Streamflow prediction in ungauged basins through geomorphology-based hydrograph transposition

A. de Lavenne, H. Boudhraâ and C. Cudennec

ABSTRACT

Geomorphology-based rainfall–runoff models are particularly helpful for predicting hydrology in ungauged basins. The robustness, generality and flexibility of the modelling approach make it able to deal with a wide variety of processes, events and scales. It allows a rainfall–runoff transfer function to be estimated for any basin without needing to measure discharge. The aim of this study is to transpose hydrological observations from gauged to ungauged basins to predict streamflow hydrographs. It considers pairs of nested and neighbouring basins, the first one providing information for the second ungauged one. A time-series of the donor basin's discharge is deconvoluted by inverting its geomorphology-based transfer function to assess the time-series of net rainfall. The latter is then transposed to the receiver basin, where it is convoluted with the reciever basin's transfer function to predict the hydrograph therein. The methodology was implemented with virtual and real rainfall–runoff events on a set of basins in temperate Brittany, France. Different time scales and spatial configurations were tested. Goodness-of-fit of model predictions varied by basin pair. High prediction accuracy was observed when transposing hydrographs between nested basins differing greatly in size. Several ways to improve the approach are identified by relaxing simplifying assumptions.

Key words | geomorphological unit hydrograph, inverse modelling, prediction in ungauged basins (PUB), rainfall–runoff modelling, regionalisation, ungauged basin

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INTRODUCTION

Runoff prediction in ungauged basins is necessary for better water resource management (Sivapalan *et al.* 2003b; Blöschl *et al.* 2013; Hrachowitz *et al.* 2013). In this context, transposition of information from gauged basins to ungauged basins plays an important role. Concepts of regional basin similarity are often used to extrapolate observations to neighbouring basins. This facilitates the transfer of hydrological measurements (Sauquet *et al.* 2008; Andreassian *et al.* 2012) and model parameters (Fernandez *et al.* 2000; Merz & Blöschl 2004; Buytaert & Beven 2009) and allows basins to be classified (McDonnell & Woods 2004; Wagener *et al.* 2007; He *et al.* 2011).

In data-sparse regions, streamflow prediction models also take advantage of the generality and flexibility of geomorphological observations in basins. Since Sherman (1932) introduced the concept of the unit hydrograph, two main approaches for identifying it have been developed (Cudennec 2007): (1) the topological approach and (2) the geomorphometric approach.

The first one, initiated by Rodríguez-Iturbe & Valdès (1979), is the original Geomorphological Instantaneous Unit Hydrograph. It is based on a probability density function (*pdf*) of water travel-time through the river network by describing transition probabilities between Strahler orders via Horton–Strahler ratios. Several studies have discussed and improved this approach (Gupta *et al.* 1980; Gupta & Waymire 1983; Kirshen & Bras 1983; Rinaldo *et al.* 1991; Cudennec *et al.* 2004).

The second one uses observable geomorphometric functions, employing a schematisation of the flow path length, to determine the Width Function Instantaneous Unit

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Hydrograph (Shreve 1969; Kirkby 1976; Foroud & Broughton 1981; Gupta & Waymire 1983; Gupta & Mesa 1988; Beven & Wood 1993). By being more physically based, the second approach is often prefered to the first one. Indeed, parameterisation of the approach (mainly the flow velocity) can thus be physically estimated in comparison to the first approach in which this parameter is rather a calibration parameter (Franchini & O'Connell 1996). This is the reason why the present work followed the second approach.

Based mainly on easily observable features, thoses studies have opened perspectives for modelling ungauged basins. Indeed, it follows the idea that the shape of the unit hydrograph can be derived mainly from basins' geomorphological characteristics (Rinaldo *et al.* 1995; Rigon *et al.* 2011). The connection between travel times inside the network and over the hillslope provides the main basin response (D'Odorico & Rigon 2003), which is why accurate topological description of the network is important (Moussa 2008a, b) when generating a geomorphology-based unit hydrograph.

In this study, we aim to estimate streamflow in ungauged basins using their neighbouring (or nested) gauged basins' hydrological observations. The approach uses a geomorphometry-based model that was originally applied to virtual rainfall–runoff events in semiarid Tunisian basins (Boudhraâ *et al.* 2006, 2009; Boudhraâ 2007). We employed this methology and put it to the test in a totally different geographic context (French Brittany region) in order to check its genericity. Following a 'top-down' approach (Klemeš 1983; Sivapalan *et al.* 2003a), we introduced complexity from the treatment of real runoff events which allows the limits of the methodology's simplifying assumptions to be identified.

DATA AND METHOD

A geomorphology-based model

The modelling approach is based on defining a production function over the hillslope and a geomorphometry-based transfer function across the network (Wang *et al.* 1981; Gupta & Mesa 1988; Robinson *et al.* 1995; Woods & Sivapalan 1999; Sivapalan *et al.* 2002; Sivapalan 2003).

The transfer function *TF* is built from morphometric analysis of the river network. The flow path length inside the network L (hydraulic length) is calculated throughout the basin from a regular sample grid using the hydrostruct software tool (Cudennec *et al.* 2009; Aouissi *et al.* 2013). This allows the $pdf(L)$ of hydraulic length to be built. Assuming a linear transfer function through the river network (Naden 1992; Beven & Wood 1993; Blöschl & Sivapalan 1995; Robinson *et al.* 1995; Yang *et al.* 2002; Giannoni *et al.* 2003a, b; Rodriguez *et al.* 2005), the mean channel flow velocity is then needed to estimate the *pdf* of the water travel time t through the river network ($pdf(t)$). Mean channel flow velocity was estimated from a sample of runoff events detected between 2000 and 2008 (on average per basin, 60 runoff events detected per year). For each basin and each runoff event, channel flow velocity is calculated from the following equation:

$$v_i = \frac{\bar{L}}{t_i} \tag{1}$$

where $\bar{L}$ is the mean hydraulic length of the basin and t_i the rise time of the runoff event i. The mean velocity for each basin is then calculated to provide a constant velocity over time and space. In this approach, estimation of channel flow velocity requires runoff measures. These data are not available in ungauged basins, but in this study we do not address the challenge of estimating velocity in ungauged basins. As runoff measures were available for each basin, we calibrated a velocity using runoff data for each basin.

Assuming a linear and time invariant basin response, each impulse of net rainfall vector $R_n[m]$ is spread over time $t[s]$ according to the unit hydrograph $pdf(t) = TF(t)$ in order to estimate the discharge at the outlet $Q[m^3 \cdot s^{-1}]$. This calculation is made by the following convolution:

$$Q(t) = S \cdot R_n(t) * TF(t) \tag{2}$$

where $S[m^2]$ is the basin's surface area. When used in previous studies (Cudennec *et al.* 2005, 2009; Rodriguez *et al.* 2005), this approach was able to handle spatio-temporal variability well.

