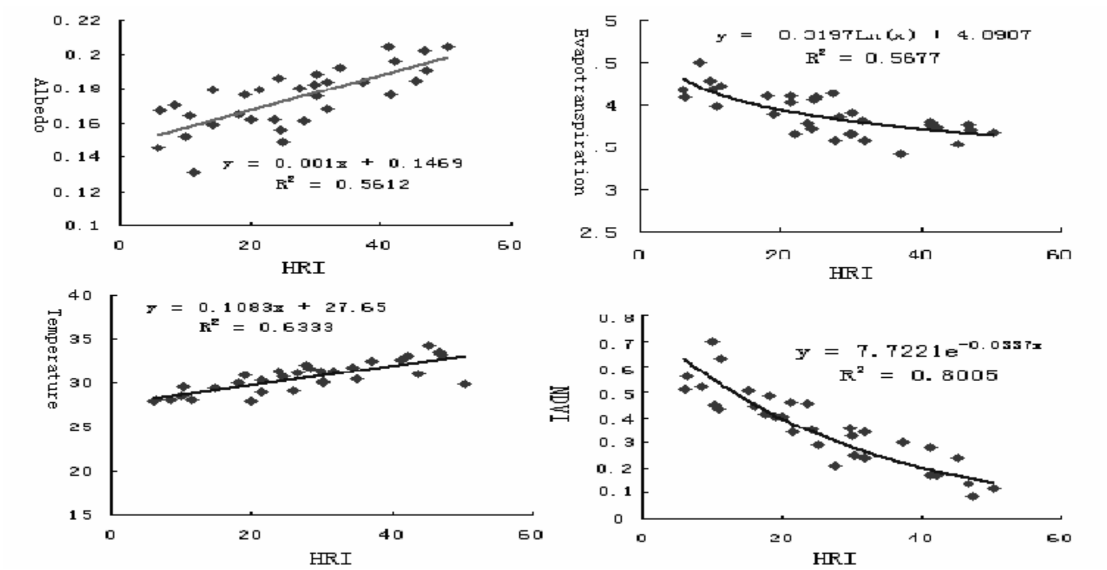

Fig. 4 The correlation relationship between HRI and some geographical parameters.

HUR extraction There are likely to be a lot of land use and soil types, or their combinations. Different combinations have different hydrological responses in a structurally complex basin. According to the value of the HRI and normal difference vegetation index (NDVI) at each pixel, the classification was carried out for every sub-basin which was first extracted by topographic index (Fig. 5). Then the GIS overlay operation was performed for two feature layers. Within the new layer, each polygon has a similar HRI and NDVI value and a relatively conformable hydrological response feature. The development stages of HUR are shown as Fig. 6. Thirty-two hydrological response units were obtained for the whole basin in accordance with the above steps.

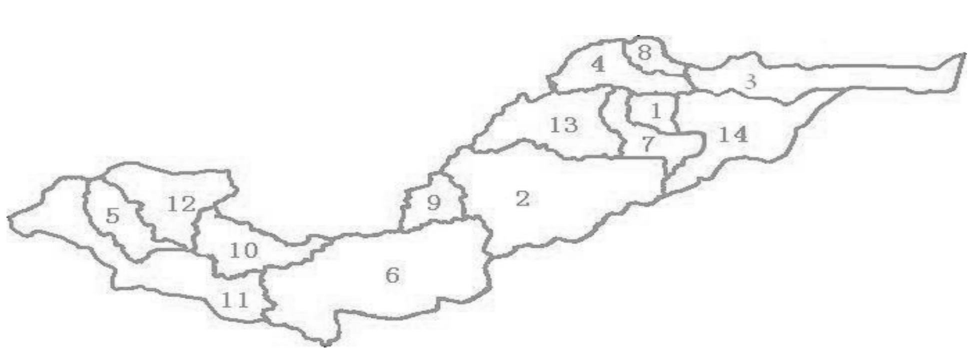

Fig. 5 Sub-basin of the study area by topographic index of TOPMODEL.

