

# Evaluation of an instantaneous dryness index-based calibration-free continuous hydrological model in India

Swagat Patnaik, Vimal Chandra Sharma and Basudev Biswal

## ABSTRACT

Traditional continuous hydrological models have a large number of free parameters whose values need to be determined through calibration, and thus their applicability is limited to gauged basins. For prediction in ungauged catchments, hydrologists generally follow regionalization methods to develop region-specific calibration-free continuous models. An alternative attempt was made recently to develop a calibration-free model by proposing an empirically derived universal 'decay function' that enables definition of instantaneous dryness index as a function of antecedent rainfall and solar energy. The model was earlier tested in the USA, and its performance was found to be comparable to that shown by regionalization-based models. Here, we test the instantaneous dryness index-based calibration-free model considering data from 108 Indian catchments. The medians of coefficient of determination ( $R^2$ ), Nash–Sutcliffe efficiency ( $NSE$ ) and Kling–Gupta efficiency ( $KGE$ ) values for the study catchments, respectively, are 0.50, 0.38 and 0.40. Furthermore, the model's performance significantly improved upon Box–Cox transformation ( $R_{BC}^2$ ,  $NSE_{BC}$  and  $KGE_{BC}$ , respectively, are 0.70, 0.52 and 0.57), suggesting that the model predicts discharge quite well except during flood periods. Overall, our results suggest the model can be used as an alternative platform for predicting discharge in ungauged catchments in the USA and peninsular India, if not in every part of the world.

**Key words** | decay function, instantaneous dryness index, prediction in ungauged catchments, universal calibration-free continuous hydrological model

**Swagat Patnaik** (corresponding author)  
**Vimal Chandra Sharma**  
 Department of Civil Engineering,  
 Indian Institute Technology,  
 Hyderabad,  
 India  
 E-mail: ce14resch11003@iith.ac.in

**Basudev Biswal**  
 Department of Civil Engineering,  
 Indian Institute Technology,  
 Bombay,  
 India  
 and  
 Interdisciplinary Programme (IDP) in Climate  
 Studies,  
 Indian Institute Technology,  
 Bombay,  
 India

## INTRODUCTION

Flow of water on the Earth's surface varies significantly in both space and time. Water resources management is a challenging task, particularly because most parts of the world are ungauged, i.e., they lack discharge data (Blöschl 2006; Zhang *et al.* 2008; Hrachowitz *et al.* 2013; Razavi & Coulibaly 2013; Yaşar 2013). Furthermore, traditional hydrological models are not a solution to the ungauged region problem as we need historical discharge time series data to determine model parameter values, a process called model calibration (e.g., Oudin *et al.* 2008; Razavi & Coulibaly 2013; Beck *et al.* 2016). In other words, prediction in ungauged catchments requires a calibration-free continuous hydrological model. Hydrologists generally develop calibration-free models for ungauged catchments following regionalization

approaches. This is typically achieved by transferring information from gauged catchments to ungauged catchments, e.g., by relating a model's parameters with easily measurable catchment characteristics (e.g., Merz & Blöschl 2004; Oudin *et al.* 2008; Beck *et al.* 2016). However, the main limitation of a regionalization method is that reliable transfer of model parameters happens from gauged catchments only to hydrologically similar ungauged catchments, mainly due to uncertainties in estimation of model parameters (Post 2009; Samaniego *et al.* 2010; Razavi & Coulibaly 2013). In other words, a regionalization-based calibration-free model is not expected to be universally applicable (Table 1).

Early attempts to develop a universal calibration-free hydrological model were made by climatologists (Schreiber

**Table 1** | Modelling options for prediction in ungauged catchments

Modelling option	Continuous simulation capability?	Calibration free?	Universally applicable?	Remark
Hydrological models with regionalized parameters	Yes	Yes	No	Regionalization-based calibration-free models can be used to predict discharge in hydrologically similar ungauged catchments only
Budyko model	No	Yes	Yes	Budyko model is not capable of performing continuous discharge simulation
Instantaneous dryness index-based model	Yes	Yes	Needs to be tested	This study poses the question if the instantaneous dryness index-based model is universal

1904; Oldekop 1911; Budyko 1948) who proposed the concept of dryness index, the ratio of mean potential evapotranspiration to mean rainfall ( $\phi$ ). Among all the dryness index-based models, the Budyko model is the most popular for its performance (e.g., Arora 2002). It can be used to predict mean discharge ( $\langle Q \rangle$ ) from mean rainfall ( $\langle R \rangle$ ) for any real world catchment as:  $\langle Q \rangle = \langle R \rangle \cdot f(\phi)$ , where  $f(\phi)$  is the Budyko function:

$$f(\phi) = 1 - (\phi \cdot \tanh(\phi^{-1}) \cdot (1 - e^{-\phi}))^{0.5} \quad (1)$$

Unlike a regionalization approach-based calibration-free continuous model, the Budyko model is a ‘universal’ calibration-free model but cannot be used for continuous hydrological simulation (Table 1). We thus need a universal calibration-free model that can be used for continuous hydrological modelling. Such a model will help us not only to predict discharge in ungauged catchments for which no regionalization-based model is available but also to understand hydrological processes in more detail (e.g., Perrin et al. 2008; Andréassian et al. 2014).

A new framework (Biswal 2016) was recently proposed to construct a calibration-free continuous hydrological model by proposing the concept of instantaneous dryness index, i.e., dryness index as a function of time. In particular, Biswal (2016) defined instantaneous dryness index as a function of antecedent rainfall and solar energy inputs with the help of a ‘decay function’. The decay function was empirically derived considering data from 15 US catchments belonging to the MOPEX dataset (Duan et al. 2006) by imposing the following two criteria: (i) the total modelled discharge from all the catchments equals the total observed discharge (mass balance) and (ii) the modelled recession flow power law exponent equals the observed exponent. In other words, unlike the case of traditional models, the instantaneous

dryness index-based zero-parameter model was obtained without using detailed information on spatio-temporal variation of discharge. The model was then tested in 63 MOPEX catchments (including those 15 catchments) situated across a wide variety of climatic and geologic regions and its performance was found to be comparable to that shown by complex regionalization-based calibration-free models in terms of Nash–Sutcliffe efficiency (Biswal 2016).