Principle of deconvolution and hydrograph transposition

This study aimed to transpose streamflow hydrographs from a donor basin to a receiver basin. Simulation is based on estimation of a net rainfall R_n time-series and its transposition between basins. Net rainfall is defined as the depth of runoff provided by a basin's hillslope to its river network. Considering pairs of nested and neighbouring basins, estimated net rainfall of one is used to represent the other. The time-series of discharge of the donor basin is deconvoluted by inverting its geomorphology-based transfer function to estimate the time-series of net rainfall. The latter is then transposed to the receiver basin, where it can be reconvoluted with its own transfer function to predict the hydrograph therein (Figure 1). By using only a basin's transfer function, production functions do not need to be estimated, thereby avoiding development of heterogeneous and highly non-linear functions.

Basins studied and transpositions tested

Six gauged basins were studied in Brittany, France (Figure 2). Five gauged basins were located in the surroundings of the Coët-Dan basin around Naizin, part of the French network of basins for environmental research (SOERE RBV, focused on the critical zone, www.inra.fr/ore_agrhys_eng (Gascuel-Odoux *et al.* 2010)). Implemented transpositions included the Coët-Dan basin around Naizin (CN, 4.9 km^2), to investigate its role as a data source, and the Fremeur basin around Guénin (FG, 15.1 km^2), to investigate additional spatial configurations. Hydrographs of these two basins are transposed to every other which are: Fremeur around Plumeliau (FP, 5.8 km^2), Coët-Organ around Quistinic (CQ, 47.7 km^2), Claie around Saint-Jean-Brévelay (CS, 137 km^2) and Evel around Guénin (EG, 316 km^2). In this way, hydrographs were transposed by exploring the following spatial configurations: (1) between nested basins (e.g., FP and FG), (2) between neighbouring basins (e.g., CN and CQ) and (3) between basins with large size differences (e.g., CN and EG).

The region has relatively high annual rainfall (mean of 817 mm per hydrological year at CN's raingauge over the period studied), homogeneous geology in the EG basin (shale; mostly granite and metamorphic schist in the others) and high agricultural land use (>80% on average).

Hydrograph transpositions were performed at annual and runoff-event temporal scales for the period from October 2000 to October 2008. Except for CN, which is instrumented at a high-resolution time step (6 min), runoff data were obtained from the national French database (HYDRO, www.hydro.eaufrance.fr) at a variable time step for each basin. Runoff measures were thus available for every basin. However, when a basin was considered 'ungauged', its runoff measures were not used for simulations (except to estimate its channel flow velocity for its transfer function). Simulations were performed on a 1-hour time step.

Net rainfall estimation

Deconvolution aims to determine the net rainfall vector series R_n that best reconstitutes the observed outflow vector series Q_{obs} according to the model given by

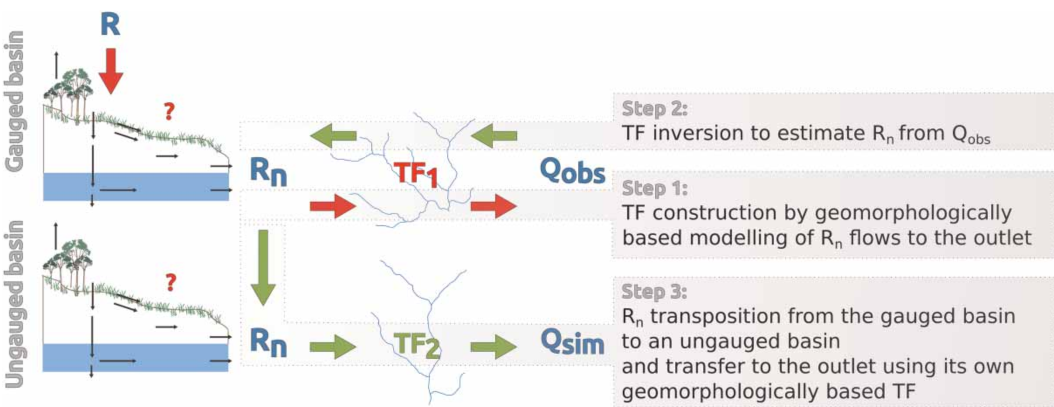

Figure 1 | The principle of streamflow hydrograph transposition.

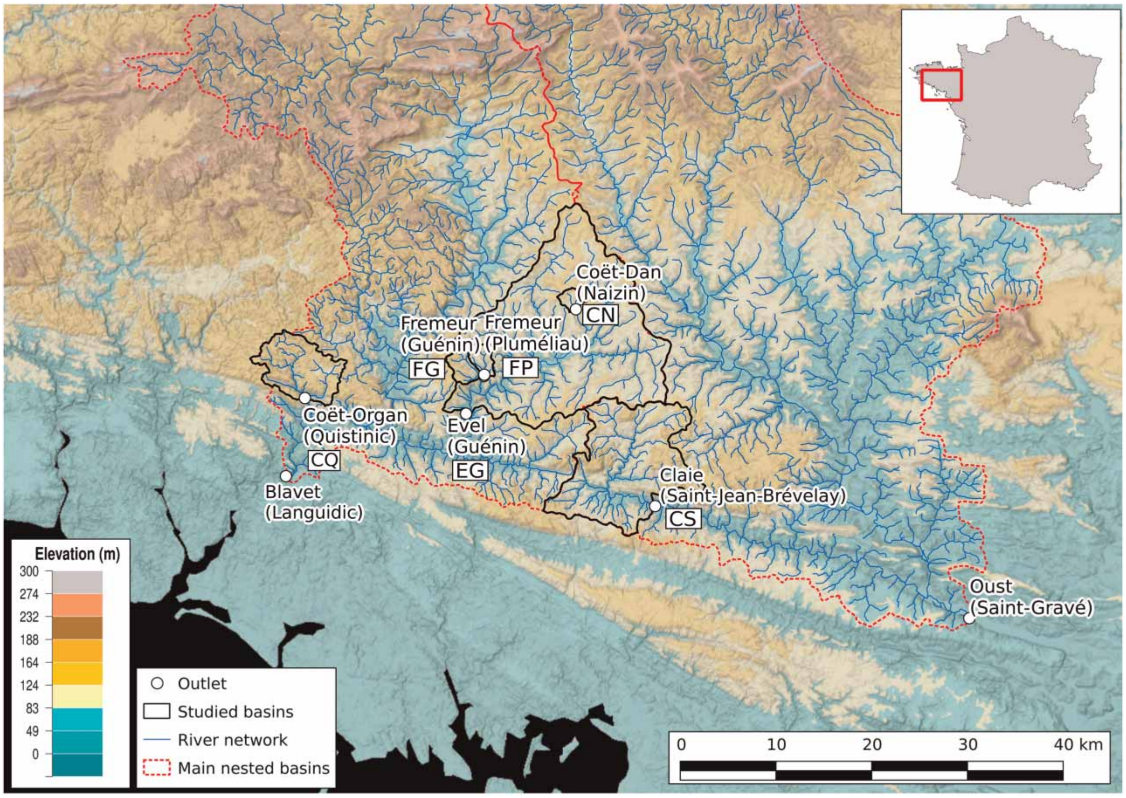

Figure 2 | Spatial organisation of the six basins studied in Brittany, France.

