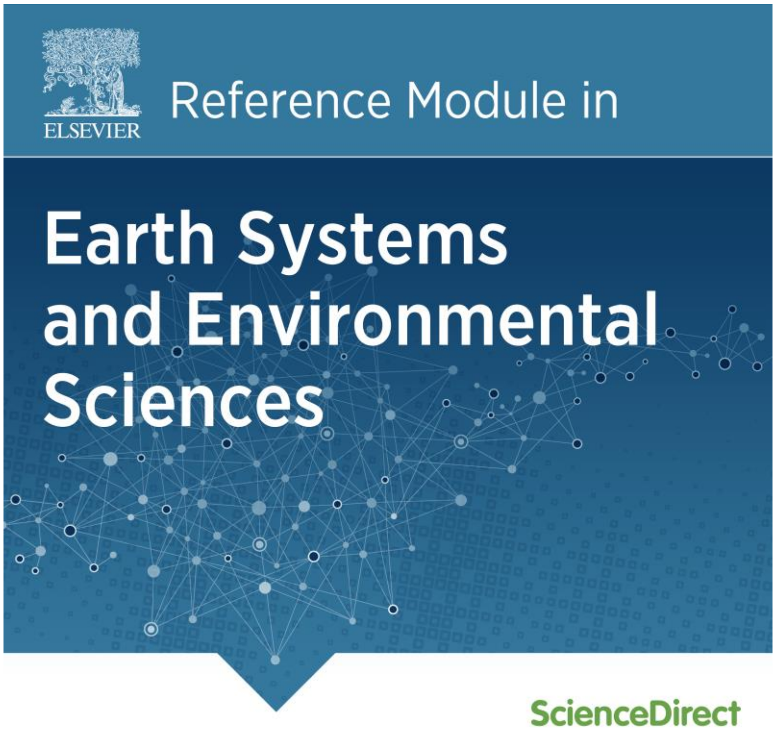

Birkel Christian, and Barahona Alicia Correa, Rainfall-Runoff Modeling: A Brief Overview, Reference Module in Earth Systems and Environmental Sciences, Elsevier, 2019. 27-Nov-19 doi: 10.1016/B978-0-12-409548-9.11595-7.

Rainfall-Runoff Modeling: A Brief Overview

Christian Birkel, Department of Geography and Water and Global Change Observatory, University of Costa Rica, San José, Costa Rica; Northern Rivers Institute, University of Aberdeen, Aberdeen, Scotland
Alicia Correa Barahona, Department of Geography and Water and Global Change Observatory, University of Costa Rica, San José, Costa Rica

Preface

This short article on rainfall-runoff modeling attempts to give a brief overview on a rather vast topic in the hydrological sciences. We, unfortunately, cannot go into details of any special branch of modeling. Nonetheless, we rather settle on introductory materials that might offer guidance for hydrology, engineering, geography and environmental science students, postgraduate students, professionals and anybody looking for hints to catch up on reading relevant literature, concepts and tendencies (for a comprehensive source in this direction we refer to Beven, 2012).

Our focus will be on rainfall-runoff modeling or how the transformation of rainfall into runoff can be simulated with different mathematical tools describing runoff generation processes.

Regarding the spatial scale, most model applications are carried out at catchment scales, despite relevant global scale (Bierkens et al., 2015) or smaller scale hillslope (Anderson and Brooks, 1996 follow on from Kirkby, 1978) or even pedon-scale (Lin, 2012) modeling efforts. In terms of temporal scale, model applications range from minute-wise flood forecasting (Hapuarachchi et al., 2011; Adams and Pagano, 2016) to thousands of years reconstructing paleo-hydrometeorological conditions (Kalma and Sivapalan, 1995; Gasser, 2015). Rainfall-runoff models also often serve as input to, for example, hydraulic models (de Paiva et al., 2013) or biogeochemical models (Futter et al., 2007), which we mention but have to abstain from presenting detailed facts.

Here, based on personal and professional experiences, we describe why we use hydrological models, their advantages and challenges. We briefly outline the historical advances in rainfall-runoff model development, the type of models one encounters in the literature and the world-wide web. Furthermore, we underline the fact that all models need calibration, and how we evaluate models and attempt to assess model uncertainties. Considering the above, we lastly talk from our perspectives about some novel tendencies in rainfall-runoff model development.

With that, we hope to have provided some motivating facts about rainfall-runoff modeling as a great tool in hydrology encouraging readers to move well beyond this article.

Why Model?

The main reasons for a hydrologist to apply modeling tools are in our opinion to (Fig. 1):

(i) Simulate processes to learn about system behavior,
(ii) support decision making and to
(iii) project future behavior.

Of course, and depending on the specific purpose of the modeling exercise at hand there are other motivations we can think of, but even modeling for design purposes from an engineering perspective could be grouped into (ii) and even (iii) as, for example, most frequency analysis of extreme events extrapolates well beyond the commonly available observations (think of a 1000-year return period flood). Therefore, we use models to ideally provide robust numbers that can be used in decision making and for management purposes. That, however, requires accurate simulation results from robust models and then we can report such results in between some reasonable uncertainty bounds or assign a probability of occurrence to our results (the reader is referred here for some entertainment to Silver, 2012). Most importantly, reporting results based on a reasonable uncertainty assessment should be considered good practice in hydrological modeling and any result reported as a single hard number should be handled with caution (Pappenberger and Beven, 2006).