Given that the calibration-free instantaneous dryness index-based model performs reasonably well across geographical and climatic gradients in the USA, one may wonder here if the instantaneous dryness index-based model is also applicable in other parts of the world, i.e., if the model is universally applicable (Table 1). Although to answer such a question we need to test the model in basins from each part of the world, the aim of this study is to test the model in a large number of Indian catchments, situated far from the region where the model was developed.

## THE STRUCTURE OF THE INSTANTANEOUS DRYNESS INDEX-BASED MODEL

The instantaneous dryness index-based zero-parameter continuous model has a two-stage hydrologic partitioning scheme. At any instant of time, the input rainfall ( $R$ ) needs to satisfy first an evapotranspiration ( $ET$ ) demand equal to the potential evapotranspiration ( $PET$ ) or available energy. Thus, no discharge is produced in the first stage. The remaining rain water ( $W$ ) then enters into the second stage:  $W(t) = R(t) - PET(t)$  when  $PET(t) < R(t)$ , else  $W(t) = 0$ . Note that energy transforms liquid water into water vapour or  $ET$ , which means energy entering into the

second phase ( $H$ ) can be given as:  $H(t) = PET(t) - R(t)$  when  $PET(t) > R(t)$ , else  $H(t) = 0$ . In the second stage, available water ( $W$ ) and available energy ( $H$ ) interact with each other to produce both streamflow and evapotranspiration. Mathematically,  $W$  can be written as summation of effective rainfall ( $ER$ ), the portion of  $W$  that ultimately transforms into streamflow, and rainfall loss ( $RL$ ), the portion of  $W$  that ultimately evaporates:  $W(t) = ER(t) + RL(t)$ .

It is hypothesized that the partitioning of  $W$  into  $ER$  and  $RL$  at an instant of time is determined mainly by the soil moisture state which is controlled by antecedent  $W$  and  $H$  inputs (Biswal 2016). Effects of  $W$  and  $H$  on a catchment's soil moisture state are expected to decay with time. Assuming that the principle of superposition holds good, one can now define functional  $W$  ( $FW$ ) and functional  $H$  ( $FH$ ) influencing the soil moisture state considering a

single decay function as  $FW(t) = \int_{t-N}^t W(\tau) \cdot x(t-\tau) \cdot d\tau$

and  $FH(t) = \int_{t-N}^t H(\tau) \cdot x(t-\tau) \cdot d\tau$ . The term  $x(\cdot)$  in the equations above is the decay function.  $N$  is the number of days for which  $W$  and  $H$  can affect the soil moisture state. Similar to the definition of dryness index, one can define dryness index at an instant of time or instantaneous dryness index:  $\varphi(t) = FH(t)/FW(t)$ . Partitioning of  $W$  into  $ER$  and  $RL$  is done as (Biswal 2016):

$$ER(t) = W(t) \cdot f(\varphi) \quad (2)$$

where  $f(\varphi)$  is the Budyko function with  $\varphi$ :  $f(\varphi) = 1 - (\varphi \cdot \tanh(\varphi^{-1}) \cdot (1 - e^{-\varphi}))^{0.5}$  (see Equation (1)). Finally, it is assumed that the same decay function also explains production of discharge ( $Q$ ) from effective rainfall:

$$Q(t) = -\frac{d}{dt} \left[ \int_0^t (ER(\tau) \cdot x(t-\tau)) \cdot d\tau \right] \quad (3)$$

The decay function was empirically obtained by imposing the mass balance condition and performing recession flow analysis (Biswal 2016), and its form is given as:  $x(t) = x(0)/(1 + 0.4 \cdot t)$ , where  $x(t)$  is the quantity available at time  $t$  from an original quantity of  $x(0)$  and  $t$  is in days. Furthermore, the value of  $N$  is considered to be 365 days (Biswal 2016). The model can be applied at daily time-step by properly discretizing the equations above (Biswal 2016).

## STUDY REGION AND MODEL EVALUATION

### About the study region

Water resources are still poorly managed in India as highlighted by the recent droughts and floods (Joseph et al. 2015; Mondal & Mujumdar 2015; Selvaraj et al. 2016), suggesting that India needs to improve its water management practices (Wilk & Hughes 2002; Srinivasa Raju & Nagesh Kumar 2004; Bharati et al. 2009; Pechstädt et al. 2011; Goldin 2016). In fact, most of the streams in India are ungauged. This makes India a relevant place to test the instantaneous dryness index-based calibration-free continuous model as a positive outcome of our experiment would imply that we can apply the model in the country for water resources management applications. In total, 147 basins were selected for preliminary investigation in this study (see Tables S1 and S2 of the Supplementary material, available with the online version of this paper). Since the model does not consider spatial variation of rainfall and travel time delays in channel networks, only small- to medium-sized catchments are selected here. The drainage areas for the selected catchments range between 258 km<sup>2</sup> and 26,453 km<sup>2</sup>. The study basins receive rainfall mainly during the monsoon season (June–October). Additional information about all the basins can be found in the India-WRIS website (<http://india-wris.nrsc.gov.in/wris.html>).

### Data preparation

The instantaneous dryness index-based model requires only rainfall ( $R$ ) and potential evapotranspiration ( $PET$ ) time series data (input variables) for simulating discharge. In total, four gridded datasets are used in this study: rainfall, minimum temperature, maximum temperature, and average temperature grids. Daily rainfall data (Pai et al. 2014) span from 1901 to 2015 and daily temperature data (Srivastava et al. 2009) from 1951 to 2014. The spatial resolutions of rainfall data and temperature data are  $0.25^\circ \times 0.25^\circ$  and  $1^\circ \times 1^\circ$ , respectively. All the data products were obtained from the Indian Meteorological Department (IMD). Additionally, for the purpose of model evaluation, we obtained available daily discharge data from Central Water Commission (CWC), India. Note that catchments with

four or more years of near continuous streamflow data (with not more than two consecutive missing data points) only were used for this study. Furthermore, for many of the basins we discarded parts of discharge data which showed only zero values continuously for more than a year.