Equation (2). It is an inverse problem (Tarantola & Valette 1982; Menke 1989) that consists of minimising the following:

$$(Q - Q_{\text{obs}})^T \cdot (C_Q^{\text{obs}})^{-1} \cdot (Q - Q_{\text{obs}}) + (R_n - R_n^{ap})^T \cdot (C_{Rn}^{ap})^{-1} \cdot (R_n - R_n^{ap}) \quad (3)$$

where R_n^{ap} is initialising *a priori* information about the vector sought, C_{Rn}^{ap} and C_Q^{obs} are covariance matrices for vectors R_n^{ap} and Q_{obs}, and superscript T is the matrix transpose. R_n^{ap} is estimated from specific discharge of Q_{obs} delayed by its time of rise.

Based on previous studies (Boudhraâ *et al.* 2006, 2009; Boudhraâ 2007), and according to the inverse problems theory (Tarantola & Valette 1982; Menke 1989), a maximum likelihood solution can be obtained as follows:

$$R_n = R_n^{ap} + C_{Rn}^{ap} \cdot TF^T \cdot (TF \cdot C_{Rn}^{ap} \cdot TF^T + C_Q^{\text{obs}})^{-1} \cdot (Q_{\text{obs}} - TF \cdot R_n^{ap}) \quad (4)$$

Performing this deconvolution is based on: (1) assessing errors related to the Q_{obs} and R_n^{ap} data that need to be parameterised, assuming that errors are 0-centred Gauss-distributed, and (2) initialising via *a priori* assessment of the R_n^{ap} parameters sought.

Prediction accuracy

Prediction accuracy was assessed with three criteria. The first one is the Nash–Sutcliffe efficiency (NSE) criterion calculated for annual simulations and runoff-event simulations (Equation (5)).

$$\text{NSE} = 1 - \frac{\sum_{i=1}^{N} (P_i - O_i)^2}{\sum_{i=1}^{N} (O_i - \bar{O})^2} \quad (5)$$

where P and O are predicted and observed runoff values, respectively. The second and the third criteria are calculated for runoff-event simulations only. It is the absolute differences in specific discharge ΔQ and the absolute temporal difference ΔT between predicted peak flow and observed peak flow. These two criteria are added in order to put the NSE into perspective which can decrease largely simply because of a lag translation or an homothetic ratio (Moussa 2010).

Three additional simulations were performed to appreciate the effect of the inversion.

The first assessed robustness of the deconvolution: net rainfall estimated by hydrograph deconvolution was convoluted onto the same basin, enabling accuracy of the donor basin's net rainfall to be checked before transposing it to a second basin.

The second was performed after transposing estimated net rainfall to the receiver basin. Predicted runoff on the receiver basin was compared to the transposed specific discharge using:

$$Q_2 = \frac{A_2}{A_1} Q_1 \quad (6)$$

where Q_1 and A_1 are respectively the observed runoff and the area of the donor basin, and Q_2 and A_2 are respectively the observed runoff and the area of the receiver basin.

The third was performed with 'virtual runoff events'. Eight runoff events per hydrological year, from 2000 to 2008, were chosen from the CN basin (Figure 2) by selecting the eight largest annual runoff values. By assessing the corresponding net rainfall time-series (applying inversion to the CN basin), 'virtual runoff events' were simulated (convolution of CN's net rainfall time-series on every basin using their own transfer functions). The resulting 64 runoff simulations, an idealised scenario of homogeneous net rainfall among basins, were then considered as 'observed' runoff events with which the model could be run. To compare this idealised case to reality, corresponding 'real events' were obtained by selecting runoff observations that occurred during the same temporal boundaries as those of the 'virtual events'. All algorithms were implemented in R 2.14 (R Development Core Team 2012).

RESULTS

Model parametrisation and consistency of net rainfall estimation

The two most sensitive parameters in the inversion algorithm have proved to be Ap and Tp (Boudhraâ et al. 2006, 2009; Boudhraâ 2007). These parameters are constants used in the calibration of C_{Rn}^{ap} which quantify the error made by R_n^{ap} to estimate R_n. A parameterisation is performed from the 64 virtual runoff events in order to estimate Ap and Tp values. For each runoff event, the net rainfall estimated by hydrograph deconvolution was convoluted onto the same basin. For each basin, isomaps showed NSE close to 1 for most parameter combinations (Figure 3). These high NSE values demonstrate that estimated net rainfall was consistent with the donor's transfer function, indicating high robustness of the inversion. The Tp optimum values from the NSE isomaps of Figure 3 are relatively similar between basins. In contrast, the Ap optimum values decreased with basin area (Table 1).

Annual runoff simulations

When compared to a control simulation based on transposed specific discharge, median NSE values of the eight annual simulations for transposed specific discharge had high NSE values between basins of similar size (Table 2). These results were sometimes more accurate than when inversion was used (e.g., simulation from FG to FP). However, prediction accuracy of specific discharge Q_{spec} decreased as the difference in size between donor and receiver basins increased (e.g., simulations from FG to EG).

