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Strategies for smarter catchment hydrology models: incorporating scaling and better process representation

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Abstract

Hydrological models have proliferated in the past several decades prompting debates on the virtues and shortcomings of various modelling approaches. Rather than critiquing individual models or modelling approaches, the objective here is to address the critical issues of scaling and hydrological process representation in various types of models with suggestions for improving these attributes in a parsimonious manner that captures and explains their functionality as simply as possible. This discussion focuses mostly on conceptual and physical/process-based models where understanding the internal catchment processes and hydrologic pathways is important. Such hydrological models can be improved by using data from advanced remote sensing (both spatial and temporal) and derivatives, applications of machine learning, flexible structures, and informing models through nested catchment studies in which internal catchment processes are elucidated. Incorporating concepts of hydrological connectivity into flexible model structures is a promising approach for improving flow path representation. Also important is consideration of the scale dependency of hydrological parameters to avoid scale mismatch between measured and modelled parameters. Examples are presented from remote high-elevation regions where water sources and pathways differ from temperate and tropical environments where more attention has been focused. The challenge of incorporating spatially and temporally variable water inputs, hydrologically pathways, climate, and land use into hydrological models requires modellers to collaborate with catchment hydrologists to include important processes at relevant scales—i.e. develop smarter hydrological models.

Keywords: Hydrological processes, Remote sensing, Catchment models, Hydrological connectivity, Spatial–temporal scaling, Flexible model structure, Parsimonious models

Introduction

Hydrological models have evolved with greater complexity due to increased computational power and spatial–temporal data availability from satellites. Precipitation–runoff processes have been simulated at scales ranging from hillslopes to catchments to large river basins to continents with varying degrees of specificity of flow paths that generally decrease at broader scales (e.g., Quinn et al. 1991; Refsgaard and Knudsen 1996; Thanapakpawin et al. 2007; Gosling et al. 2011; Abbaspour et al. 2015; Beck et al 2017). Nevertheless, just because models now have more discrete spatial and temporal characterization of catchment attributes (i.e. more complex), does not necessarily equate with an improved representation of hydrological processes, including how water and material transport (e.g., nutrients, pollutants, sediments) processes change with increasing spatial scale (Cammeraat 2002; Lane et al. 2009; Mockler et al. 2016; Sidle et al. 2017). As such, a critical observer may ask whether we are creating more complex hydrological models that focus on accuracy of spatially explicit model outputs for

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the wrong reasons. This begs the need to ensure hydrological models capture reasonably accurate processes at appropriate scales (Blöschl and Sivapalan 1995; Sidle 2006). Furthermore, in many remote and developing regions of the world where data are sparse, huge assumptions are required to parameterize the spatial complexity of drainage basins, thus requiring extensive calibration to produce questionable spatially explicit results (Andersen et al. 2001; Chen et al. 2017). Clearly, for many applications, there is a need to develop 'smarter' hydrological models that are compatible with the available data, characterize processes across multiple scales, capture relevant water sources, are not excessively complex, and, importantly, address the relevant questions at hand.

One of the limitations of most catchment or river basin hydrology models is that they are tested based on runoff responses at their outlets. While this practice may seem reasonable and is certainly appropriate for applications such as downstream flood assessment at a specific site, it does not ensure that internal processes within the catchment are accurately captured (Sidle 2006). As such, it is difficult, if not impossible, to quantitatively assess the effects of spatially distributed land management practices or heterogeneous inputs of precipitation on runoff behaviour. Of course, many distributed models can incorporate complex patterns of land use (e.g., Heuvelmans et al. 2004; Cuo et al. 2008; Tan et al. 2015; Yang et al. 2017); however, if accuracy and robustness of model predictions are only evaluated based on hydrological response at catchment outlets, many combinations of land management effects could produce similar outcomes (Moore and Grayson 1991). This issue of equifinality plagues many contemporary catchment hydrology model applications (Klemeš 1986).