You can also think of the case where models can be used to build knowledge (not necessarily solve a problem) useful to subsequently inform management efforts. In this case (i), we are concerned with learning about how our system behaves the way it does, and we attempt to quantitatively describe the processes that dominate the hydrological cycle of the system of interest (Dunn

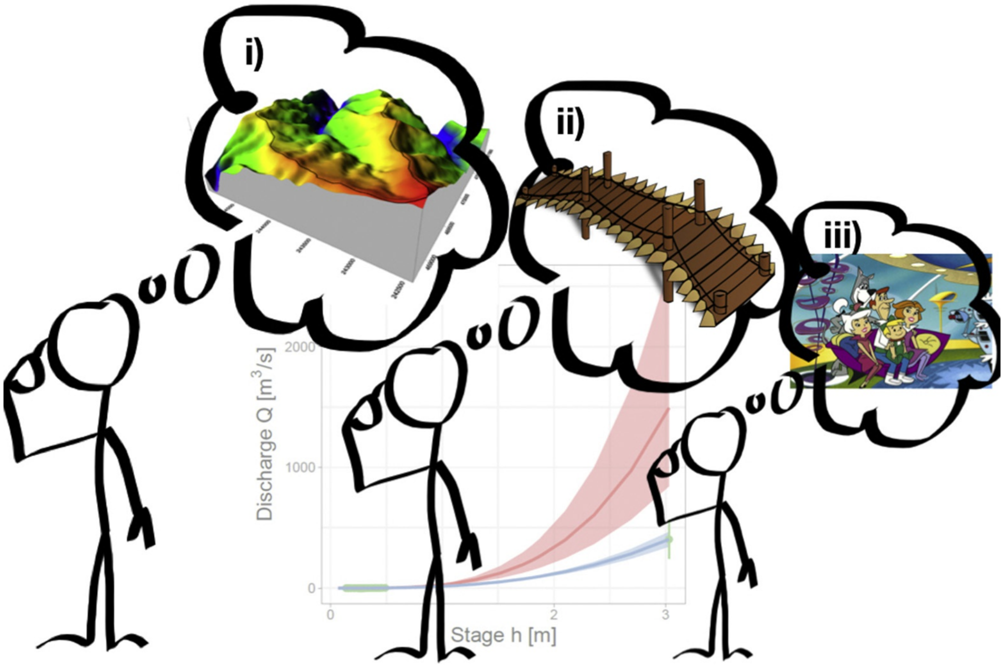

Fig. 1 Reasons to apply a hydrological model can be (i) to learn about the system, (ii) to support decision making (or here rather design) and (iii) to project what the future might hold illustrated with a cartoon image from the 1960s US sci-fi series "The Jetsons." The opaque "uncertain" rating curve example in the background keeps us thinking about errors, uncertainties and possibly how to responsibly communicate them. Courtesy of Ida Westerberg, SLU and Valentin Mansanarez, Stockholm University.

et al., 2008). In doing so, we likely need to look beyond the hydrograph deciphering the integrated information from everything that is happening in the catchment and flowing toward the point of gauging (McDonnell et al., 2007). The latter forces us to gravitate around the questions of:

(a) where does the water come from and when? (geographical sources, e.g., soil or groundwater; temporal sources, e.g., seasonal or short-term contributions during extreme rainfall events),
(b) which flow pathways does water take to the outlet?
(c) what is the biogeochemical cycling involved in water fluxes?
(d) what are the time scales of water being transported and stored in a catchment? and
(e) how do anthropogenic influences impact hydrological processes?

These questions were already formulated as early as 1967 by workers such as Hewlett and Hibbert (1967) but with some exceptions have not acquired too much momentum since. Hydrologists rather focused on fitting the hydrograph with evermore sophisticated methods (Savenije, 2009). Arguably a more "academic" interest of the process hydrologist but learning about adequately describing system behavior in models can increase the confidence in our results. The process-based model that matches system behavior might, in the end, be a more robust tool for decision making along the lines of Kirchner (2006). It might well be that we hit a barrier with our hydrometric data in this context and to infer water sources, mixing processes and transit times additional data is needed, such as in the form of environmental or artificial tracers (Leibundgut et al., 2009). We will, however, come back to the data issue later in the outlook section (Fig. 2).

Historical Perspective

So, what has happened in the context of model advancements over the last let us say 200 years? Many state Mulvany (1851) "Rational method," an empirical relationship to estimate peak discharge in small impervious catchments, as one of the earliest hydrological model (Todini, 2007 provides a historical overview with emphasis on flood forecasting and Beven et al., 2015 a synthesis on past and present models). However, Dooge (1974) in an essay on "developments of hydrological concepts in Britain and Ireland" states that Dalton (1802) already presented detailed water balance models for Britain. If one was to dig deeper in Hydrology history books such as Biswas (1970) other early workers might well appear. One astonishing contribution to modern hydrology came from Da Vinci in the 1600s (Pfister et al., 2009). The historical notion of a hydrological cycle and a quantifiable water balance was recently presented by Duffy (2017), but this pulls us quite far away from hydrological modeling.