In comparison, accuracy of model predictions was more constant, median NSE values of the 8 years varying from 0.01 to 0.90. The highest accuracy was obtained for the two small nested basins FG and FP (NSE = 0.85 and 0.90 when FG was donor and receiver, respectively). The lowest accuracy was observed when simulating from FG to CN even though they looked quite similar according to their basins' area. In contrast, good accuracy was also obtained between basins with large size differences (e.g.,

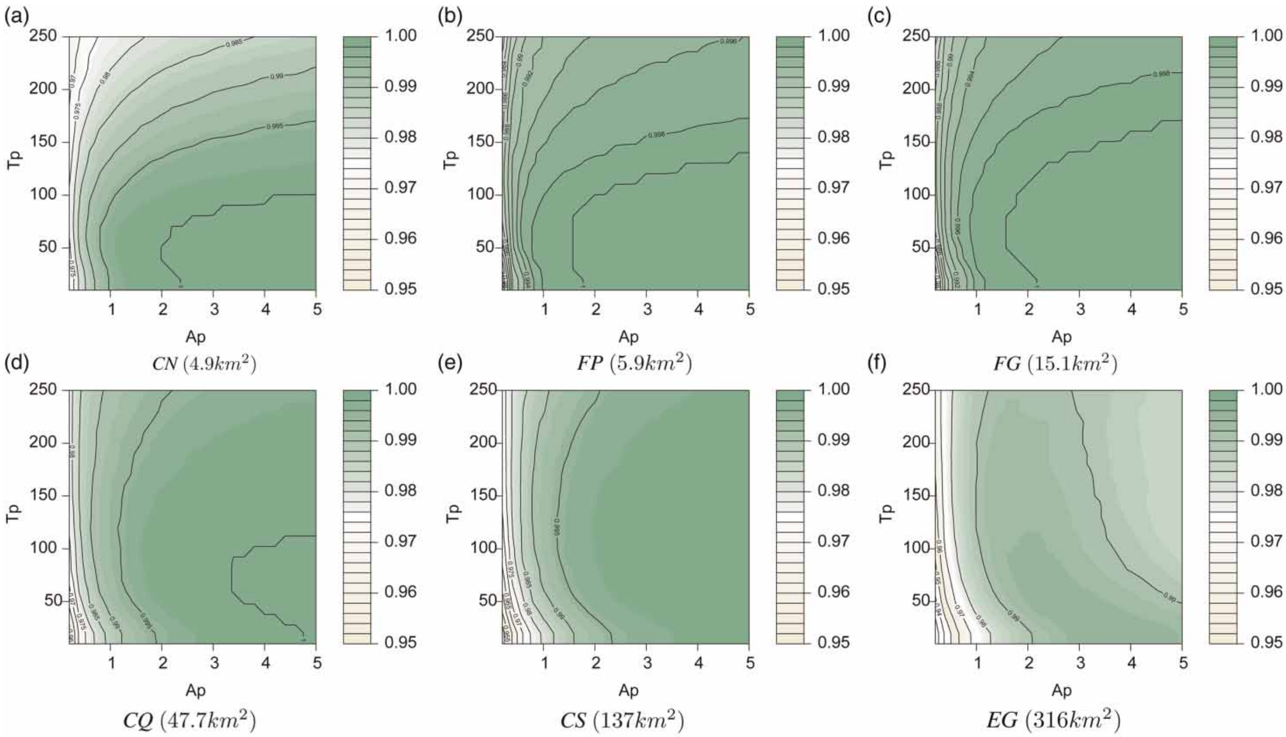

Figure 3 | Isomaps of mean NSE coefficients of predicted runoff of 64 discharge events for six basins according to variations in the two most sensitive parameters (*Ap* and *Tp*). For each basin, estimated net rainfall is convoluted onto the same donor basin.

Table 1 | Parameters selected for inversions

Basin	Ad	Ap	Bd	Bp	Tp	Dd
CN	0.2	5	0.01	0.01	50	1
FP	0.2	5	0.01	0.01	50	1
FG	0.2	5	0.01	0.01	50	1
CQ	0.2	5	0.01	0.01	50	1
CS	0.2	4	0.01	0.01	50	1
EG	0.2	3	0.01	0.01	50	1

between CN and EG). These results indicate that the model is particularly useful for transposing hydrological data between basins with large size differences. In other words, these results confirm the interest of estimating net rainfall as a scale-independent intermediate variable which makes the hydrograph transposition easier than a simple specific discharge transposition.

Simulation predictions involving CN were generally more accurate at an 8-year scale compared to a one-year scale (eight simulations summarised by the NSE median value). In contrast, simulation predictions involving FG were generally more accurate at the 1-year scale, demonstrating variability in prediction accuracy among years.

Even though prediction accuracy differed at an 8-year scale compared to a 1-year scale, the previous conclusion about scale-independent quality of the model is still valid. For example, despite a large size difference between CN (donor) and EG (receiver), runoff predictions fit observed runoff well throughout the year (Figure 4(a)). In contrast, between CQ (donor) and FG (receiver), simulation consistently overestimated runoff, especially between runoff events, which may illustrate differences in their characteristics that produce runoff (Figure 4(b)). The latter result emphasises the need for a better understanding of the hydrological similarity between the donor and the receiver basin in order to be able to predict and/or improve the accuracy of each transposition. Indeed, the methodology allows us to go beyond the challenge of transposing hydrological measures between small and large basins, relatively, to each other.

Table 2 | Median NSE criteria for one runoff simulation of 8 hydrologic years and eight simulations of 1 hydrologic year. Predicted runoff is compared to a control simulation based on transposition of specific discharge (Q_{spec})

		8-year simulation		1-year simulations	
Donor basin	Receiver basin	NSE model	Q_{spec}	Median NSE model	Q_{spec}
CN	CQ	0.68	0.65	0.58	0.57
	CS	0.83	0.65	0.77	0.52
	EG	0.88	0.68	0.88	0.66
	FP	0.67	0.69	0.64	0.67
	FG	0.56	0.56	0.55	0.57
FG	CQ	0.37	0.13	0.75	0.58
	CS	0.11	−0.66	0.57	0.01
	EG	−0.08	−0.99	0.59	−0.15
	FP	0.75	0.82	0.85	0.93
	CN	−0.82	−0.62	0.01	−0.07
CQ	CN	0.22	0.43	0.12	0.31
CS		0.68	0.63	0.66	0.59
EG		0.77	0.70	0.77	0.68
FP		0.17	0.30	0.34	0.35
CQ	FG	0.57	0.62	0.53	0.61
CS		0.62	0.52	0.67	0.55
EG		0.56	0.48	0.63	0.53
FP		0.86	0.89	0.90	0.94

Moreover, for a given pair of basins, NSE values varied depending on which basin was considered to be the donor. For instance, in contrast to FG, CN gave more accurate predictions as a donor than as a receiver. However, the same results were observed on the Q_{spec} transposition which allows the conclusion that this was not due to the inversion calculation. This result was also noticed at a runoff-event time scale, but where multicriteria evaluation of simulations allows the reason to be dealt with in depth.

Runoff-event simulations

From a general overview of the NSE, the efficiency of the runoff simulations is much lower at an event time scale (Table 3) than at the annual scale (Table 2). This analysis can be related to the fact that annual efficiency qualifies the global behaviour of the model and how it fits the water balance. In contrast, with event time scale models, simulation evaluation qualifies a restricted period of time which might, for instance, be very dependent on the exact timing of the peak.