We used minimum, maximum and average temperature gridded datasets to obtain gridded *PET* gridded data using Hargreaves' method (Hargreaves & Samani 1985). For finding daily average observed *R* and *PET* time series for a catchment, we used its boundary shapefile, which was obtained in the following process. Digital elevation model data (DEM) for the study catchments were collected from Consortium for Spatial Information (CGIAR-CSI, see <http://srtm.csi.cgiar.org/>). The flow direction and the flow accumulation maps were created using D8 algorithm (O'Callaghan & Mark 1984). We then obtained the boundary shapefile for each catchment using the outlet coordinates given by India-WRIS (<http://india-wris.nrsc.gov.in/wris.html>). Once the boundary shapefile is ready, the average rainfall and the average *PET* time series for the catchment were obtained by performing weighted aerial averaging of *R* and *PET* values from different pixels belonging to the catchment area. The entire processing was done in MATLAB-2016a and R-3.3.0 (Ihaka & Gentleman 1996) frameworks.

### Evaluation of the model's performance

One of the biggest challenges in model evaluation is the presence of errors in observed data. Errors in input data may lead to erroneous prediction (Zhang et al. 2008), and hence it is often recommended to discard data points with unrealistic values. For example, Yanto et al. (2017) selected only five out of 19 Indonesian catchments for a modelling study by imposing a number of criteria. In this study, 108 of the 147 catchments were finally selected for evaluating the (see Table S1 of the Supplementary material) instantaneous dryness index-based calibration-free model. The remaining catchments are discarded for the following reasons. We exclude ten catchments from our analyses as they show runoff ratio greater than one (Table S2 of the Supplementary material), which is very unrealistic from the perspective of mass balance law. We also exclude 29 more basins (see Table S2) whose runoff ratios are less than 0.1

as dry catchments are known for poor data quality and high spatial variation of rainfall (e.g., Pilgrim et al. 1988). For two catchments (Cholachguda and Sarati), rainfall in the year 2005 is unusually high and not matched well with the streamflow response. We thus do not include the data points from that year in the remaining analysis as they indicate association of significant observational errors.

The model's performance is then evaluated here considering the following lumped metrics: coefficient of determination ( $R^2$ ); Nash–Sutcliffe efficiency (*NSE*); Kling–Gupta efficiency (*KGE*); Box–Cox transferred  $R^2$  ( $R_{BC}^2$ ), *NSE* ( $NSE_{BC}$ ) and *KGE* ( $KGE_{BC}$ ); and a unit-less metric (*B'*) accounting for water balance error.  $R^2$  is one of the widely used measures of model performance, which is expressed as:

$$R^2 = \frac{\sum_{i=1}^n (Q_o^i - \langle Q_o \rangle)(Q_m^i - \langle Q_m \rangle)}{\sqrt{\sum_{i=1}^n (Q_o^i - \langle Q_o \rangle)^2} \sqrt{\sum_{i=1}^n (Q_m^i - \langle Q_m \rangle)^2}},$$

where  $Q_o$  is the observed discharge,  $Q_m$  is the modelled discharge and  $n$  is the number of observations.  $R^2$  ranges between 0 (no relationship) and 1 (perfect fit).  $R^2$  is insensitive to systematic error, and hence it is generally considered along with other metrics for model evaluation, most commonly *NSE*, defined as:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_m^i - Q_o^i)^2}{\sum_{i=1}^n (Q_o^i - \langle Q_o \rangle)^2}.$$

The value of *NSE* can range between  $-\infty$  (no agreement) and 1 (perfect agreement). *NSE* may not incorporate water balance error accurately, which is why it is recommended to compute *KGE* (Gupta et al. 2009). It is computed as:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{Q_m}}{\sigma_{Q_o}} - 1\right)^2 + \left(\frac{\langle Q_m \rangle}{\langle Q_o \rangle} - 1\right)^2},$$

where  $r$  is the Pearson correlation coefficient, and  $\sigma$  denotes standard deviation of discharge. *KGE* has the same range as *NSE*. It should be noted that all the three metrics above,  $R^2$ , *NSE* and *KGE*, give undue importance to high flows as in their formulations square of error is counted. Therefore, it is often advised to transform discharge before computing them such that all discharge values are given fairly equal importance. One common way of ensuring this, which we follow here, is to perform

Box–Cox transformation:  $Q_{BC} = \frac{Q^{0.3} - 1}{0.3}$  (El Nasr et al. 2005; Wagener et al. 2009; Biswal & Singh 2017). Note

that the instantaneous dryness index-based model does not consider travel time delays due to flow in channel networks. For computations of all these metrics modelled discharge time series is shifted such that  $NSE$  is maximum (Kirchner 2009; Biswal 2016). We also compute model bias expressed in terms of the unit-less metric  $B' = 1 - \left| \frac{\langle Q_m \rangle - \langle Q_o \rangle}{\langle Q_o \rangle} \right|$  as suggested by Beck *et al.* (2016).  $B' = 1$  when the model has no water balance error; otherwise, its value will be less than 1.