Nonlinear dynamics in hydrological systems poses substantial challenges in catchment models (Beven 1995). Point scale parameters (e.g., saturated hydraulic conductivity, K_s) or flow descriptors (e.g., Richards equation, Hortonian overland flow contributions) cannot be easily upscaled and thus are often calibrated against the predictor variable (e.g., discharge at the catchment outlet) or within the flow equations. The spatial variability of K_s has been recognized and assessed across landscapes with respect to geomorphology and impacts of land management (e.g., Mohanty and Mousli 2000; Ziegler et al. 2006, 2007; Bevington et al. 2016). Variability in K_s plays an important role in routing subsurface water through hillslopes and catchments and controlling where and to what extent infiltration-excess overland flow propagates during storms (Sidle et al. 2007; Gomi et al. 2008; Miyata et al. 2019). While the dependency of K_s measurements on scale is known (Pachepsky and Hill 2017), it is usually not applied in catchment models. In most (but not all) cases, larger size samples (or domains) for characterizing in situ K_s yield higher and more realistic values for field-scale applications in heterogeneous media compared to small size (e.g., soil cores) samples (Arya et al. 1998; Nilsson et al. 2001). At hillslope scales, effective K_s appears to be more affected by self-organized behaviour of the soil fabric rather than simple randomness of K_s in the landscape (Blöschl and Sivapalan 1995; Sidle et al. 2000).

Other examples of nonlinear hydrologic responses include timing and spatial organization of preferential flow (Tsuboyama et al. 1994; Sidle et al. 2001), infiltration/runoff domains (Gomi et al. 2008; Miyata et al. 2019), discharge from zero-order basins (hollows) (Sidle et al. 2000; Tsuboyama et al. 2000), rapid subsurface flow generation (Scaife et al. 2020), areas of saturation overland flow (Dunne and Black 1970; Tanaka et al. 1988), exfiltration from fractured bedrock (Montgomery et al. 1997; Kosugi et al. 2006), and baseflow/groundwater storage relationships (Wittenberg 1999). These natural hydrologic nonlinearities are exacerbated by both extensive (e.g., agriculture, forest management, grazing) and intensive (e.g., roads, trails, building sites) management practices. Such anthropogenic activities create complex assemblages of runoff and flow disruptions in surface and subsurface soils, which pose problems for modelling.

This paper represents a further development of the 2017 AOGS Hydrological Sciences Distinguished Lecture delivered by the author and suggests ways of better incorporating process knowledge and scaling information into hydrological models for various applications. Herein, I attempt to articulate some of these process scaling concepts in a domain that formerly focused on statistical scaling (e.g., Gupta and Dawdy 1995; Gupta et al. 1996). Firstly, the strengths and weaknesses of a range of modelling approaches are evaluated and discussed. Next, examples of: (1) using better algorithms and representation of spatially and temporally distributed hydrological processes, including the more efficient use of remotely sensed data; (2) introducing the concept of hydrological connectivity to improve runoff prediction; and (3) employing flexible model structures are presented.

Hydrological modelling approaches

Hydrological modelling approaches can be divided in three general groups: (1) empirical or statistical models; (2) conceptual models; and (3) physical or process-based models (Refsgaard and Knudsen 1996; Sitterson et al. 2017; Beven 2019). Here and in the sections that follow, the focus is on attributes of models or model advances that may facilitate better opportunities for process representation and hydrological scaling, not simply the ability of models to simulate reasonably accurate downstream hydrographs. In this regard, identifying and differentiating amongst the dominant water sources and hydrological processes is essential for selecting the most effective or efficient model, as well as articulating the best conceptual representation of runoff behaviour, regardless of scale. Such considerations and improvements will greatly benefit the utility of models to capture internal catchment processes and advance their use in assessing spatially and temporally distributed land use practices.