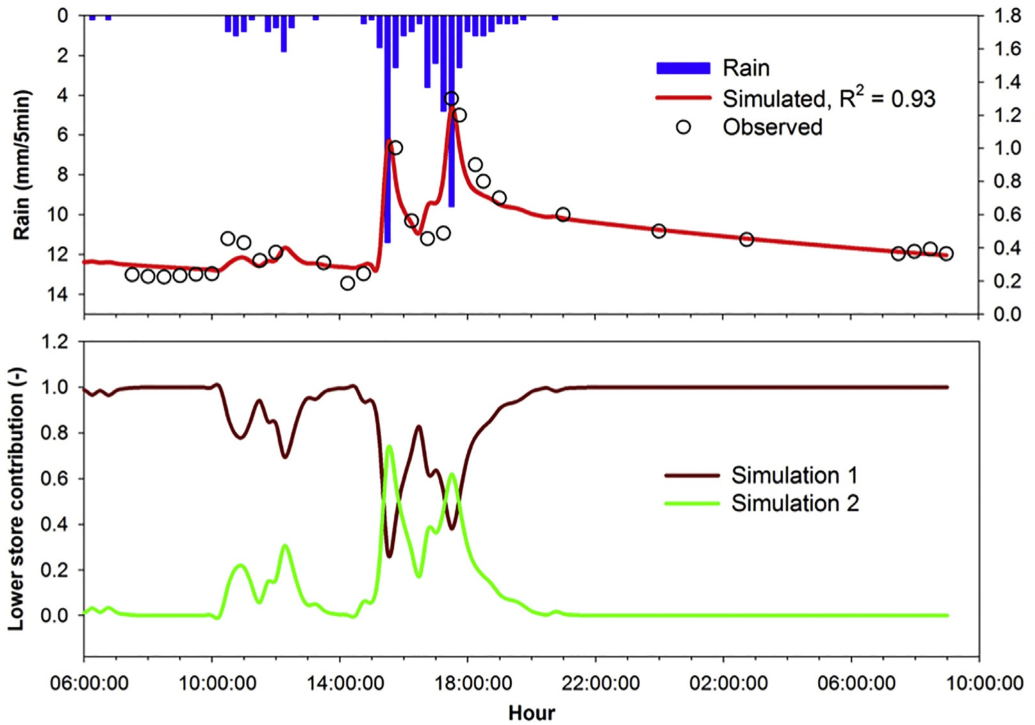

Fig. 2 Illustrating the observed rainfall-runoff relationship for an arbitrarily selected 5 min event with some arbitrarily simulated hydrograph (Qsim). The simulation matches the observations well ($R^2 = 0.93$), but we cannot directly derive information on water sources, flowpaths and transit times from the hydrograph alone. At least you need a model to infer water sources, but the lower panel shows two radically different water sources that result in exactly the same hydrograph: Simulation 1 generates the storm response from an upper reservoir conceptualizing near-surface water, while simulation two uses "groundwater" from a lower model store to simulate the storm hydrograph.

Manning (1891) and his work on open water channel flow followed shortly after Mulvany (1851). The Unit Hydrograph model was introduced in Sherman (1932) and the class of conceptual "tank" models later by Sugawara (1967). Horton's (1933, 1945) infiltration and overland flow perceptual models can surely be counted as major progress and were summarized by Beven (2004), but it was not until the modern computer revolution helped to leap forward due to the possibility to outsource mechanical mathematical processing with little or virtually no errors (Crawford and Linsley, 1966). Freeze and Harlan's (1969) blue-print of a 3D physically-based hillslope hydrological model was made possible by computers and eventually developed into SHE (Système Hydrologique Européen by Abbott et al. (1986)) what is even until today known as one of the most complex hydrological models. The latter SHE is a fully distributed (spatial disaggregation) and physically-based model resolving the energy balance for evapotranspiration estimates, the Richard's equation (Richards, 1931) for unsaturated porous media flow and the superficial kinematic wave approach (Wooding, 1965). The widely-used conceptual model HBV was developed in Sweden by Bergström (1976) and a more physically-based approach was taken by Beven and Kirkby (1979) with their TOPMODEL. We only mention these two models among many other conceptual models here as both transcend the hydrological sciences even today. Novel optimization techniques (Sorooshian and Gupta, 1983) paved the way for automatic and more efficient calibration of complex models. Klemeš (1986) and Beven's (1989) critical assessments of physically-based models caused a paradigm shift in many ways towards re-thinking how complex or simple our models should be (Jakeman and Hornberger, 1993), an ongoing debate even today that transcends the hydrological sciences (Paola, 2011 for an example from geomorphology and Gunawardena, 2014 representing this debate in biology). Although the use of tracers as additional data to the hydrograph in hydrological models dates back to the 1970s (Przewlocki and Yurtsever, 1974; Niemi, 1978), research has considerably developed in the past 20 years (for a review on the topic we refer to Birkel and Soulsby, 2015). The integration of tracers into hydrological models opened a new dimension towards the possibility to constrain model parameters and a more comprehensive evaluation of catchment functioning (Son and Sivapalan, 2007) as mentioned above and in Fig. 1(i). The collection of landmark hydrological modeling papers by Loague (2010) provides an excellent overview and in-depth information on model development over the past decades. Additionally, Fatichi et al. (2016) illustrate more recent developments in distributed, process-based modeling and the historical context of where these novelties are coming from.

Types of Models and Applications

In the above brief section on historical model developments, we already mentioned quite a spectrum of different types of models. Usually, models are classified depending on the mathematical techniques used to build a model, the spatial discretization of the system and the degree of complexity (Beven, 2012):

- The most common math's used to build hydrological models is of a deterministic or stochastic nature.
- The catchment can be treated as a whole (lumped) or can be compartmentalized into subcatchments or useful spatial units (semi-distributed) or the fully distributed case of discretizing the catchment in form of a spatial grid based on topography (Digital Elevation Model, DEM or Triangular Irregular Network, TIN).
- The complexity criterion classifies models from low complexity empirical models to medium complexity conceptual models and complex physically-based models.

However, there are many examples of "hybrid" models that borrow techniques from more than one classification scheme and the above model categories should not be seen as rigid limits. In general, the computational cost of models increases with spatial complexity and higher temporal resolution at the potential benefit of a more detailed process representation. Higher level of process representation involves on the other hand, a larger number of model parameters that need calibration and can, therefore, increase the model's uncertainty. Beven (2012) stated that the increase of input data and computing power will increase the use and accuracy of distributed models. However, he also stated that conceptual models are a simpler way of predicting distributed responses in a catchment. Singh and Frevert (2002a,b) present a collection of many models still applied today. But overall, the (a) purpose and (b) data availability strongly influence the type of model to be used and the modeler should be clear from the onset of a project. For example, if questions around land use change impacts on the hydrological response are an objective, it will be very difficult if not impossible to work with an empirical and lumped model. The minimum requirement would be a semi-distributed model accommodating different land uses and some at least "conceptual" hydrological processes (e.g., Birkel et al., 2012). It is also clear that for such a purpose, more complex feedback mechanisms on soil hydraulic properties or the energy balance cannot be answered, and the modeler should carefully consider the options. The latter can essentially only be addressed with a distributed, process or physically-based model. On the other hand, the modeler should consider if for a flood forecasting system a complex model is needed or if whether a simple data-based transfer function model that can be efficiently trained to match peak flows and volumes is the preferred choice (Young, 2003). In a model, as a simplified proxy of the hydrological system, unmeasured assumptions are reflected in the model parameters. Depending on the complexity of the hydrological system, the number of parameters is largely variable. It is recommended to keep the number of parameters as small as possible but enough to provide simulations comparable with observational data (e.g., flow-rate measurements). The more parameters are used, the less identifiable are they, and consequently, the uncertainty in the model results increases. Additionally, working in data-scarce regions further constrains the model choice. Most complex models are data-hungry, and the modeler should take care of the boundary conditions, spatial variability, local heterogeneity and data requirements to properly setup a complex model (already discussed by Freeze and Harlan, 1969). If the model is not supported by enough information content from observational data, the resulting interpolation errors and increased parameter uncertainty rapidly outweigh the benefits of a complex model.