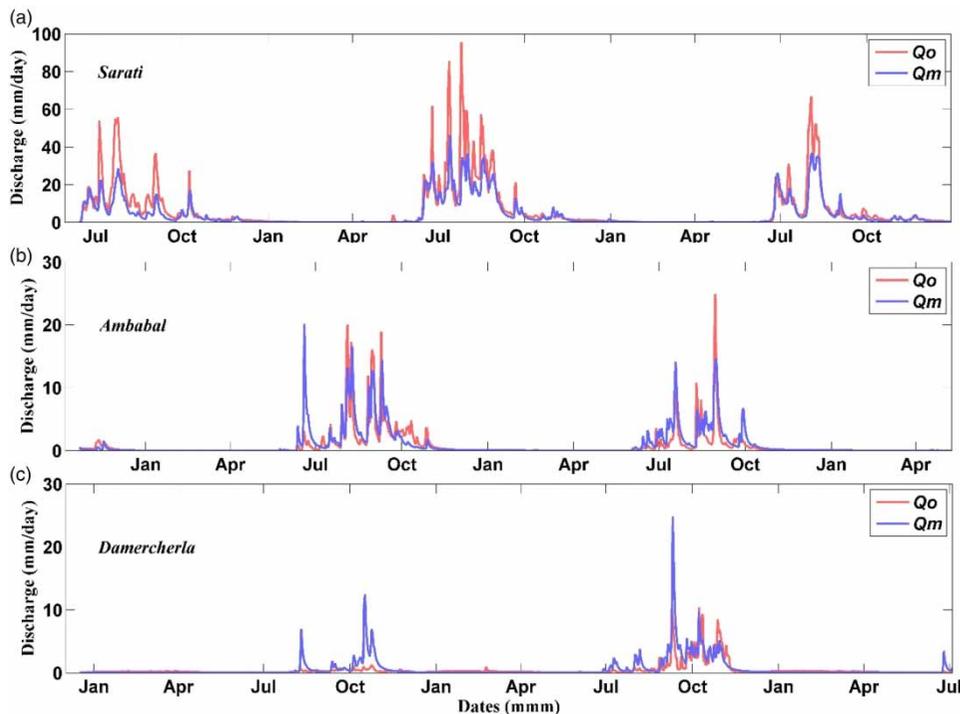
We would like to emphasize here that deviation of observed discharge from modelled discharge may occur not only due to errors in the data, but also due to the model's ability to mimic hydrological processes. Individual assessment of these two factors is practically impossible. As a result, no lumped metric is a perfect measure of a hydrological model's performance (Di Baldassarre & Montanari 2009; Tian *et al.* 2016). Many researchers have suggested to carefully examine a model's ability to mimic key hydrological processes (e.g., Clark *et al.* 2015; Biswal & Singh 2017). For example, it is now well known that  $dQ/dt-Q$  relationship for a catchment is dynamic, which means if we plot

( $dQ/dt, Q$ ) data points in log-log space they would exhibit significant scatter. We apply this test here to evaluate the instantaneous dryness index-based model. Lastly, but most importantly, by applying the instantaneous dryness index-based calibration-free model outside the country where it was developed (USA), we want to investigate if the model can be considered as a potential universal calibration-free hydrological model. The reasoning is that if a calibration-free model can perform reasonably in both the USA and India, it may give a similar performance in other regions.

## RESULTS AND DISCUSSION

### Model performance in the 108 study catchments

Figure 1 shows simulated discharge vs. observed discharge for a two-year time period for three sample catchments. This figure intends to show that the model is able to capture rainfall-runoff relationship without employing a single free-parameter. The figure also intends to show that the model does not perform equally well in all catchments – while



**Figure 1** | Two-year plot between the observed discharge ( $Q_o$ ) and the modelled discharge ( $Q_m$ ) for three catchments: (a) Sarati, (b) Ambabal and (c) Damercherla. The figure provides an overview of the model's performance in peninsular India; its performance varies from one catchment to other.

the model captures the streamflow dynamics of Sarati quite well, it does not work so well in Dameracherla. The values of all the performance indicators for each catchment are shown in Table S1 (available with the online version of this paper). Figure 2(a)–2(c) show maps of  $R^2$ ,  $NSE$  and  $KGE$ , whose median values for the study catchments, respectively, are 0.50, 0.38 and 0.40. Interpretation of these results needs a proper context; since the model does not require calibration and is especially designed for prediction in ungauged catchments, it can be compared only to regionalization-based calibration-free models. Unfortunately, no regionalization-based study so far has considered our study catchments. In fact, Pechlivanidis & Arheimer (2015) for the first time used a hydrological model (HYPE) with regionalized parameters to simulate discharge for 12 Indian catchments. The median  $KGE$  reported by them is 0.44, which is quite close to our median  $KGE$  (0.40). Another Indian study (Swain & Patra 2017) also reported similar  $NSE$  range (median  $NSE$  approximately equals to 0.5) for prediction of discharge at ungauged basins using a SWAT model and regionalized parameters. It is also difficult to make a comparison by considering results from application of regionalization-based calibration-free hydrological models in other regions as very different performance ranges are reported in the hydrological literature. Some studies report median  $NSE$  greater than 0.7 (e.g., Oudin et al. 2008; Samaniego et al. 2010), whereas some other studies report median  $NSE$  as low as 0 (e.g., Xia et al. 2012; Beck et al. 2016). The instantaneous dryness index-based calibration-free model can thus be considered

to be very competitive, in particular if we consider its simple structure. Similar arguments can be found elsewhere in the hydrological literature (e.g., Andréassian et al. 2014).

The values of performance metrics like  $NSE$  depend on the ability of the model in mimicking processes as well as the quality of the data (Razavi & Coulibaly 2013; Beck et al. 2016). In particular, runoff ratio for ten catchments is greater than one (Table S2, available online), which might be implying that observed discharge data have large systematic errors. For example, Di Baldassarre & Montanari (2009) found that discharge observation alone may contain up to 42 percentage error. We therefore excluded catchments based on their runoff ratios before evaluating the model, but this does not ensure that the remaining catchments are error free. Also, our study catchments are heavily influenced by human activities which may have altered the natural discharge time series. Figure 3 shows the scatter plot between observed mean discharge and modelled mean discharge with coefficient of determination equal to 0.74. Although the model generally performs well in capturing long-term water balance, it shows significant biases for some of the study catchments (see  $B'$  values in Table S1). Nevertheless, the results here are quite remarkable if we consider performances of other hydrological models with the capability to predict in ungauged catchments. For example, Beck et al. (2016) applied ten regionalization-based models to a large number of catchments and found  $B'$  ranging between 0.50 and 0.66. In comparison, the median  $B'$  obtained for the study catchments using the instantaneous dryness-index model is 0.72.