Empirical/statistical models are typically 'black box', data driven, and lack connections with physical processes in the catchment. Examples of such models include the Curve Number approach, Artificial Neural Networks, and regression models. There are two types of applications: (1) models developed and trained on rainfall–runoff relationships, such as artificial neural network models (e.g., Srinivasula and Jain 2006); and (2) models developed for ungauged catchments where no discharge data exist, and predictions are made based on empirical parameters transposed from hydrologically similar and proximate gaged catchments (e.g., Blöschl 2005). Advancements have been achieved in both model types to capture some aspects of catchment characteristics (e.g., Blöschl 2005; Young 2006; Asadi et al. 2019), and their relative simplicity in terms of data requirements makes these models attractive in data-sparse regions or in ungagged catchments; however, physical processes operating at different scales within the catchment are not captured. Thus, one of the main errors in these models results from poor representation of spatially and temporally distributed precipitation, although they may accurately predict discharge at the calibrated downstream location (but not within the catchment) (Sitterson et al. 2017). While significant improvements have been made in capturing the nonlinear behaviour of rainfall–runoff processes (e.g., Sivakumar et al. 2001; Mehr and Nourani 2017), given that empirical/statistical models lack fundamental catchment information that affects hydrological response, they are not ideal for prediction proposes in catchments or basins where complex land cover and geomorphic units exist, nor can they capture land use change effects.

Conceptual hydrological models link various hydrological components in the catchment with relatively simple, but functional, algorithms that describe the overall hydrologic processes. Parameters imbedded in these algorithms may not have a direct physical interpretation and must be calibrated to achieve an optimal agreement between outputs of the system and model (Wagener et al. 2001). These models may comprise multiple reservoirs or tanks linked in series to represent exchange of water amongst the atmosphere, surface, and subsurface, including soil and groundwater components. Extensive meteorological and hydrological data are usually required to calibrate and ultimately test the sensitivity of different parameters with respect to hydrological system response (Freer et al. 1996; Wagener et al. 2001). The calibration involves curve fitting, which requires a period of historical data to calibrate the model and complicates inferences related to land use change (Beven and O'Connell 1982; Devi et al. 2015). In heavily parameterized conceptual models, as well as complex process-based models, various approaches to sensitivity analysis may need to be compared prior to hydrological modelling to facilitate the most robust model performance and to screen out unnecessary parameters (Song et al. 2015).

The tank model concept, introduced in Japan (Sugawara 1961), has gained popularity given its lumped representation of runoff processes, description of hydrologic pathways, simple structure, ease of calculations, and often better performance compared to other models (Yokoo et al. 2001; Johnson et al. 2003; Phuong et al. 2018). Such conceptual models generally do not consider detailed catchment characteristics or their spatial variability (Sitterson et al. 2017); however, within the last decade applications have successfully applied linked multi-tank models to distinct geomorphic features and soil water pathways in catchments (Sidle et al. 2011).

The Stanford Watershed Model (Crawford and Linsley 1966) was the parent of many subsequent conceptual hydrological models and modelling platforms, including HSPF, SWMM, and BASINS, which were adopted and further developed by US Environmental Protection Agency to deal with pressing point- and non-point pollution issues from the late 1970s onwards. A more recent semi-distributed conceptual model that has been widely used is TOPMODEL (Beven and Kirkby 1979). In addition to being quasi-physically based, TOPMODEL has a simplified structure with flexible time steps, alleviating some of the concerns raised about fixed time-stepping schemes in many conceptual models (Clark and Kavetski 2010). The widely used Soil and Water Assessment Tool (SWAT) is a hybrid model as it benefits from physical process information within the catchment, but in turn, employs conceptual and empirical algorithms like the curve number approach and the hydrological routing function (Arnold 2012; Nguyen et al. 2018).