We would also like to further draw the reader's attention to the issue of the necessary and important distinction between the perceptual and conceptual model in guiding model choice. As Beven (2012) points out, the perceptual model can be personalized and somewhat subjective depending on experience, field site visits, etc., but is essential to take an informed decision in terms of what type of model should be used for the purpose. The perceptual model is therefore at the very beginning of the so-called "model cycle" of environmental sciences in general and hydrological sciences in particular (for an introduction see Smith and Smith, 2007). The perceptual model includes apart from getting the purpose of the model exercise straight, the knowledge about data availability and the complexity of the hydrological system of the study site. If you are to use a model developed for a specific purpose in a unique climatic and geomorphic setting, that model applied to a different hydrological context should be critically evaluated or even better adapted to the new environment as the foundation of hydrological processes originally incorporated are likely to be out of bounds. We, therefore, recommend being at least critical and very careful about the "one model fits all" approach.

Picture the simple example that you work in the tropics under constant high temperature, frequent cloud cover and rainfall paired with high relative humidity close to saturation. You need to get evapotranspiration (ET) estimates for your hydrological model with limited data availability. The least data-hungry ET model you can find is Thornthwaite (1948) only needing temperature and latitude to run. However, based on the perceptual model and site-specific characteristics of the tropical setting, it is clear that temperature alone is hardly the driver of ET dynamics. Luckily, alternative data sources are now more and more available that help close the observational data gap in the future (starting with e.g., Schmugge et al., 2002 and Pietroniro and Prowse, 2002). Remote sensing and global products might help to get relative humidity and radiation data for a more sophisticated but much needed ET model. The latter open access to data is of particular importance in data-scarce areas where local precipitation data to drive a rainfall-runoff model is often lacking. As an alternative source of model input data, different global precipitation products merge remotely sensed precipitation from satellite imagery calibrated against global rain gauge networks (Sun et al., 2018 provides a comprehensive review of global precipitation products). These data products still need some type of evaluation (e.g., Zambrano-Bigiarini et al., 2017) and perhaps calibration to be operational at the scale and location of the application, particularly at higher-resolution spatio-temporal scales. The issue of spatial rainfall data that is difficult to obtain with rain gauges as they represent a point measurement is an ongoing research topic. Weather radars were thought to fill that gap (Sauvageot, 1994), but there are important issues since the radar signal needs to be converted into ground rainfall rates depending on in situ rain gauges and calibrated for the type of rainfall using disdrometers for raindrop size distributions. Radars and disdrometers are not everywhere available, as their costs are usually prohibitive (Villarini and Krajewski, 2010 for a review on sources of uncertainty in radar rain measurements). New developments to obtain spatial rainfall data include the attenuation of existing microwave signals from wireless communication networks (Messer et al., 2006), such as using the extensive network of cellular communication radio links (Leijnse et al., 2007) and more recently broadcast TV satellite links (Mercier et al., 2015).

Now that you made a model choice and have the data to run it, your model will need calibration or in other words, we train the model by tweaking some parameters to match the observations, which in hydrology is usually the hydrograph. And yes, all models require calibration, even physically-based models that in theory should work based only on measured quantities. That is in parts due to a mismatch between the small-scale and idealized physics (think of Darcy and Richard's porous media, "sand box" flow) and the complex real-world applications. Previously mentioned critiques by Beven (1989), Beven and Germann (1982) and the follow-up Beven and Germann (2013) dealing particularly with soil water movement give more details on this ongoing debate. For this article, we have to consider our options in dealing with the need for calibration:

(i) The simplest, but subjective form of calibration is to visually adjust the simulated hydrograph to match the observed by changing parameter values.
(ii) More complex, automated and objective methods are to optimize towards minimizing model residuals, which in the best-case results in a single optimal solution.
(iii) Accepting that there may be more than one feasible solution to our calibration problem, you can run multiple iterations (e.g., Monte Carlo or Markov Chain Monte Carlo) of the model to find a suitable set of parameters representing the observations. It is here where considerations of uncertainty come into play.

A simple visual calibration reported as a single best-fit model is arguably not timely anymore but can be a valuable exercise to get familiarized with the model by observing the impact changing model parameters have on the simulation. In fact, we use this exercise in teaching hydrological modeling before any more sophisticated technique, where we ask students to pay attention to match the different parts of the observed hydrograph such as peak and low flows, but also the recession, wetting-up after dry periods and the overall hydrodynamics. Seibert and Vis (2012) give a great example of teaching conceptual hydrological models. It is only in a second step that additionally to the visual exercise, we encourage students to look at a statistical performance criterion such as the widely-used Nash-Sutcliffe efficiency (NSE, Schaefli and Gupta, 2007 for a discussion on NSE), its logarithmic version (LogNSE), a volumetric error (VE, Criss and Winston, 2008), the Kling-Gupta efficiency (KGE, Gupta et al., 2009), etc. The use of different statistics to evaluate the model simulation generates awareness of the specific objective behind the different criteria and that for example, using an NSE instead of logNSE to calibrate the model for a drought assessment is exactly the type of misconception that should be avoided. To the contrary, creating a balanced model that can reflect most components of the hydrograph can benefit from a multiobjective evaluation using a combination of different statistics (Efstratiadis and Koutsoyiannis, 2010) as a single performance criterion alone can be misleading.

At this point, automatization for objectivity of the calibration process is the next logical step and multiple options exist to use an optimization algorithm whereby the different algorithms search for a global minimum or maximum of the performance statistic used to evaluate the model (see e.g., Andrews et al., 2011 for a comparison of different optimization algorithms in hydrological modeling). Optimization is usually fast and relatively easy to apply even with complex models, but the modeler has to be aware of the risk of finding only a local minimum or maximum further away from a global solution (Kuczera, 1997). Optimization also attempts to find a single best solution omitting the fact that "always" more than one feasible solution exists to a calibration problem, an issue termed "equifinality" by Beven and Binley (1992).