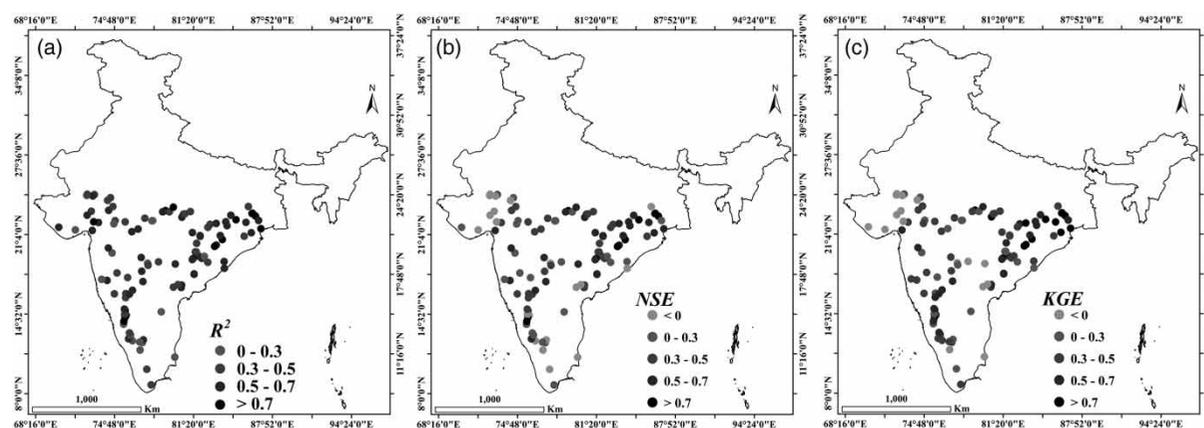
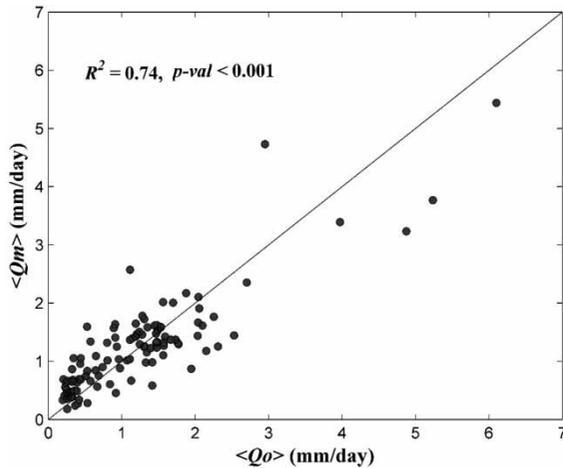
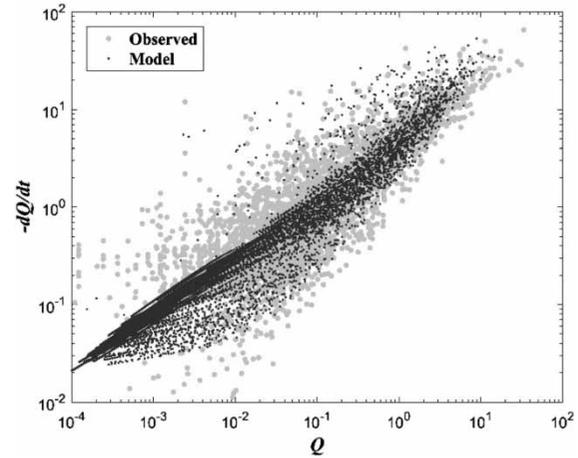


Figure 2 | Maps of the three performance metrics for the study catchments: (a) coefficient of determination ( $R^2$ ), (b) Nash-Sutcliffe efficiency ( $NSE$ ) and (c) Kling-Gupta efficiency ( $KGE$ ).



**Figure 3** | Scatter plot between mean observed discharge ( $\langle Q_o \rangle$ ) and mean modelled discharge ( $\langle Q_m \rangle$ ) for the 108 Indian catchments considered in model evaluation.  $\langle Q_m \rangle$  matches quite well with  $\langle Q_o \rangle$  ( $R^2 = 0.74$ ), which suggests the model performs well in terms of water balance across catchments.



**Figure 4** |  $dQ/dt$  vs.  $Q$  plots for modelled discharge (small black dots) as well as observed discharge (large grey dots) as suggested by Biswal & Singh (2017). The data points belong to recession periods with minimum length of 5 days. The modelled dots and the observed dots occupy almost the same region in the log-log space, an indication that model captures well the dynamic relationship between  $dQ/dt$  and  $Q$ .