True physical or process-based models are mathematical formulations that describe the physical laws that govern hydrological processes within a catchment—conservation of mass, momentum, and energy, in and between the surface and subsurface domains; thus, the solutions are three-dimensional and typically numerical (Kampf and Burges 2007; Fatichi 2016). The ability of these models to link parameters with the physical catchment system is their greatest strength, particularly when precise distributed data are available, physical processes of the hydrological system are well understood, and proper consideration is given to scaling (Zehe and Blöschl 2004; Sidle et al. 2017; Sitterson et al. 2017). These models have been criticized because of their complexity and large data demands (e.g., Beven and O'Connell 1982; Grayson et al. 1992), but more fundamental issues with most physically based models include misapplication of model assumptions and algorithms, nonlinearity, and incompatibility of the scale of measurements with their use in models (Grayson et al. 1992; Beven 2001; Zehe and Blöschl 2004; Kampf and Burges 2007), thus implying greater insights into inherent hydrological processes than warranted. Nevertheless, the prospect of obtaining better spatially and temporally explicit predictions together with advances in remotely sensed data acquisition and advanced computational power make these models relevant for many applications, such as land use change and non-stationary climates (Fatichi et al. 2016). Examples of popular physically based hydrological models include DHSVM, MIKE SHE, KINEROS, CATFLOW, VELMA, and HEC-HMS. Given the three-dimensional exchange depicted by many of these models (i.e. air-surface-soil/aquifer), they can simulate catchment interactions with sediments, nutrients, and chemicals (Sitterson et al. 2017).

The spatial representation of hydrological processes in models is somewhat, but not completely, aligned with the previous three model types. This spatial depiction controls how water inputs are applied and routed as surface and subsurface flow through the catchment as affected by vegetation, surface topography, surface and subsurface soil properties, and geology. The spatial structure of hydrological models can be characterized as lumped, semi-distributed, and fully distributed (Sitterson et al. 2017).

Lumped models do not consider heterogeneity of parameters and the entire catchment is generally treated as a homogenous domain (e.g., Moradkhani and Sorooshian 2008). These models require little data, but 'average' catchment properties, if required, are challenging to estimate and often arbitrary. As such, these models are not appropriate for large topographically complex catchments. Most empirical and some conceptual models fall into this category due to their inherent generalizations.

Semi-distributed hydrological models incorporate some degree of spatial variability in the simulation process. The parameters in semi-distributed models can be lumped by sub-catchments (e.g., Ajami et al. 2004) or by geomorphic properties within catchments (e.g., Sidle et al. 2011). While these models produce spatially explicit results, this does not necessarily result in more accurate outputs as more data are required for spatial calibration and evaluation of model performance. Conceptual and hybrid models like TOPMODEL and SWAT are characteristic of semi-distributed models, although some physically based models can be included in this category (Sitterson et al. 2017).

Fully distributed hydrological models are the most complex and data demanding but offer some unique advantages as well as challenges. Because these models specify hydrological processes at small grid scales, they require spatially discrete input parameters to take advantage of their complex structure. Each cell within the distributed model interacts with neighbouring cells to route water through surface and subsurface elements of the catchment. These models have often been criticized for not properly accounting for nonlinear behaviour of hydrological dynamics, difficulties surrounding a priori estimation of model parameters, scale issues, and equifinality, to name a few (e.g., Beven 2001). Although distributed models contain nonlinear functional relationships at the element scale, these equations do not average simply and may not adequately represent the extremes of the nonlinear system of responses (Beven 2001). Furthermore, if distributed models are parameterized using fine-scale hydrological properties (e.g., hydraulic conductivity derived from soil core samples, which over-represents matrix flow and underestimates preferential flow), then scaling behaviour may not be accurately represented in model results (e.g., Sidle et al. 2017). Nevertheless, fully distributed models that effectively capture the spatial distribution of physical properties across the catchment can be used to estimate flow in ungauged basins, providing that the relationships between model parameters and spatial properties are considered (Refsgaard 1997). Fully distributed models are generally physically based (e.g., MIKE SHE, DHSVM, VELMA, Wflow) and are frequently used to simulate the effects of land use changes on streamflow regime at various spatial and temporal scales (e.g., Cuo et al. 2008; Im et al. 2009; Golden and Knightes 2011; Gebremicael et al. 2019).