Recognizing the fact of an inherent model parameter uncertainty due to the equifinality phenomenon provides the opportunity to attempt estimation of uncertain model parameters on our simulation results. Recently, two main strands of a "formal" and "informal" uncertainty estimation emerged maintaining an ongoing debate about which is the preferable and more robust method (see e.g., the debates by Vrugt et al., 2008; Beven, 2009; Clark et al., 2012). The Bayesian approach is used to "formally" estimate the statistical likelihood of a simulation with some criticism related to the error model of normally distributed residuals. Besides that, the more "informal" Generalized Likelihood Uncertainty Estimation (GLUE) by Beven and Binley (1992) and revisited in Beven and Binley (2014) allows for a more flexible parameter uncertainty estimation where the expert criterion defines what is acceptable or not. The main point of critique, however, was and is the degree of subjectivity in selecting this threshold of acceptability. Now, in light of the need for responsible uncertainty assessments of our model results and their pragmatic communication (Di Baldassarre et al., 2010), both methods represent a way forward toward this common goal going beyond misleading single optimal solutions.

We should also not forget about the inherent errors and uncertainties in our data we use to feed and evaluate models. Such epistemic data errors according to Beven and Westerberg (2011) should be carefully assessed and in obvious cases of discharge errors omitted from calibration to avoid training a model to match such errors. Many modelers are well aware of the colloquial expression that "the model is only as good as the data you feed it with" referencing the many sources of errors in rainfall measurements (Kavetski et al., 2006) and the challenge to take a point rainfall gauge measurement to represent catchment precipitation. Model structural errors can also be summed to the overall sources of uncertainty and multimodel experiments were used to detect and select the most appropriate model structure for the type of application and information available (Renard et al., 2010). Taking a conceptual model in the form of a mathematical construct of differential equations to be coded for execution requires an efficient numerical solution to avoid numerical errors as pointed out by Clark and Kavetski (2010). On top of all the combined error sources already mentioned, there is also the human factor. The modeler significantly influences the results with certain decisions along the modeling process and should be aware of this fact in selecting and preparing the input and output data, selecting model structures and evaluation techniques (Hrachowitz et al., 2014). We now summarize the numerous sources of possible errors and uncertainty in models again:

- Model structure uncertainty
- Model parameter uncertainty
- Data uncertainty
- Numerical uncertainty
- Modeler's choice

We, therefore, can never expect from our models that are only a simplification of a complex system to perfectly match reality. As disheartening as this may sound to newcomers, it also provides a tremendous potential for improvements in our data measurements, theory and model techniques (Fig. 3).

Outlook and Tendencies

The tremendous potential for future development in hydrological modeling comes partly from novel technology such as remote sensing towards a vision to observe the hydrological cycle from above and only use our e.g., rainfall buckets and soil humidity sensors for ground-truthing. More widely available laser spectrometers now allow measuring at a much-reduced cost, stable water and vapor isotopes in the field generating more high-resolution data than ever for use in testing our models against independent data (Birkel et al., 2014). There is, however, also a great potential to further develop and test hydrological theory and an example may be the Navier-Stokes equations accounting for preferential flow which can substitute the Richards unsaturated porous media flow (Germann, 2016). The combination of novel data and theory may drive us towards integrated models of catchment functioning and away from the pure hydrograph-fitting exercise of the past to better understand the complex, nonlinear, heterogeneous and hysteretic nature of water (Birkel et al., 2015). For those models, the use or development of suitable statistical metrics beyond the Nash-Sutcliffe efficiency needs to be considered in order to evaluate their uncertainty in a reliable manner. So, what type of future modeler do we need to get us closer working towards integrated models? Others with a lot more experience than us (check Beven, 2016 and his advice to young hydrologists and Burt and McDonnell, 2015) should be in a better position to give career

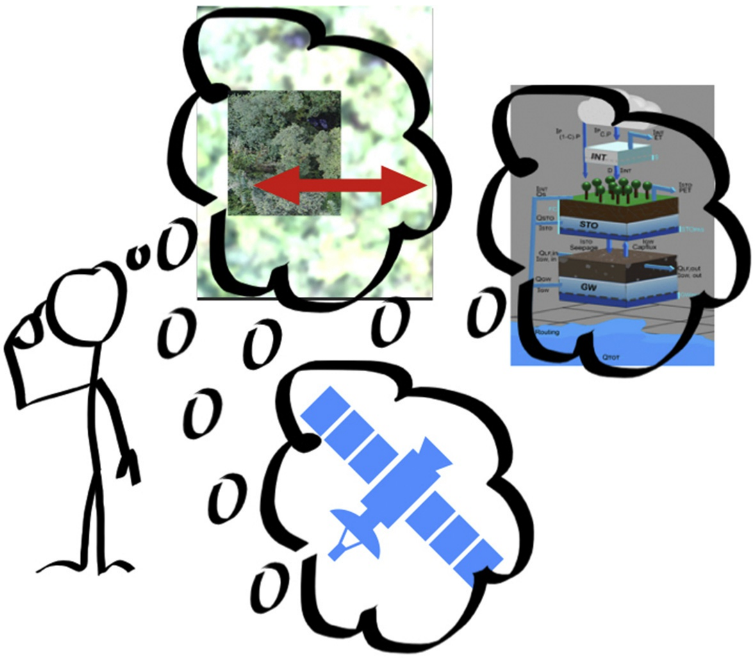

Fig. 3 The model cycle forces us to think about diverse sources of errors such as the uncertainty around model structures, our data used to drive models and sourced from point measurements we need to upscale to match catchment scales. We also constantly face the need to further develop new methods such as remote sensing products useful to feed and evaluate our models with towards more robust and trustworthy models.

advice, but the one thing that we want to mention here is that we see a clear need for a combination of fieldwork and numerically literate, keen, young scientists to work along the lines of Seibert and McDonnell (2002).

It might well be that this can only be achieved and put to good practice for society through interdisciplinary collaboration. Despite the challenges a truly motivating prospect!

Acknowledgments

The authors would like to thank the University of Costa Rica, the Department of Geography, the Water and Global Change Observatory (OACG) and UCREA for supporting the work on this article.