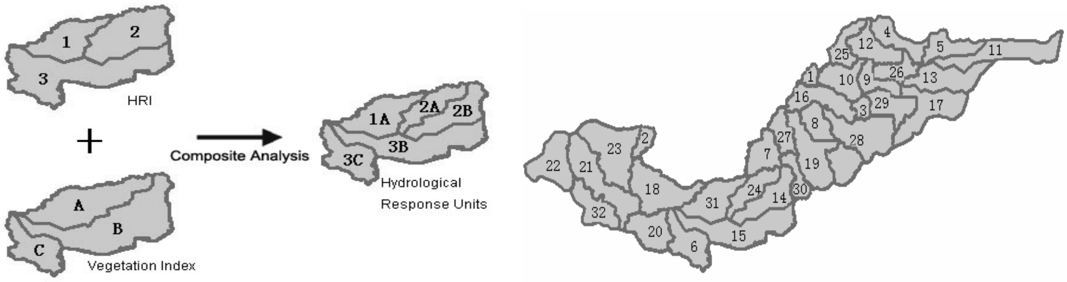

Fig. 6 Development stages and result of HUR.

TOPMODEL parameter calibration and validation

A manual calibration was carried out using 20 observed floods for 1990–2001. The criterion of the parameter calibration involved the correlation coefficient and average runoff error between simulated and observed flow discharge. The same criteria were used to validate the parameter sets with another 10 floods. The relative errors of the peak discharge and time are shown in Table 2.

The parameters were first calibrated using the flood data for the eighth sub-basin which has a stream gauging station. Then, the average HRI of each HRU was calculated for the whole sub-basin. The calibrated parameters can be then transformed to the HRU according to HUI value which is close to the calibrated sub-basin or using the average parameters of the calibrated sub-basin. The dominant parameters of TOPMODEL in 32 HRU can be obtained.

Table 2 Validation of flood discharge and time Q_{mc}: the simulated flood discharge; Q_{mo}: the observed flood discharge; D_q: the error of flood discharge; D_t: the error of the peak appeared.

No.	Q_{mc} (m^3/s)	Q_{mo} (m^3/s)	D_q (m^3/s)	D_q (%)	D_t
800701	810.24	760.13	–50.11	–6.59	0
820629	740.32	808.13	67.81	8.39	–1
830729	1820.06	1720.62	–99.44	–5.77	–2
830816	450.64	420.67	–29.97	–7.12	0
840908	810.20	880.32	70.12	7.96	+1
850912	1500.24	1420.37	–-79.87	–5.62	–1
880519	3410.05	3520.19	110.14	3.12	+3
890710	1350.71	1300.23	–50.48	–3.88	+1
980804	850.16	920.47	70.31	7.63	+1
990729	1301.24	1361.38	60.14	4.41	0
Average	1304.39	1311.25	6.87	0.25	0.2

RESULTS AND DISCUSSION

Regionalisation schemes of model parameters

Correlation analysis of HRI and the parameters *m* The parameters *m* of TOPMODEL refers to the rate of the exponential decay of the soil infiltration, which is in proportion to the soil infiltration rate. The soil infiltration is generally faster and HRI is relatively small in areas of high vegetation coverage. While in urban areas, as the impervious surface area increases, the soil infiltration is lower and the HRI is larger. Based on these cases, the correlation relationship between *m* and HRI was established (Fig. 7(a)). There is a logarithmic relationship between *m* and HRI with the correlation coefficient $R^2 = 0.78$. As the higher HRI is always in locations with low vegetation coverage, the soil infiltration rate of the area is relatively lower. From the derived relations between the two terms, we can calculate their spatial distribution map (Fig. 7(b)).

Correlation analysis of HRI and $\ln T_0$ The $\ln T_0$ is the average of the natural logarithm of infiltration velocity when the soil is just getting to saturation. There is a relationship between $\ln T_0$ and HRI. From Fig. 8(a), the relationship between HRI and $\ln T_0$ is a linear decay and the