### Does the model capture hydrological processes well?

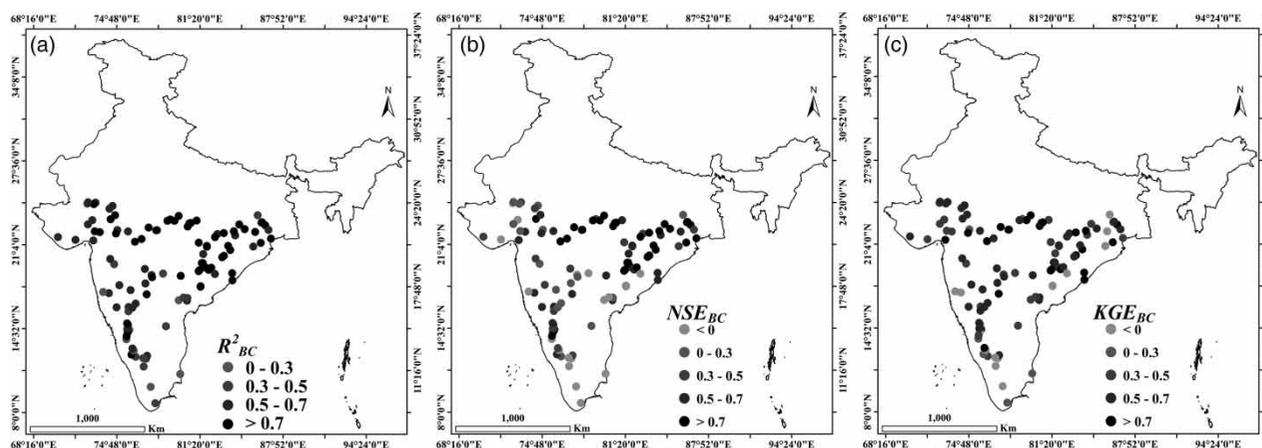
It should be emphasized that it is not easy to judge a model's performance using lumped indicators like *NSE* or *KGE* as they may not explain fully the performance of a model. For example, Biswal & Singh (2017) compared a channel network morphology-based routing model with a linear routing model to compare the ways they represent hydrological processes. In particular, they performed  $dQ/dt$ - $Q$  analysis and found although both the models give similar performances in terms of lumped metrics like *NSE*, the linear model produces unrealistic  $dQ/dt$ - $Q$  relationship. We therefore performed  $dQ/dt$ - $Q$  analysis in this study and found that the instantaneous dryness-index model is able to reproduce similar power law relationship between  $dQ/dt$  and  $Q$ . Figure 4 shows ( $dQ/dt$ ,  $Q$ ) data points occupying almost the same region in the log-log space. Other catchments too showed similar behaviour. However, this should not come as a surprise here as the decay function used to route flow by the model (Equation (3)) is derived through recession flow analysis.

With respect to the discussion above, we would like to point out that the model's performance improved significantly upon Box-Cox transformation of discharge (Figure 5). The median values of  $R_{BC}^2$ ,  $NSE_{BC}$  and  $KGE_{BC}$ , respectively, are 0.70, 0.52 and 0.57. This indicates that the model gives good prediction in general, but it is not able to

simulate flood peaks well. This might be particularly because the model's simple routing component, the single power law equation (Equation (3)), does not transform effectively rainfall into streamflow during flood periods. In fact, it is well known that streamflow is generated through several types of physical mechanisms and we need to consider them while modelling hydrological response. Particularly, it is known that higher intensity effective rainfall inputs produce higher proportion of overland flow that gives rise to steeper hydrograph limbs. That means, contrary to the linearity assumption by Equation (3), hydrograph peak non-linearly increases with effective rainfall (Beven 2011). Hydrological models, in general, partly address this issue by partitioning total flow into quick overland flows that dominate during flood periods and slow subsurface flows that dominate during dry periods (e.g., Moore 2007; Biswal & Singh 2017). This is, of course, carried out by adding free parameters which this study intends to avoid. Future research therefore needs a focus on developing calibration-free routing models that can separately consider quick flow and slow flow.

### Is the instantaneous dryness index-based model universally applicable?

Finally, we wonder if the instantaneous dryness index-based model is a universal calibration-free model. Although



**Figure 5** | Maps of the three performance metrics for the study catchments obtained after Box-Cox transformation of discharge: (a) coefficient of determination ( $R^2_{BC}$ ), (b) Nash-Sutcliffe efficiency ( $NSE_{BC}$ ) and (c) Kling-Gupta efficiency ( $KGE_{BC}$ ).

answering this question requires application of the model in a large number of catchments situated across continents, the fact the model gives very similar performances in the USA and India seems to suggest that the model is structurally very robust. Observations here are important for two reasons. (i) The model can be directly applied to any real ungauged catchment for simulating discharge in India and the USA. On the other hand, for prediction in an ungauged catchment a traditional regionalization-based calibration-free model requires information from a hydrologically similar gauged catchment (Oudin et al. 2008; Andréassian et al. 2014; Coron et al. 2014). The instantaneous dryness index-based model is thus relevant especially for catchments for which it is not possible to find a regionalization-based calibration-free model. (ii) Since the model employs no free parameter, we may conclude that natural catchments' geographical regions are strikingly similar to each other and that we need to exploit catchment hydrological similarities to develop universal calibration-free models instead of over-parameterizing hydrological models.

## CONCLUDING REMARKS

Continuous hydrological models are typically designed for prediction in gauged catchments as they retain multiple free parameters whose values need to be determined through calibration using historical discharge data. For prediction in ungauged catchments, we thus need a calibration-free model. Hydrologists generally develop calibration-free models

following regionalization approaches. However, a regionalization-based calibration-free model, by definition, is not universally applicable. On the other hand, dryness index-based calibration-free Budyko models are universally applicable (e.g., Budyko 1948) but cannot be used for continuous discharge simulation. An alternative approach was recently proposed to develop a calibration-free continuous hydrological model by defining an instantaneous dryness index as a function of antecedent rainfall and solar energy inputs (Biswal 2016). The model was originally developed and tested in the USA. In this study, we evaluated the model in 108 Indian catchments and observed that the model shows equally good performance in India. Furthermore, in terms of standard performance metrics, the model is comparable to standard regionalization-based calibration-free models.

Since the model performs reasonably well in the USA (Biswal 2016) as well as in India (this study), it can be concluded that the model is capable of performing well in a wide variety of climatic and geologic regions without any calibration. Nevertheless, to know if the model is universally applicable or not, we need to test the model in a multiple continents considering large datasets. We would like to emphasize that the idea of having universal calibration-free continuous models is worth pursuing primarily for two reasons. (i) Instead of transforming information from a gauged catchment to an ungauged catchment, we can use universal calibration-free models to directly predict discharge at the ungauged location. (ii) The possibility of having a universal calibration-free model will further

strengthen the earlier perception that natural catchments around the world follow certain universal laws to organize themselves as well as to function hydrologically (e.g., Rodríguez-Iturbe & Rinaldo 2001; Biswal & Marani 2014). It is believed now that the Budyko model encodes the *principle of maximum entropy production* to explain long-term hydrological partitioning (Wang et al. 2015; Westhoff et al. 2016). Since the instantaneous dryness index-based model explains hydrological partitioning at small timescales, in future it may help us in further advancing our knowledge on hydrological partitioning at different timescales.