Advances in hydrological scaling and process conceptualization

Clearly, spatial and temporal scaling issues represent important challenges for hydrological modelling. New conceptualizations and approaches have been developed to assess the hydrologic dynamics in soils, runoff behaviour, streamflow response, and coupling atmospheric energy with water balances at various spatial and temporal scales (e.g., Mengelkamp et al. 1999; Batelaan and De Smedt 2007; Sidle et al. 2017; Miyata et al. 2019). Recent developments in remote sensing and passive microwave sensors facilitate better assessment of changes in land cover, precipitation, surface temperatures, snow water equivalent, soil moisture, energy budgets, and demographic shifts, as well as near real-time land surface changes, thus improving our ability to better conceptualize how such changes affect hydrological processes (e.g., Schumann et al. 2009; Quinton et al. 2011; Wang et al. 2012; Mohanty et al. 2017; Singh 2018; Jiang and Wang 2019; Koci et al. 2020). Capturing these dynamics at relevant temporal and spatial scales is critically important to better represent hydrological processes in models, as well as associated transport of sediments, nutrients, and contaminants.

Debate persists on the benefits and importance of understanding and articulating fine-scale processes in hydrological models (e.g., Grayson et al. 1992; Beven 2001; Zehe and Blöschl 2004; Silberstein 2006; Kampf and Burges 2007). The answer to this depends on the question being asked and is not always straightforward. While numerous statistical approaches have been applied to upscale hydrological data and, at the same time, infer process changes at different spatial scales (e.g., Gupta and Dawdy 1995; Gupta et al. 1996), these approaches have focused on discharge at catchment outlets and fail to adequately account for within-catchment processes (Blöschl 2005; Sidle 2006).

Numerous methods and approaches have been proposed to select the most appropriate hydrological model and parameters for specific applications (e.g., Freer et al. 1996; Chen and Chau 2006; Moreda et al. 2006; Clark et al. 2008a; Song et al. 2015). Additionally, progress has been made in examining scaling issues related to model parameterization (Kumar et al. 2013) and assessing model errors (Clark et al. 2008b), but hydrological process representation remains a challenge. Even in the well-established, semi-distributed Storm Water Management Model (SWMM), calibrated model parameters were highly uncertain in catchments with large impermeable areas and permeable areas that rapidly recover from wet to dry conditions (Awol et al. 2018). While such examples of using statistical approaches to facilitate efficient and parsimonious parameter selection and error analysis are commendable, a necessary first step is to ensure that hydrological process representation and associated scaling measures are robust; in turn, this will help guide model selection and parameterization.

Recent applications of machine learning (ML) and deep learning (DL) models in catchment hydrology have the potential to improve runoff predictions because they are trained on large and highly variable data sets derived from multiple catchments (Kratzert et al. 2019; Nearing et al. 2021). A fundamental premise is that these models have much more degrees of freedom than conceptual models facilitating the development and transferability of hydrological relationships and improving scaling relationships. Also, such models have been applied in ungauged catchments based on the assumption that sufficient data exist in hydrologically similar catchments to provide more accurate simulations in ungauged catchments than other calibrated catchment models (Kratzeret et al. 2019; Oppel and Schumann 2020). While these approaches attempt to seek "truth" in hydrological modelling, the issue of accurately representing internal hydrological behaviour, and therefore the effects of anthropogenic activities remain elusive.

Moving from statistical to more process-based approaches that can be incorporated into models has proven to be challenging. Drawing on a personal example of subsurface flow at a hillslope scale that invoked a series of hydrometric (Sidle et al. 1995; Tsuboyama et al. 2000; Noguchi et al. 2001), conservative tracer (Tsuboyama et al. 1994), staining (Noguchi et al. 1999), and conceptual (Sidle et al. 2000) studies, we can see how the fine-scale behaviour of subsurface flow during rainfall events is important to properly characterize catchment runoff, particularly defining the sources of nonlinearity and hydrological thresholds related to storm runoff. Upscaling these processes to the catchment scale was accomplished via a nested set of sub-catchments in which measurements were conducted at scales ranging from the entire catchment to a small portion of a hillslope. The findings revealed that exceeding a hydrological threshold of soil moisture was necessary to activate preferential flow in the soil, which ultimately contributed up to 25% of the total catchment stormflow during the wettest conditions (Sidle et al. 1995). Furthermore, while individual preferential flow paths were quite short, they self-organized and connected to substantial distances upslope as the catchment became wetter (Tsuboyama et al. 1994; Noguchi et al. 1999; Sidle et al. 2001). These field results were later confirmed by a small-scale modelling study that showed how disconnected macropores were able to expand and become connected as the degree of saturation increased (Nieber and Sidle 2010). Nonlinear behaviour was also observed in zero-order basins (hollows), where hydrologic response was triggered by soil moisture thresholds affected by soil depth (Sidle et al. 2000; Tsuboyama et al. 2000). Articulating these nonlinear responses not only improves our understanding of hillslope hydrology, but also specifies which portions of the catchment are most likely to be 'hydrologically active' under various moisture conditions. The temporal contributions of various hydrological pathways in this small Japanese forest catchment were successfully simulated in a semi-distributed, multi-tank model (Kim et al. 2011) coupled with a kinematic wave model to route water within the riparian area and channel (Sidle et al. 2011). This long-term investigation underlines the importance of carefully designed field data collection, experimentation, and conceptualization within a nested catchment structure, followed by informed modelling.