Similarly to annual scale results, higher values of NSE were obtained between FG and FP. However, for this pair of basins, simulations still have shown lower efficiency than from transposing Q_{spec}. Transposition involving distant and neighbouring basins (e.g., transpositions to CQ) were often less accurate than close or nested basins, highlighting a spatial limitation of hydrograph transposition. Once again, the advantage of the model compared to Q_{spec} transposition was here confirmed when the area of the donor and the receiver basins is quite different (transpositions involving CN or EG).

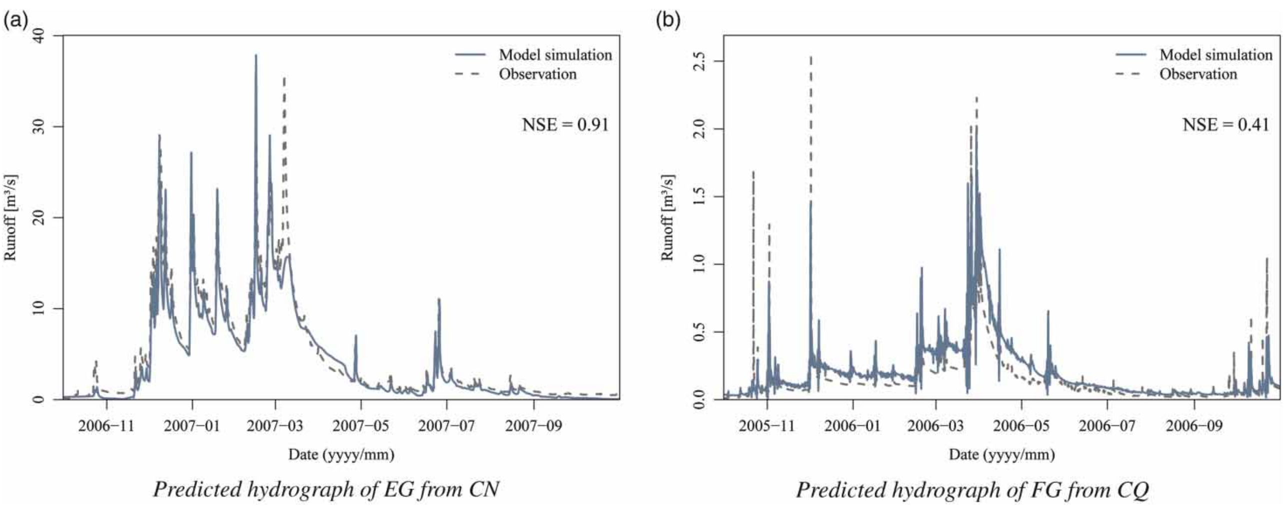

Figure 4 | Predicted annual runoff for two hydrograph transpositions. (a) Basin CN's net rainfall transposed to basin EG for the hydrological year 2006–2007. (b) Basin CQ's net rainfall transposed to basin FG for the hydrological year 2005–2006.

Table 3 | Median efficiency criteria for 64 runoff-event simulations: NSE, difference in specific discharge ΔQ(10^{-9}m · s^{-1}) and difference in time ΔT(h) between observed and predicted peak flows. Predicted runoff is compared to a control simulation based on transposition of specific discharge. Virtual runoff events, made by convoluting basin CN's net rainfall events onto the other basins, are compared to the corresponding observed runoff events

		Virtual events						**Observed events**					
Donor	**Receiver**	**Median NSE**		**Median ΔT**		**Median ΔQ**		**Median NSE**		**Median ΔT**		**Median ΔQ**	
basin	**basin**	**model**	Q_{spec}	**model**	Q_{spec}	**model**	Q_{spec}	**model**	Q_{spec}	**model**	Q_{spec}	**model**	Q_{spec}
CN	CQ	1.00	– 0.05	0.00	7.00	0.02	13.57	– 2.29	– 2.52	5.00	4.00	15.63	16.92
	CS	1.00	– 1.44	0.00	19.00	0.02	15.23	– 0.42	– 3.06	6.00	15.00	10.32	13.51
	EG	1.00	– 2.11	0.00	25.00	0.03	16.87	– 0.21	– 3.18	7.00	18.00	5.85	25.50
	FP	1.00	0.80	0.00	1.00	0.03	2.61	– 0.25	– 0.09	2.00	2.00	19.86	19.00
	FG	1.00	0.96	0.00	0.00	0.03	2.92	0.15	0.16	1.00	1.00	30.03	22.19
FG	CQ	1.00	– 0.02	0.00	8.00	0.07	8.79	– 0.88	– 2.14	4.00	4.00	13.36	20.79
	CS	1.00	– 1.38	0.00	19.00	0.05	9.99	– 1.75	– 6.39	6.00	14.00	12.99	33.51
	EG	1.00	– 2.07	0.00	25.00	0.03	12.04	– 1.37	– 6.70	7.00	18.00	12.53	41.16
	FP	1.00	0.93	0.00	1.00	0.10	0.20	0.55	0.83	1.00	0.00	5.54	9.47
	CN	1.00	0.97	0.00	0.00	0.29	2.92	– 1.00	– 0.56	2.00	1.00	33.38	22.19
CQ	CN	1.00	0.40	0.00	7.00	1.48	13.57	– 2.04	– 0.70	5.00	4.00	19.47	16.92
CS		0.99	– 0.30	0.00	19.00	2.71	15.23	– 0.15	– 0.56	5.00	15.00	14.30	13.51
EG		0.96	– 0.43	0.00	25.00	4.96	16.87	– 0.17	– 0.38	6.00	18.00	13.47	25.50
FP		1.00	0.81	0.00	1.00	0.35	2.61	– 1.34	– 0.23	3.00	2.00	21.14	19.00
CQ	FG	1.00	0.34	0.00	8.00	0.75	8.79	– 0.65	– 0.08	5.00	4.00	16.14	20.79
CS		1.00	– 0.39	0.00	19.00	1.54	9.99	0.01	– 0.42	4.00	14.00	30.99	33.51
EG		0.98	– 0.52	0.00	25.00	3.03	12.04	– 0.12	– 0.53	7.00	18.00	34.40	41.16
FP		1.00	0.93	0.00	1.00	0.14	0.20	0.70	0.87	2.00	0.00	13.59	9.47