## ACKNOWLEDGEMENTS

This study was partly supported by Ministry of Human Resources Development (MHRD), Government of India, through FAST Center of Excellence in Sustainable Urban Development, IIT Hyderabad. The code to compute *PET* was supplied to us by Anita Nag, IIT Hyderabad.

## REFERENCES

- Andréassian, V., Bourgin, F., Oudin, L., Mathevet, T., Perrin, C., Lerat, J., Coron, L. & Berthet, L. 2014 Seeking genericity in the selection of parameter sets: impact on hydrological model efficiency. *Water Resources Research* **50** (10), 8356–8366.
- Arora, V. 2002 The use of the aridity index to assess climate change effect on annual runoff. *Journal of Hydrology* **265** (1), 164–177.
- Beck, H. E., van Dijk, A. I. J. M., de Roo, A., Miralles, D. G., McVicar, T. R., Schellekens, J. & Bruijnzeel, L. A. 2016 Global-scale regionalization of hydrologic model parameters. *Water Resources Research* **52** (5), 3599–3622.
- Beven, K. J. 2011 *Rainfall-runoff Modelling: The Primer*. John Wiley & Sons, Chichester, UK.
- Bharati, L., Smakhtin, V. & Anand, B. 2009 Modeling water supply and demand scenarios: the Godavari-Krishna inter-basin transfer, India. *Water Policy* **11** (S1), 140–153.
- Biswal, B. 2016 Dynamic hydrologic modeling using the zero-parameter Budyko model with instantaneous dryness-index. *Geophysical Research Letters* **43** (18), 9696–9703.
- Biswal, B. & Marani, M. 2014 'Universal' recession curves and their geomorphological interpretation. *Advances in Water Resources* **65**, 34–42.
- Biswal, B. & Singh, R. 2017 Incorporating channel network information in hydrologic response modelling: development of a model and inter-model comparison. *Advances in Water Resources* **100**, 168–182.
- Blöschl, G. 2006 Rainfall-runoff modeling of ungauged catchments. In: *Encyclopedia of Hydrological Science* (M. G. Anderson & J. J. McDonnell, eds). John Wiley & Sons, New York, pp. 1–19.
- Budyko, M. I. 1948 *Evaporation Under Natural Conditions*. Gidrometeorizdat, Leningrad. English translation by IPST, Jerusalem.
- Clark, M. P., Nijssen, B., Lundquist, J. D., Kavetski, D., Rupp, D. E., Woods, R. A., Freer, J. E., Gutmann, E. D., Wood, A. W., Brekke, L. D., Arnold, J. R., Gochis, D. J. & Rasmussen, R. M. 2015 A unified approach for process-based hydrologic modeling: 1. Modeling concept. *Water Resources Research* **51** (4), 1–17.
- Coron, L., Andréassian, V. & Perrin, C. 2014 On the lack of robustness of hydrologic models regarding water balance simulation: a diagnostic approach applied to three models of increasing complexity on 20 mountainous catchments. *Hydrology and Earth System Sciences* **18** (2), 727–746.
- Di Baldassarre, G. & Montanari, A. 2009 Uncertainty in river discharge observations: a quantitative analysis. *Hydrology and Earth System* **13** (6), 913–921.
- Duan, Q., Schaake, J., Andreassian, V. & Franks, S. 2006 Model Parameter Estimation Experiment (MOPEX): an overview of science strategy and major results from the second and third workshops. *Journal of Hydrology* **320** (1), 3–17.
- El Nasr, A., Arnold, J. & Feyen, J. 2005 Modelling the hydrology of a catchment using a distributed and a semi-distributed model. *Hydrological Processes* **19** (3), 573–587.
- Goldin, T. 2016 Groundwater: India's drought below ground. *Nature Geoscience* **9** (2), 98–98.
- Gupta, H. V., Kling, H., Yilmaz, K. K. & Martinez, G. F. 2009 Decomposition of the mean squared error and NSE performance criteria: implications for improving hydrological modelling. *Journal of Hydrology* **377** (1), 80–91.
- Hargreaves, G. & Samani, Z. 1985 Reference crop evapotranspiration from temperature. *Applied Engineering in Agriculture* **1** (2), 96–99.
- Hrachowitz, M., Savenije, H. H. G., Blöschl, G., McDonnell, J. J., Sivapalan, M., Pomeroy, J. W., Arheimer, B., Blume, T., Clark, M. P., Ehret, U., Fencica, F., Freer, J. E., Gelfan, A., Gupta, H. V., Hughes, D. A., Hut, R. W., Montanari, A., Pande, S., Tetzlaff, D., Troch, P. A., Uhlenbrook, S., Wagener, T., Winsemius, H. C., Woods, R. A., Zehe, E. & Cudennec, C. 2013 A decade of predictions in ungauged basins (PUB) – a review. *Hydrological Sciences Journal* **58** (6), 1198–1255.
- Ihaka, R. & Gentleman, R. 1996 R: a language for data analysis and graphics. *Journal of Computational and Graphical Statistics* **5** (3), 299–314.
- Joseph, S., Sahai, A. K., Sharmila, S., Abhilash, S., Borah, N., Chattopadhyay, R., Pillai, P. A., Rajeevan, M. & Kumar, A. 2015 North Indian heavy rainfall event during June 2013: diagnostics and extended range prediction. *Climate Dynamics* **44** (7–8), 2049–2065.
- Kirchner, J. W. 2009 Catchments as simple dynamical systems: catchment characterization, rainfall-runoff modeling, and doing hydrology backward. *Water Resources Research* **45** (2), W02429.