References

Abbott MB, Bathurst JC, Cunge JA, O'Connell PE, and Rasmussen J (1986) An introduction to the European hydrological system—Système Hydrologique Européen, SHE, 1: History and philosophy of a physically-based, distributed modelling system. *Journal of Hydrology* 87: 45–59.

Adams TE and Pagano TC (2016) *Flood forecasting: A global perspective*. Amsterdam: Elsevier.

Anderson M and Brooks S (1996) *Advances in Hillslope Processes*, vol. 2, p. 1306. Hoboken, NJ: John Wiley.

Andrews FT, Croke BFW, and Jakeman AJ (2011) An open software environment for hydrological model assessment and development. *Environmental Modelling and Software* 26(10): 1171–1185.

Bergström S (1976) *Development and application of a conceptual runoff model for Scandinavian catchments*, p. 134. RHO 7 Norrköping: SMHI.

Beven KJ (1989) Changing ideas in hydrology—The case of physically-based models. *Journal of Hydrology* 105: 157–172.

Beven K (2004) Robert E. Horton's perceptual model of infiltration processes. *Hydrological Processes* 18: 3447–3460. https://doi.org/10.1002/hyp.5740.

Beven KJ (2009) Comment on 'Equifinality of formal (DREAM) and informal (GLUE) Bayesian approaches in hydrologic modeling?' By Jasper A. Vrugt, Cajo J. F. ter Braak, Hoshin V. Gupta and Bruce A. Robinson. *Stochastic Environmental Research and Risk Assessment* 23: 1059–1060. https://doi.org/10.1007/s00477-008-0283-x.

Beven KJ (2012) *Rainfall-runoff modelling: The primer*, 2nd edn. Chichester: Wiley-Blackwell.

Beven K (2016) Advice to a young hydrologist. *Hydrological Processes* 30: 3578–3582. https://doi.org/10.1002/hyp.10879.

Beven KJ and Binley AM (1992) The future of distributed models: Model calibration and uncertainty prediction. *Hydrological Processes* 6: 279–298.

Beven K and Binley A (2014) GLUE: 20 years on. *Hydrological Processes* 28: 5897–5918. https://doi.org/10.1002/hyp.10082.

Beven K and Germann P (1982) Macropores and water flow in soils. *Water Resources Research* 18: 1311–1325. https://doi.org/10.1029/WR018i005p01311.

Beven K and Germann P (2013) Macropores and water flow in soils revisited. *Water Resources Research* 49: 3071–3092. https://doi.org/10.1002/wrcr.20156.

Beven KJ and Kirkby MJ (1979) A physically based variable contributing area model of basin hydrology. *Hydrological Sciences Bulletin* 24: 43–69.

Beven KJ and Westerberg I (2011) On red herrings and real herrings: Disinformation and information in hydrological inference. *Hydrological Processes* 25: 1676–1680. https://doi.org/10.1002/hyp.7963.

Beven K, Bathurst J, O'Connell E, Littlewood I, Blackie J, and Robinson M (2015) Hydrological modelling. In: Rodda JC and Robinson M (eds.) *Progress in modern hydrology: Past, present and future*. John Wiley & Sons. https://doi.org/10.1002/9781119074304.ch7.

Bierkens MFP, Bell VA, Burek P, Chaney N, Condon L, David CH, de Roo A, Döll P, Drost N, Famiglietti JS, Flörke M, Gochis DJ, Houser P, Hut R, Keune J, Kollet S, Maxwell R, Reager JT, Samaniego L, Sudicky E, Sutanudjaja EH, van de Giesen N, Winsemius H, and Wood EF (2015) Hyper-resolution global hydrological modelling: What is next? *Hydrological Processes* 29: 310–320. https://doi.org/10.1002/hyp.10391.

Birkel C and Soulsby C (2015) Advancing tracer-aided rainfall–runoff modelling: A review of progress, problems and unrealised potential. *Hydrological Processes* 29: 5227–5240. https://doi.org/10.1002/hyp.10594.

Birkel C, Soulsby C, and Tetzlaff D (2012) Modelling the impacts of landcover change on streamflow dynamics of a tropical rainforest headwater catchment. *Hydrological Sciences Journal* 57: 1543–1561. https://doi.org/10.1080/02626667.2012.728707.

Birkel C, Soulsby C, and Tetzlaff D (2014) Developing a consistent process-based conceptualization of catchment functioning using measurements of internal state variables. *Water Resources Research*. https://doi.org/10.1002/2013WR014925.

Birkel C, Soulsby C, and Tetzlaff D (2015) Conceptual modelling to assess how the interplay of hydrological connectivity, catchment storage and tracer dynamics controls nonstationary water age estimates. *Hydrological Processes* 29: 2956–2969. https://doi.org/10.1002/hyp.10414.

Biswas AK (1970) *History of hydrology*. Amsterdam: North-Holland Publishing Company.

Burt TP and McDonnell JJ (2015) Whither field hydrology? The need for discovery science and outrageous hydrological hypotheses. *Water Resources Research* 51: 5919–5928. https://doi.org/10.1002/2014WR016839.

Clark MP and Kavetski D (2010) Ancient numerical daemons of conceptual hydrological modeling: 1. Fidelity and efficiency of time stepping schemes. *Water Resources Research* 46: W10510. https://doi.org/10.1029/2009WR008894.

Clark M, Kavetski D, and Fenicia F (2012) Reply to K. Beven et al., comment on Clark et al., pursuing the method of multiple working hypotheses for hydrological modeling, W09301, 2011. *Water Resources Research* 48(11). https://doi.org/10.1029/2012WR012547.

Crawford NH and Linsley RK (1966) *Digital simulation in hydrology, Stanford watershed model IV*. Tech. Rep. 39 Department of Civil Engineering Stanford University.

Criss RE and Winston WE (2008) Do Nash values have value? Discussion and alternate proposals. *Hydrological Processes* 22: 2723–2725. https://doi.org/10.1002/hyp.7072.

Dalton J (1802) Experiments and observations to determine whether the quantity of rain and dew is equal to the quantity of water carried off by the rivers and raised by evaporation, with an enquiry into the origin of springs. In: *Memories and Proceeding of the Manchester Literary Philosophical Society of Manchester 5, Part 2*, pp. 346–372.

de Paiva RCD, et al. (2013) Large-scale hydrologic and hydrodynamic modeling of the Amazon River basin. *Water Resources Research* 49: 1226–1243.