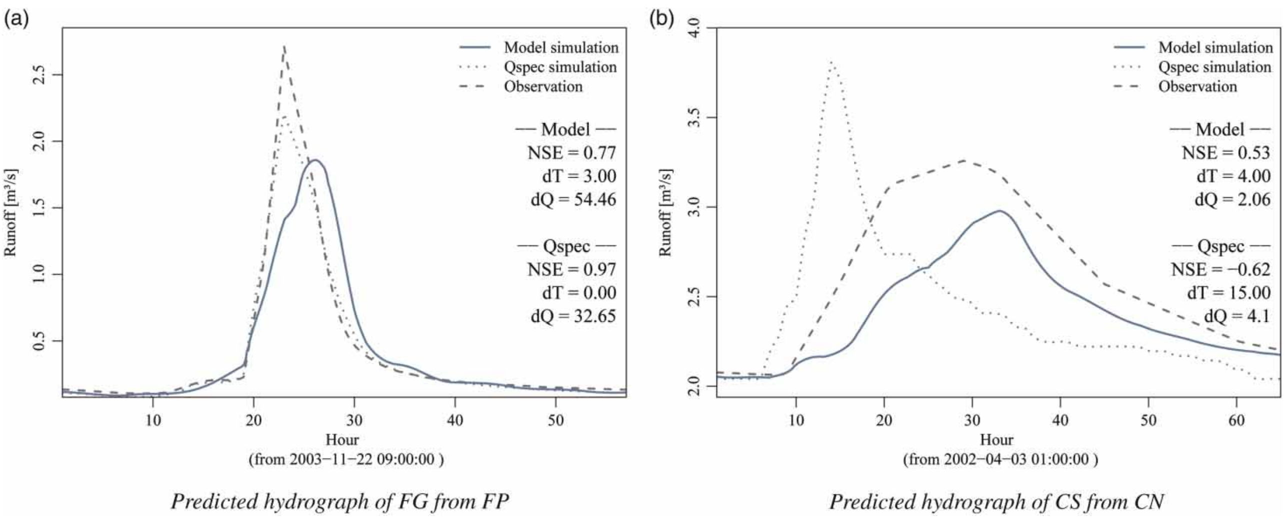

Figure 5 | Predicted single-event runoff for two hydrograph transpositions. (a) Basin FP's net rainfall transposed to basin FG for one runoff event. (b) Basin CN's net rainfall transposed to basin CS for one runoff event.

Different prediction errors occurred, such as delay and underestimation (respectively overestimation) of predicted peak flow, which can be explained by underestimating (respectively overestimating) the channel flow velocity used in the transfer function. Between the two nested basins FG and FP (Figure 5(a)), and from the look of Q_{spec} transposition which described better timing of the peak, it seems that the runoff characteristic of the donor basin would have helped to estimate this velocity. If this is true between those two nested basins, this is however far from the truth when basins' size difference increased as important delays are observed using Q_{spec} transposition (Figure 5(b)). In this way, the reason for the benefit of the model is highlighted by the fact that the model is able to consider the receiver's own channel flow velocity.

However, velocity estimation was not the only possible error observed. In other simulations, such as from CN to CS, even if channel flow velocity seemed to be well described, the model underestimated runoff throughout the runoff event (Figure 5(b)), which can be interpreted as differences in rainfall and/or runoff production between basins. This result highlights a weak point of the model: net rainfall heterogeneity between the donor and the receiver basins is not accounted for. However, for this particular pair of basins and despite the hypothesis of net rainfall homogeneity, the model enables access to simulations that fit much better the observation than the Q_{spec} transposition.

Similarly for annual time scale observations, for a given pair of basins, no reciprocity was noticed between simulation efficiency when donor and receiver roles were switched. Comparisons of the different criteria helped to understand the reason. Indeed, from the look of ΔT and ΔQ, no differences can be noticed between Q_{spec} simulation efficiency when donor and receiver roles were switched. Nevertheless, from the look of the NSE criteria differences are observed, and this can be explained by the mathematical formulation of the NSE criteria where observation and simulation vectors cannot be switched (cf. Equation (5)). For this reason, as opposed to ΔT and ΔQ, the NSE criteria cannot be used to check the reciprocity of simulation quality when donor and receiver roles are switched. When focusing on ΔT and ΔQ to check donor and receiver role reciprocity, some differences of simulation efficiency were observed when using the model but not when using Q_{spec} simulations. This allows the conclusion that deconvolution/convolution calculation introduces a bias in the donor and receiver role simulation's efficiency reciprocity. This bias is very low from the look of ΔT but can be relatively important when looking at ΔQ (e.g., $\Delta Q = 1.253 \cdot 10^{-8} \mathrm{m \cdot s^{-1}}$ when transposing from FG to EG but $\Delta Q = 3.440 \cdot 10^{-8} \mathrm{m \cdot s^{-1}}$ when transposing from EG to FG).

In the idealised context of an homogeneous net rainfall between basins, high quality simulations were observed with NSE criteria equal to 1, and with ΔT and ΔQ close or equal to 0. In comparison, transposition of Q_{spec} implied much lower quality simulation. This result highlights the approach robustness. In comparison to real event simulation, it also highlights the importance of the hypothesis of an homogeneous net rainfall between basins underlying its transposition. Nevertheless, this result demonstrates the high potential of the approach if a correction of the net rainfall can be provided before being transposed to another basin.

Even for virtual events, some pairs of basins however implied simulation quality inferior to the others with NSE values under 1 (but still very close to 1). Once again, a slight bias due to the deconvolution/convolution process was observed. Indeed, net rainfall estimated by inversion was not exactly the one that was used to build the virtual event. This bias was particularly noticeable when inversion was done on larger basins (CS and EG), yet the inversion on those two basins used a parameterisation of the inversion slightly different. It is then possible to make the hypothesis that this bias is due to parametrisation.

DISCUSSION AND CONCLUSION

A net rainfall time-series can be estimated in a robust and general manner by inversing a geomorphology-based network transfer function. This unmeasurable variable is useful hydrological information that can be estimated easily from every gauged basin. Transposing it to an ungauged basin enables a streamflow hydrograph to be predicted. We applied this methodology to pairs of nested and neighbouring basins, with size varying from 5 to 316 km^2 in Brittany, temperate oceanic France. Simulations were performed at different time scales (several years, 1 year and one rainfall event). We explored model predictions of idealised virtual events (runoff based on homogeneous net rainfall among basins) and observed events.

For each pair of basins, the model made accurate predictions for virtual events, but accuracy decreased for observed events. Consequently, prediction accuracy should increase if estimates of net rainfall can be corrected before being transposed, suggesting the potential of the approach. However, this correction involves being able to assess differences in net rainfall production between the gauged and ungauged basin. And for this reason, next efforts should focus on accounting for the fact that the donor and receiver basins might not have received the same gross rainfall and their hillslope might not behave the same for producing runoff.