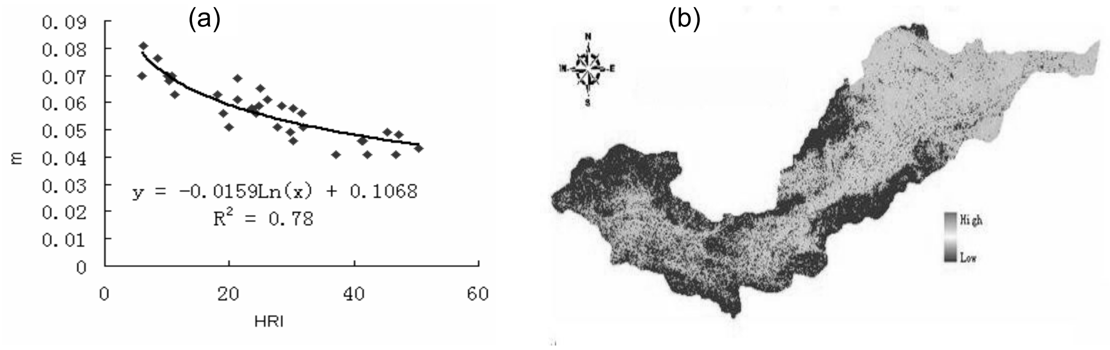

Fig. 7 (a) Correlation between HRI and *m*. (b) Spatial distribution map of parameter *m*.

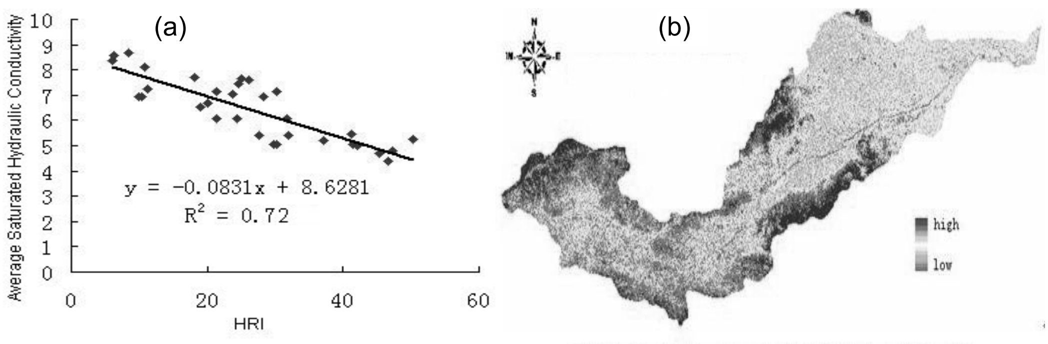

Fig. 8 (a) The correlation of $\ln T_0$ and HRI. (b) Spatial distribution map of $\ln T_0$.

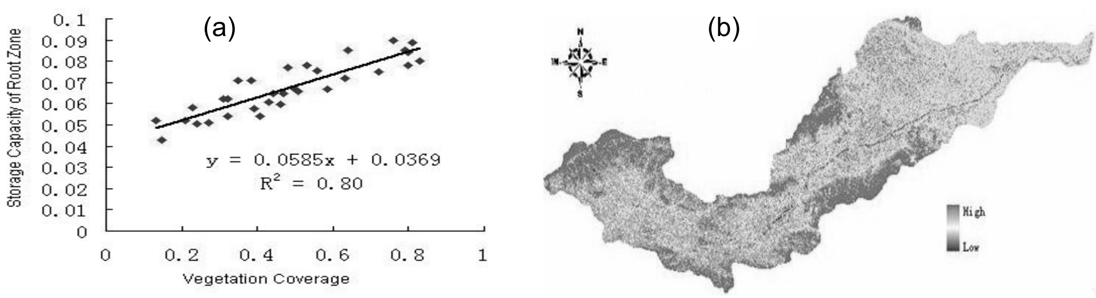

Fig. 9 (a) Related analysis of f_g and SR_{max}. (b) Spatial distribution of SR_{max}.

R^2 is 0.72. The reason is mainly that the increasing of HUI value results in increase of the capacity to produce runoff and the $\ln T_0$ certainly has a smaller value. The spatial distribution is shown in Fig. 8(b).

Correlation analysis of vegetation coverage and SR_{max} The SR_{max} is the maximum storage capacity of the root zone. The average vegetation cover of 32 HUR can be calculated with the flowing formulation using Landsat data.

$$f_g = (NDVI - NDVI_{min})/(NDVI_{max} - NDVI_{min}) \quad (3)$$

The relationship between fg and SR_{max} was established with the correlation coefficient $R^2 = 0.80$ Fig. 9(a). SR_{max} is increasing as vegetation coverage increases. The higher vegetation coverage can result in more soil porosity and thicker humus, so the root maximum water storage capacity is greater. The SR_{max} spatial distribution can be derived from the relationship, Fig. 9(b).