Di Baldassarre G, Schumann G, Bates P, Freer J, and Beven KJ (2010) Floodplain mapping: A critical discussion of deterministic and probabilistic approaches. *Hydrological Sciences Journal* 55(3): 364–376. https://doi.org/10.1080/02626661003683389.

Dooge JCI (1974) The development of hydrological concepts in Britain and Ireland between 1674 and 1874. *Hydrological Sciences Journal* 19(3): 279–302. https://doi.org/10.1080/02626667409493917.

Duffy CJ (2017) The terrestrial hydrologic cycle: An historical sense of balance. *WIREs Water* 4: e1216. https://doi.org/10.1002/wat2.1216.

Dunn SM, Freer J, Weiler M, Kirkby MJ, Seibert J, Quinn PF, Lischeid G, Tetzlaff D, and Soulsby C (2008) Conceptualization in catch-ment modelling: Simply learning? *Hydrological Processes*. https://doi.org/10.1002/hyp.7070.

Efstratiadis A and Koutsoyiannis D (2010) One decade of multi-objective calibration approaches in hydrological modelling: A review. *Hydrological Sciences Journal* 55(1): 58–78.

Fatichi S, Vivoni ER, Ogden FL, Ivanov VY, Mirus B, Gochis D, Downer CW, Camporese M, Davison JH, Ebel B, Jones N, Kim J, Mascaro G, Niswonger R, Restrepo P, Rigon R, Shen C, Sulis M, and Tarboton D (2016) An overview of current applications, challenges, and future trends in distributed process-based models in hydrology. *Journal of Hydrology* 537: 45–60. https://doi.org/10.1016/j.jhydrol.2016.03.026.