Annual simulations demonstrate that prediction accuracy varies from year-to-year but can be high, even when donor and receiver basins have greatly different sizes. This emphasises the benefit of assessing a scale-independent intermediate variable in order to transpose outlet runoff measurements. Lower accuracy of annual simulations was often due to over- or underestimating baseflow. Indeed, the geomorphology-based approach is better adapted to describe surface runoff rather than runoff production over hillslopes or slow flow components such as groundwater flow. Consequently, differences in these processes between basins could decrease prediction accuracy. However, when basins have similar runoff production from hillslopes, prediction accuracy is high.

At the event time scale, the model is limited by two main simplifying assumptions. First, assuming a constant channel flow velocity leads to delays in predicted peakflow. Considering temporal variability in velocity should decrease this delay, but estimating velocity in ungauged basins remains difficult. Second, assuming an homogeneity in runoff-production functions and spatio-temporal rainfall patterns between donor and receiver basins leads to differences in predicted peakflow values. However, previous works demonstrate that the approach is able to consider variability in rainfall (Cudennec *et al.* 2005; Chargui *et al.* 2009).

In conclusion, this method shows high potential to predict streamflow in ungauged basins. Based on a robust geomorphology-based transfer function, it allows assessment of a scale-independent hydrological variable that can be transfered across scales between basins. Indeed, by estimating net rainfall as the depth of runoff provided by the hillslope to the river network, one can compare and transfer hydrological information between basins with large differences in size. However, in order to be able to predict and improve simulation efficiency, this work should be carried on by studying the question of hydrological similarity which underlies an efficient transposition (Andreassian *et al.* 2012; Blöschl *et al.* 2013; Hrachowitz *et al.* 2013).

REFERENCES

Andreassian, V., Lerat, J., Le Moine, N. & Perrin, C. 2012 Neighbors: nature's own hydrological models. *J. Hydrol.* **414**, 49–58.

Aouissi, J., Pouget, J., Boudhraâ, H., Storer, G. & Cudennec, C. 2013 Joint spatial, topological and scaling analysis framework of river-network geomorphometry. *Géomorphologie: Relief, Processus, Environnement* **1**, 7–16.

Beven, K. & Wood, E. 1993 *Channel Network Hydrology*. John Wiley & Sons Ltd, Chichester, UK, pp. 99–128.

Blöschl, G. & Sivapalan, M. 1995 Scale issues in hydrological modelling: a review. *Hydrol. Process.* **9** (3–4), 251–290.

Blöschl, G., Sivapalan, M., Wagener, T., Viglione, A. & Savenije, H. 2013 *Runoff Prediction in Un-gauged Basins. Synthesis across Processes, Places and Scales*. Cambridge University Press, Cambridge, UK.

Boudhraâ, H. 2007 Modélisation pluie-débit à base géomorphologique en milieu semi-aride rural tunisien: association d'approches directes et inverses [Geomorphology-based rainfall–runoff modelling in semiarid Tunisian area: combination of direct and inverse approaches]. PhD thesis, Institut National Agronomique de Tunisie à Tunis.

Boudhraâ, H., Cudennec, C., Slimani, M. & Andrieu, H. 2006 *Inversion d'une modélisation de type hydrogramme unitaire à base géomorphologique: interprétation physique et première mise en oeuvre* [*Inversion of a geomorphology-based unit hydrograph model: physical interpretation and first implementation*]. IAHS Publ. 303, 391–399, IAHS Press, Wallingford, UK.

Boudhraâ, H., Cudennec, C., Slimani, M. & Andrieu, H. 2009 *Hydrograph Transposition between Basins through a Geomorphology-based Deconvolution-reconvolution Approach*. IAHS Publ. 333, 76–83, IAHS Press, Wallingford, UK.

Buytaert, W. & Beven, K. 2009 Regionalization as a learning process. *Water Resour. Res.* **45** (11), W11419.

Chargui, S., Cudennec, C., Slimant, M., Pouget, J. & Aouissi, J. 2009 *Robust and Flexible Hydroinformatics to Account for Rainfall Space-Time Variability in a Data-sparse Region*. IAHS Publ. 333, 295–301, IAHS Press, Wallingford, UK.

Cudennec, C. 2007 On width function-based unit hydrographs deduced from separately random self-similar river networks and rainfall variability: discussion of "Coding random self-similar river networks and calculating geometric distances: 1. General methodology" and "2. Application to runoff simulations". *Hydrolog. Sci. J.* **52** (1), 230–237.

Cudennec, C., Fouad, Y., Gatot, I. & Duchesne, J. 2004 A geomorphological explanation of the unit hydrograph concept. *Hydrol. Process.* **18** (4), 603–621.

Cudennec, C., Slimani, M. & Le Goulven, P. 2005 Accounting for sparsely observed rainfall space-time variability in a rainfall-runoff model of a semiarid Tunisian basin. *Hydrolog. Sci. J.* **50** (4), 617–630.

Cudennec, C., Pouget, J., Chargui, S., Boudhraâ, H., Jaffrezic, A. & Slimani, M. 2009 *Geomorphology-structured Hydroinformatics for Downward Basin Modelling with Flexible Accounting for Net Rainfall Variability*. IAHS Publ. 331, 254–260, IAHS Press, Wallingford, UK.

D'Odorico, P. & Rigon, R. 2003 Hillslope and channel contributions to the hydrologic response. *Water Resour. Res.* **39** (5), 1–9.

Fernandez, W., Vogel, R. & Sankarasubramanian, A. 2000 Regional calibration of a watershed model. *Hydrolog. Sci. J.* **45** (5), 689–707.

Foroud, N. & Broughton, R. S. 1981 Flood hydrograph simulation model. *J. Hydrol.* **49** (1–2), 139–153.

Franchini, M. & O'Connell, P. E. 1996 An analysis of the dynamic component of the geomorphologic instantaneous unit hydrograph. *J. Hydrol.* **175** (1–4), 407–428.

Gascuel-Odoux, C., Weiler, M. & Molenat, J. 2010 Effect of the spatial distribution of physical aquifer properties on modelled water table depth and stream discharge in a headwater catchment. *Hydrol. Earth Syst. Sci.* **14** (7), 1179–1194.

Giannoni, F., Roth, G. & Rudari, R. 2003a Can the behaviour of different basins be described by the same model's parameter set? A geomorphologic framework. *Phys. Chem. Earth* **28** (6–7), 289–295.

Giannoni, F., Smith, J. A., Zhang, Y. & Roth, G. 2003b Hydrologic modeling of extreme floods using radar rainfall estimates. *Adv. Water. Resour.* **26** (2), 195–203.