Correlation analysis of NDVI and the water deficit SR_0 The water deficit SR_0 of the root soil saturated area is an evapotranspiration parameter of TOPMODEL. When the gravity drainage layer is exhausted, soil moisture will still evaporate with the rate of E_α. It is calculated with the following formulation:

$$E_{\alpha} = E_{p}(1 - \frac{SR_{0}}{SR_{\max}}) \tag{4}$$

where $SR_{\max}$ is the root maximum water storage capacity; E_p is the evapotranspiration capacity. SR_0 is closely related to evapotranspiration (Fig. 10(a)), correlation coefficient $R^2 = 0.75$. From Fig. 10(a), SR_0 will decrease logarithmically as NDVI increases. A large number of studies show that a strong positive correlation exists between the vegetation evapotranspiration and NDVI. Thus, SR_0 will reduce with the increase of NDVI. The spatial distribution of SR_0 is shown in Fig. 10(b).

(a)

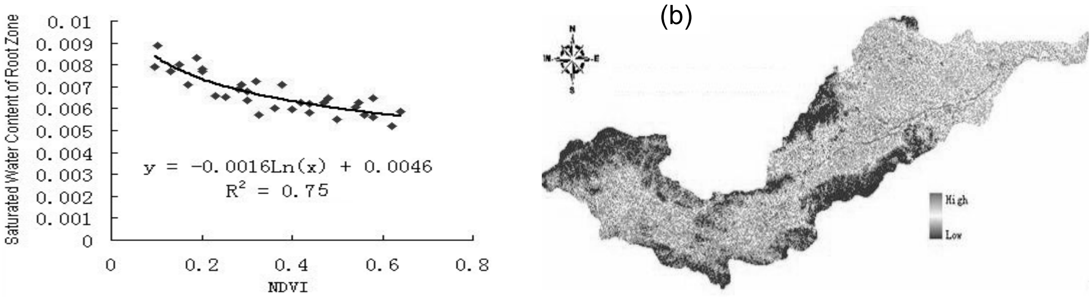

Fig. 10 (a) Correlation of SR_0 and NDV. (b) Distribution map of SR_0.

Test in the verification basin

In order to validate the reliability of the derived parameters using an ungauged basin, this paper uses the artificial calibration parameter set of the artificial calibration as the true value. The efficiency comparison between the derived and calibrated parameters was carried out. Changshui, a sub-basin, was selected as the validation basin, having nine precipitation stations. The simulation results of eight floods for the period 1980–1989 are showed in Table 3; the results of the two parameter sets are very close. This demonstrates that the proposed method is reliable and can be used for flood simulation in data-sparse regions.

Table 3 Simulation result of Changshui sub-basin.

	LDJG: artificial calibration parameters			TZZJG: derived parameters		
	DC	DQ (%)	Δt/h	DC	DQ	Δt/h
820731	0.8541	–8.67	–2	0.8619	–9.04	–1
830729	0.8150	10.82	+1	0.8079	10.21	+2
831003	0.9013	–4.61	0	0.9106	–3.94	–1
850912	0.7963	–12.64	+1	0.7908	–11.56	0
850914	0.7794	11.38	–3	0.7681	12.52	–4
870215	0.8723	8.91	0	0.8813	8.76	+1
880519	0.8817	–8.98	+2	0.8675	–10.28	0
890710	0.8045	10.83	–3	0.8079	10.80	–3

DC: certainty coefficient, DQ: relative errors of the flood peak value; Δt: time errors of peak time appearance.

CONCLUSION

This paper discusses the regionalisation of the main controlling parameters of TOPMODEL. It is demonstrated that the proposal approach of constructing a hydrological response index (HRI) has the capacity for describing basin characteristics. The experimental results have also shown that HRI has the ability of a describer for the regionalisation of the main controlling parameters of

TOPMODEL. These results indicate that the proposed index can be used to represent the model parameters in the study region. Moreover, the index is capable of describing the influences of land-use changes on hydrological processes in the data-sparse region.

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