Freeze RA and Harlan RL (1969) Blueprint for a physically-based, digitally-simulated hydrologic response model. *Journal of Hydrology* 9(3): 237–258.
Futter MN, Butterfield D, Cosby BJ, Dillon PJ, Wade AJ, and Whitehead PG (2007) Modelling the mechanisms that control in-stream dissolved organic carbon dynamics in upland and forested catchments. *Water Resources Research* 43: W02424. https://doi.org/10.1029/2006WR004960.
Gasser (2015) *Hydrological modelling with tree-ring dendrochronology*. Akademikerverlag.
Germann P (2016) *Preferential flow—Stokes approach to infiltration and drainage*. Bern: Geografika Bernensia G88.
Gunawardena J (2014) Models in biology: 'Accurate descriptions of our pathetic thinking'. *BMC Biology* 12: 29.
Gupta HV, Kling H, Yilmaz KK, and Martinez GF (2009) Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology* 377(1–2): 80–91. https://doi.org/10.1016/j.jhydrol.2009.08.003. ISSN 0022-1694.
Hapuarachchi HA, Wang QJ, and Pagano TC (2011) A review of advances in flash flood forecasting. *Hydrological Processes* 25: 2771–2784. https://doi.org/10.1002/hyp.8040.
Hewlett J and Hibbert A (1967) Factors affecting the response of small watersheds to precipitation in humid areas. In: Sopper W and Lull H (eds.) *Forest hydrology*, pp. 275–290. University Park, PA: The Pennsylvania State University, Pergamon Press.
Horton RE (1933) The role of infiltration in the hydrologic cycle. *Transactions of the American Geophysical Union* 14: 446–460.
Horton RE (1945) Infiltration and runoff during the snow-melting season, with forest-cover. *Transactions of the American Geophysical Union* 26: 59–68.
Hrachowitz M, Fovet O, Ruiz L, Euser T, Gharari S, Nijzink R, Freer J, Savenije HHG, and Gascuel-Odoux C (2014) Process consistency in models: The importance of system signatures, expert knowledge, and process complexity. *Water Resources Research* 50: 7445–7469. https://doi.org/10.1002/2014WR015484.
Jakeman AJ and Hornberger GM (1993) How much complexity is warranted in a rainfall-runoff model? *Water Resources Research* 29(8): 2637–2649.
Kalma JD and Sivapalan M (1995) *Scale issues in hydrological modelling*. Chichester: Wiley.
Kavetski D, Kuczera G, and Franks SW (2006) Bayesian analysis of input uncertainty in hydrological modeling: 1. Theory. *Water Resources Research* 42: W03407. https://doi.org/10.1029/2005WR004368.
Kirchner JW (2006) Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology. *Water Resources Research* 42: W03S04. https://doi.org/10.1029/2005WR004362.
Kirkby M (ed.) (1978) *Hillslope hydrology*. New York: John Wiley.
Klemeš V (1986) Dilettantism in hydrology: Transition or destiny? *Water Resources Research* 22(9): 177–188.
Kuczera G (1997) Efficient subspace probabilistic parameter optimization for catchment models. *Water Resources Research* 33(1): 177–185. https://doi.org/10.1029/96WR02671.
Leibundgut C, Maloszewski P, and Kuells C (2009) *Tracers in hydrology*. Chichester: Wiley. https://doi.org/10.1002/9780470747148.
Leijnse H, Uijlenhoet R, and Stricker J (2007) Rainfall measurement using radio links from cellular communication networks. *Water Resources Research* 43: W03201. https://doi.org/10.1029/2006WR005631.
Lin H (2012) *Hydropedology*. Amsterdam: Elsevier.
Loague K (2010) *Rainfall-runoff modelling. IAHS Benchmark series*. Wallingford: IAHS.
Manning R (1891) On the flow of water in open channel and pipes. *Transactions of the Institution of Civil Engineers of Ireland* 20: 161–207.
McDonnell JJ, Sivapalan M, Vache K, Dunn S, Grant G, Haggerty R, Hinz C, Hooper R, Kirchner J, Roderick ML, Selker J, and Weiler M (2007) Moving beyond heterogeneity and process complexity: A new vision for watershed hydrology. *Water Resources Research* 43: W07301. https://doi.org/10.1029/2006WR005467.
Mercier F, Barthès L, and Mallet C (2015) Estimation of finescale rainfall fields using broadcast TV satellite links and a 4DVAR assimilation method. *Journal of Atmospheric and Oceanic Technology* 32: 1709–1728.
Messer H, Zinevich A, and Alpert P (2006) Environmental monitoring by wireless communication networks. *Science* 312: 713.
Mulvany T (1851) On the use of self registering rain and flood gauges in making observations of the relation of rainfall and flood discharges in given catchment. *Transactions of the Institution of Civil Engineers of Ireland* 4: 18–33.
Niemi AJ (1978) Residence time distribution of variable flow processes. *International Journal of Applied Radiation and Isotopes* 28: 855–860.
Paola C (2011) In modelling, simplicity isn't simple, FORUM environmental dynamics. *Nature Geoscience* 469: 38.
Pappenberger F and Beven KJ (2006) Ignorance is bliss: Or seven reasons not to use uncertainty analysis. *Water Resources Research* 42: W05302. https://doi.org/10.1029/2005WR004820.
Pfister L, Savenije HHG, and Fenicia F (2009) *Leonardo da Vinci's Water Theory: On the Origin and Fate of Water*. IAHS Special Publication No. 9. Wallingford: IAHS Press.
Pietroniro A and Prowse TD (2002) Applications of remote sensing in hydrology. *Hydrological Processes* 16: 1537–1541. https://doi.org/10.1002/hyp.1018.
Przewlocki K and Yurtsever Y (1974) Some conceptual mathematical models and digital simulation approach in the use of tracers in hydrological systems. *Isotope techniques in groundwater*. vol. III, pp. 425–450. Vienna: AEA.
Renard B, Kavetski D, Kuczera G, Thyer M, and Franks SW (2010) Understanding predictive uncertainty in hydrologic modeling: The challenge of identifying input and structural errors. *Water Resources Research* 46: W05521. https://doi.org/10.1029/2009WR008328.
Richards LA (1931) Capillary conduction of liquids through porous mediums. *Physics* 1: 313–333.
Sauvageot H (1994) Rainfall measurement by radar: A review. *Atmospheric Research* 35(1): 27–54. https://doi.org/10.1016/0169-8095(94)90071-X.
Savenije HHG (2009) HESS opinions the art of hydrology. *Hydrology and Earth System Sciences* 13: 157–161. https://doi.org/10.5194/hess-13-157-2009.
Schaefli B and Gupta H (2007) Do Nash values have value? *Hydrological Processes* 21: 2075–2080. https://doi.org/10.1002/hyp.6825.
Schmugge TJ, Kustas WP, Ritchie JC, Jackson TJ, and Rango A (2002) Remote sensing in hydrology. *Advances in Water Resources* 25(8–12): 1367–1385. https://doi.org/10.1016/S0309-1708(02)00065-9.
Seibert J and Vis MJP (2012) Teaching hydrological modeling with a user-friendly catchment- runoff-model software package. *Hydrology and Earth System Sciences* 16(9): 3315–3325. https://doi.org/10.5194/hess-16-3315-2012.
Seibert J and McDonnell JJ (2002) On the dialog between experimentalist and modeler in catchment hydrology: Use of soft data for multicriteria model calibration. *Water Resources Research* 38(11): 1241. https://doi.org/10.1029/2001WR000978.
Sherman LK (1932) Streamflow from rainfall by the unit graph method. *Engineering News Record* 108: 501–505. IHV.
Silver N (2012) *The signal and the noise: The art and science of prediction*. London: Penguin Books.
Singh VP and Frevert DK (eds.) (2002a) *Mathematical models of large watershed hydrology*, 891 pp. Chelsea, Michigan: Water Resource Publication.
Singh VP and Frevert DK (eds.) (2002b) *Mathematical models of small watershed hydrology and applications*, 950 pp. Chelsea, Michigan: Water Resource Publication.
Smith J and Smith P (2007) *Introduction to environmental modelling*. Oxford University Press.
Son K and Sivapalan M (2007) Improving model structure and reducing parameter uncertainty in conceptual water balance models through the use of auxiliary data. *Water Resources Research* 43: W01415. https://doi.org/10.1029/2006WR005032.
Sorooshian S and Gupta VK (1983) Automatic calibration of conceptual rainfall-runoff models: The question of parameter observability and uniqueness. *Water Resources Research* 19: 260–268.
Sugawara M (1967) *The flood forecasting by a series storage type model*, pp. 1–6. IAHS. IAHS Publication no. 85.
Sun Q, Miao C, Duan Q, Ashouri H, Sorooshian S, and Hsu K-L (2018) A review of global precipitation data sets: Data sources, estimation, and inter-comparisons. *Reviews of Geophysics* 56: 79–107. https://doi.org/10.1002/2017RG000574.
Thornthwaite CW (1948) An approach toward a rational classification of climate. *Geographical Review* 38(1): 55–94. https://doi.org/10.2307/210739.
Todini E (2007) Hydrological catchment modelling: Past, present and future. *Hydrology and Earth System Sciences* 11(1): 468–482.
Villarini G and Krajewski WF (2010) Review of the different sources of uncertainty in single polarization radar-based estimates of rainfall. *Surveys in Geophysics* 31: 107. https://doi.org/10.1007/s10712-009-9079-x.

Vrugt JA, ter Braak CFF, Gupta HV, and Robinson BA (2008) Equifinality of formal (DREAM) and informal (GLUE) Bayesian approaches in hydrologic modeling? *Stochastic Environmental Research and Risk Assessment*. https://doi.org/10.1007/s00477-008-0274-y.

Wooding RA (1965) A hydraulic model for the catchment-stream problem, I. Kinematic wave theory. *Journal of Hydrology* 3: 254–267.

Young PC (2003) Top-down and data-based mechanistic modeling of rainfall-flow dynamics at the catchment scale. *Hydrological Processes* 17: 2195–2217.

Zambrano-Bigiarini M, Nauditt A, Birkel C, Verbist K, and Ribbe L (2017) Temporal and spatial evaluation of satellite-based rainfall estimates across the complex topographical and climatic gradients of Chile. *Hydrology and Earth System Sciences* 21: 1295–1320. https://doi.org/10.5194/hess-21-1295-2017.