Other types of studies have employed nested catchment designs to effectively examine hydrological processes at different scales. Examples include using stable isotopes within a nested mesoscale catchment (Rodgers et al. 2005), a continental scale nested network to assess cumulative catchment effects (Stein et al. 2014), and using a generalized linearized regression model to estimate scaled catchment runoff coefficients for different rainfall and antecedent moisture conditions (Graeff et al. 2012).

It would be reticent not to acknowledge the advances of tracer studies to the understanding of water residence times, hydrograph separation, flow paths, and evapotranspiration processes; however, little progress has been made in seamlessly linking the findings of these extensive and expensive research investments to hydrological modelling. Use of isotope tracers in hydrology date back at least into the 1940s, but progress in bridging these findings to the solution of practical problems has been slow (Phillips 1995). While tracer techniques can help elucidate temporal and spatial patterns of various water sources and pathways, the application of this approach has mostly been confined to constraining estimates of water storage in catchments (e.g., Tetzlaff et al. 2015). Some the more promising applications of tracer techniques to modelling may come by combining this approach with nested catchment and remote sensing studies (Rodgers et al. 2005; Gomi et al. 2010; Tetzlaff et al. 2015). Nevertheless, care needs to be taken to ensure tracer approaches accurately reflect water sources and flow pathways when variable inputs and potential intercompartmental exchanges occur (Luxmoore and Ferrand, 1993; DeWalle and Swistock 1994; Noguchi et al. 1999; Sidle et al. 2000).

Examples of smarter strategies for hydrological models

Improving spatial and temporal representation in hydrological models

The availability of hydrological datasets derived from remotely sensed data has increased substantially in the past decade, and there is a growing body of research assessing remotely sensed data for hydrological applications. Variables such as topographic data, precipitation, actual evapotranspiration, soil moisture, water elevation, flood inundation extent, and terrestrial water storage variations can now be measured or predicted at different spatial and temporal scales (Houser et al. 1998; Stephens and Kummerow 2007; Schumann et al. 2009; Albergel et al. 2012; Jarihani et al. 2013, 2015b). For example, near-global coverage Digital Elevation Models (DEMs), such as Shuttle Radar Topography Mission (SRTM) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), are extensively used for hydrologic–hydrodynamic modelling in remote areas (Jarihani et al. 2015a; Pham et al. 2018). The Global Multi-resolution Terrain Elevation Data 2010 (GMTED2010) includes digital terrain elevation data from SRTM, Canadian elevation data, Spot 5 Reference3D data, and data from the Ice, Cloud, and land Elevation Satellite (ICESat), providing a high level of detail in global topographic coverage at 30-, 15-, and 7.5-arc-second spatial resolutions (Danielson and Gesch, 2011). Nevertheless, some studies have shown considerable errors for runoff and particularly sediment transport using these global remote sensing data due to gradient smoothing and other modifications; thus, such anomalies need to be considered in the selection of appropriate remote data sets (Sharma and Tiwari 2014; Pakoksung and Takagi 2020).