- Merz, R. & Blöschl, G. 2004 Regionalisation of catchment model parameters. *Journal of Hydrology* **287** (1), 95–123.
- Mondal, A. & Mujumdar, P. P. 2015 Return levels of hydrologic droughts under climate change. *Advances in Water Resources* **75**, 67–79.
- Moore, R. 2007 The PDM rainfall-runoff model. *Hydrology and Earth System Sciences* **11** (1), 483–499.
- O'Callaghan, J. & Mark, D. 1984 The extraction of drainage networks from digital elevation data. *Computer Vision, Graphics, and Image* **28** (3), 323–344.
- Oldekop, E. M. 1911 On evaporation from the surface of river basins. *Trans. Meteorol. Obs. Univ. Tartu* **4**, 200.
- Oudin, L., Andréassian, V., Perrin, C., Michel, C. & Le Moine, N. 2008 Spatial proximity, physical similarity, regression and ungauged catchments: a comparison of regionalization approaches based on 913 French catchments. *Water Resources Research* **44** (3), 1–15.
- Pai, D. S., Sridhar, L., Rajeevan, M., Sreejith, O. P., Satbhai, N. S. & Mukhopadhyay, B. 2014 Development of a new high spatial resolution ( $0.25^\circ \times 0.25^\circ$ ) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam* **65** (1), 1–18.
- Pechlivanidis, I. G. & Arheimer, B. 2015 Large-scale hydrological modelling by using modified PUB recommendations: the India-HYPE case. *Hydrology and Earth System Sciences* **19** (11), 4559–4579.
- Pechstädt, J., Bartosch, A., Zander, F. & Schmied, H. 2011 Development of A River Basin Information System for A Sustainable Development in the Upper Brahmaputra River Basin. Available at: <https://pdfs.semanticscholar.org/2754/7e6acdb6ac89c342571057da90c361eb6d50.pdf>.
- Perrin, C., Andréassian, V., Serna, C. R., Mathevet, T. & Le Moine, N. 2008 Discrete parameterization of hydrological models: evaluating the use of parameter sets libraries over 900 catchments. *Water Resources Research* **44** (8), 1–15.
- Pilgrim, D., Chapman, T. & Doran, D. 1988 Problems of rainfall-runoff modelling in arid and semiarid regions. *Hydrological Sciences* **33** (4), 379–400.
- Post, D. A. 2009 Regionalizing rainfall-runoff model parameters to predict the daily streamflow of ungauged catchments in the dry tropics. *Hydrology Research* **40** (5), 433–444.
- Razavi, T. & Coulibaly, P. 2013 Streamflow prediction in ungauged basins: review of regionalization methods. *Journal of Hydrologic Engineering* **18** (8), 958–975.
- Rodríguez-Iturbe, I. & Rinaldo, A. 2001 *Fractal River Basins: Chance and Self-Organization*. Cambridge University Press, Cambridge, UK.
- Samaniego, L., Kumar, R. & Attinger, S. 2010 Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resources Research* **46** (5), 1–25.
- Schreiber, P. 1904 Über die Beziehungen zwischen dem Niederschlag und der Wasserführung der Flüsse in Mitteleuropa. *Zeitschrift Meteorologische* **21** (10), 441–452.
- Selvaraj, K., Pandiyan, J., Yoganandan, V. & Agoramoorthy, G. 2016 India contemplates climate change concerns after floods ravaged the coastal city of Chennai. *Ocean & Coastal Management* **129**, 10–14.
- Srinivasa Raju, K. & Nagesh Kumar, D. 2004 Irrigation planning using genetic algorithms. *Water Resources Management* **18** (2), 163–176.
- Srivastava, A. K., Rajeevan, M. & Kshirsagar, S. R. 2009 Development of a high resolution daily gridded temperature data set (1969–2005) for the Indian region. *Atmospheric Science Letters* **10** (4), 249–254.
- Swain, J. B. & Patra, K. C. 2017 Streamflow estimation in ungauged catchments using regionalization techniques. *Journal of Hydrology* **554**, 420–433.
- Tian, Y., Nearing, G. S., Peters-Lidard, C. D., Harrison, K. W. & Tang, L. 2016 Performance metrics, error modeling, and uncertainty quantification. *Monthly Weather Review* **144** (2), 607–613.
- Wagener, T., Van Werkhoven, K., Reed, P. & Tang, Y. 2009 Multiobjective sensitivity analysis to understand the information content in streamflow observations for distributed watershed modeling. *Water Resources Research* **45** (2), 1–5.
- Wang, D., Zhao, J., Tang, Y. & Sivapalan, M. 2015 A thermodynamic interpretation of Budyko and L'vovich formulations of annual water balance: proportionality hypothesis and maximum entropy production. *Water Resources Research* **51** (4), 3007–3016.
- Westhoff, M., Zehe, E., Archambeau, P. & Dewals, B. 2016 Does the Budyko curve reflect a maximum-power state of hydrological systems? A backward analysis. *Hydrology and Earth System Sciences* **20** (1), 479–486.
- Wilk, J. & Hughes, D. A. 2002 Calibrating a rainfall-runoff model for a catchment with limited data. *Hydrological Sciences Journal* **47** (1), 3–17.
- Xia, Y., Mitchell, K., Ek, M., Cosgrove, B., Sheffield, J., Luo, L., Alonge, C., Wei, H., Meng, J., Livneh, B., Duan, Q. & Lohmann, D. 2012 Continental-scale water and energy flux analysis and validation for North American Land Data Assimilation System project phase 2 (NLDAS-2): 2. Validation of model-simulated streamflow. *Journal of Geophysical Research-Atmospheres* **117** (D3), 1–23.
- Yanto, M., Livneh, B., Rajagopalan, B. & Kasprzyk, J. 2017 Hydrological model application under data scarcity for multiple watersheds, Java Island, Indonesia. *Journal of Hydrology: Regional Studies* **9**, 127–139.
- Yaşar, M. 2013 Prediction of flow duration curves for ungauged basins with quasi-Newton method. *Journal of Water Resource and Protection* **5** (1), 97–110.
- Zhang, Z., Wagener, T., Reed, P. & Bhushan, R. 2008 Reducing uncertainty in predictions in ungauged basins by combining hydrologic indices regionalization and multiobjective optimization. *Water Resources Research* **44** (12), 1–13.