Gupta, V. K. & Mesa, O. J. 1988 Runoff generation and hydrologic response via channel network geomorphology – Recent progress and open problems. *J. Hydrol.* **102** (1–4), 3–28.

Gupta, V. K. & Waymire, E. 1983 On the formulation of an analytical approach to hydrologic response and similarity at the basin scale. *J. Hydrol.* **65** (1–3), 95–123.

Gupta, V. K., Waymire, E. & Wang, C. T. 1980 A representation of an instantaneous unit hydrograph from geomorphology. *Water Resour. Res.* **16** (5), 855–862.

He, Y., Bárdossy, A. & Zehe, E. 2011 The role of catchment classification in rainfall-runoff modeling. *Hydrol. Earth Syst. Sci. Discuss.* **8** (3), 6113–6153.

Hrachowitz, M., Savenije, H., Blöschl, G., McDonnell, J., Sivapalan, M., Pomeroy, J., Arheimer, B., Blume, T., Clark, M., Ehret, U., Fenicia, F., Freer, J., Gelfan, A., Gupta, H., Hughes, D., Hut, R., Montanari, A., Pande, S., Tetzlaff, D., Troch, P., Uhlenbrook, S., Wagener, T., Winsemius, H., Woods, R., Zehe, E. & Cudennec, C. 2013 A decade of Predictions in Ungauged Basins (PUB) – a review. *Hydrolog. Sci. J.* **58** (6), 1198–1255.

Kirkby, M. J. 1976 Tests of the random network model, and its application to basin hydrology. *Earth Surf. Process.* **1**, 197–212.

Kirshen, D. M. & Bras, R. L. 1983 The linear channel and its effect on the geomorphologic IUH. *J. Hydrol.* **65** (1–3), 175–208.

Klemeš, V. 1983 Conceptualization and scale in hydrology. *J. Hydrol.* **65** (1–3), 1–23.

McDonnell, J. & Woods, R. 2004 On the need for catchment classification. *J. Hydrol.* **299** (1–2), 2–3.

Menke, W. 1989 *Geophysical Data Analysis: Discrete Inverse Theory*, vol 45. Academic Press, San Diego, CA.

Merz, R. & Blöschl, G. 2004 Regionalisation of catchment model parameters. *J. Hydrol.* **287** (1–4), 95–123.

Moussa, R. 2008a Effect of channel network topology, basin segmentation and rainfall spatial distribution on the geomorphologic instantaneous unit hydrograph transfer function. *Hydrol. Process.* **22** (3), 395–419.

Moussa, R. 2008b What controls the width function shape, and can it be used for channel network comparison and regionalization? *Water Resour. Res.* **44** (8).

Moussa, R. 2010 When monstrosity can be beautiful while normality can be ugly: assessing the performance of event-based flood models. *Hydrolog. Sci. J.* **55** (6), 1074–1084.

Naden, P. S. 1992 Spatial variability in flood estimation for large catchments: the exploitation of channel network structure. *Hydrolog. Sci. J.* **37** (1), 53–71.

R Development Core Team 2012 *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria.

Rigon, R., D'Odorico, P. & Bertoldi, G. 2011 The geomorphic structure of the runoff peak. *Hydrol. Earth Syst. Sci.* **15** (6), 1853–1863.

Rinaldo, A., Marani, A. & Rigon, R. 1991 Geomorphological dispersion. *Water Resour. Res.* **27** (4), 513–525.

Rinaldo, A., Vogel, G., Rigon, R. & Rodriguez-Iturbe, I. 1995 Can one gauge the shape of a basin. *Water Resour. Res.* **31** (4), 1119–1127.

Robinson, J. S., Sivapalan, M. & Snell, J. D. 1995 On the relative roles of hillslope processes, channel routing, and network geomorphology in the hydrologic response of natural catchments. *Water Resour. Res.* **31** (12), 3089–3101.

Rodriguez, F., Cudennec, C. & Andrieu, H. 2005 Application of morphological approaches to determine unit hydrographs of urban catchments. *Hydrol. Process.* **19** (5), 1021–1035.

Rodríguez-Iturbe, I. & Valdès, J. B. 1979 The geomorphologic structure of hydrologic response. *Water Resour. Res.* **15** (6), 1409–1420.

Sauquet, E., Gottschalk, L. & Krasovskaia, I. 2008 Estimating mean monthly runoff at ungauged locations: an application to France. *Hydrol. Res.* **39** (5–6), 403–423.

Sherman, L. 1932 Streamflow from rainfall by the unit hydrograph method. *English News Record* **108**, 501–505.

Shreve, R. 1969 Stream lengths and basin areas in topologically random channel networks. *J. Geol.* **77**, 397–414.

Sivapalan, M. 2003 Process complexity at hillslope scale, process simplicity at the watershed scale: is there a connection? *Hydrol. Process.* **17** (5), 1037–1041.

Sivapalan, M., Jothityangkoon, C. & Menabde, M. 2002 Linearity and nonlinearity of basin response as a function of scale: discussion of alternative definitions. *Water Resour. Res.* **38** (2), 4.1–4.5.

Sivapalan, M., Blöschl, G., Zhang, L. & Vertessy, R. 2003a Downward approach to hydrological prediction. *Hydrol. Process.* **17** (11), 2101–2111.

Sivapalan, M., Takeuchi, K., Franks, S. W., Gupta, V. K., Karambiri, H., Lakshmi, V., Liang, X., Mcdonnell, J. J., Mendiondo, E. M., O'Connell, P. E., Oki, T., Pomeroy, J. W., Schertzer, D., Uhlenbrook, S. & Zehe, E. 2003b IAHS Decade on Predictions in Ungauged Basins (PUB), 2003–2012: shaping an exciting future for the hydrological sciences. *Hydrolog. Sci. J.* **48** (6), 857–880.

Tarantola, A. & Valette, B. 1982 Inverse problems = quest for information. *J. Geophys* **50** (3), 150–170.

Wagener, T., Sivapalan, M., Troch, P. & Woods, R. 2007 Catchment classification and hydrologic similarity. *Geography. Compass* **1** (4), 901–931.

Wang, C. T., Gupta, V. K. & Waymire, E. 1981 A geomorphologic synthesis of nonlinearity in surface runoff. *Water Resour. Res.* **17** (3), 545–554.

Woods, R. & Sivapalan, M. 1999 A synthesis of space-time variability in storm response: rainfall, runoff generation, and routing. *Water Resour. Res.* **35** (8), 2469–2485.

Yang, D., Herath, S. & Musiake, K. 2002 A hillslope-based hydrological model using catchment area and width functions. *Hydrolog. Sci. J.* **47** (1), 49–65.

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