Capturing multiple water inputs in models that fall outside of the normal precipitation domain (glacier and permafrost melt) is very important in high latitude and high elevation environments (Fig. 1). These areas, particularly in the high mountain ranges of Asia (i.e. Water Towers), are very vulnerable to effects of climate change and climate variability given their dependence on snowmelt and glacial melt supplying much of the runoff to river systems and poor communities (Immerzeel et al. 2010). Nevertheless, the impacts of climate change are not consistent, even within Central Asia, nor are the melt rates from glaciers (Immerzeel and Bierkens 2012; Knoche 2017). Hydrological modelling is essentially the only

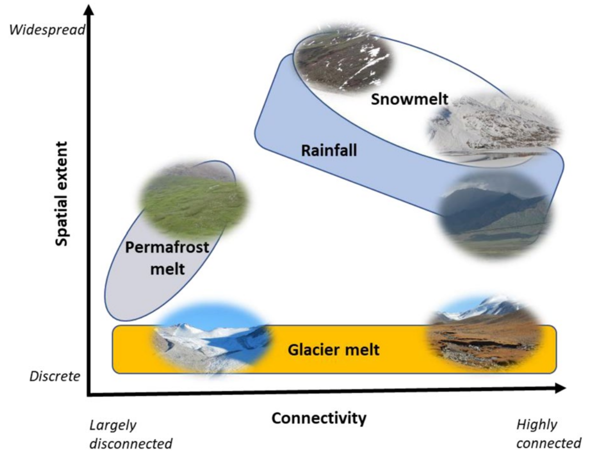

Fig. 1 Example of a conceptual relationship of the spatial extent of dominant water sources and their respective connectivity to channels in high elevation mountains of Central Asia. Such issues need to be considered in hydrological modelling

way to assess the potential effects of climate change on future changes in discharge regimes, droughts, flooding scenarios, and water-related hazards in these remote but important regions that contribute critical water supplies down river.

Given the paucity of data in these areas, hydrological models must be parsimonious, but able to quantify water sources other than rainfall, such as snowmelt, glacial melt, and even permafrost melt, and appropriately route these through the basin. For example, remotely sensed snow cover data (e.g., Moderate Resolution Imaging Spectroradiometer, MODIS) can be used to produce spatial and temporal patterns of snow cover, which can be modified to remove confounding effects of cloud cover (Gafurov et al. 2016). Relatively simple algorithms need to be developed for snowmelt, glacier melt, and permafrost melt (if relevant) considering the sparse data in these remote high-elevation regions. Glacier evolution can be simulated using a dynamic glacier retreat approach (Huss et al. 2010) and initial glacial conditions and changes can be estimated from surveys or historical remote sensing records. Thus, with rather rudimentary spatially distributed data, hydrological models can be developed to estimate the contributions and timing of various water sources in high altitude mountainous areas (e.g., Duethmann et al. 2014, 2016). Furthermore, the concept of 'hydrological connectivity' (discussed in the next sub-section) can be employed to identify susceptible areas of runoff concentration and link runoff sources to stream channels. In some areas these linkages will be direct and in other cases little runoff will reach channels (Fig. 1).

Incorporating hydrological connectivity into models

The importance of connectivity of overland flow has be recognized for several decades in terms of water and sediment routing to streams (e.g., Moore and Grayson 1991; Puigdefábregas et al. 1999; Jones et al. 2000; Sidle et al. 2004; Croke et al. 2005). Establishing the connectivity of overland flow from the land surface within the catchment to stream channels requires a conceptualization of hydrologic, land surface, and soil properties. Hydrological connectivity strongly affects the transfer of materials, energy, and even organisms within ecosystems. Examples abound describing how hydrologic connectivity affects both the cumulative and dispersed nature material transport from headwaters to downstream reaches (Gomi et al. 2002); hillslope–riparian–stream transmission of water and chemical constituents (Jencso et al. 2010); species migration, habitat, and refugia (Sedell et al. 1990); integrity of biological reserves at multiple scales (Pringle 2001); potential for groundwater contamination (Sidle et al. 1998); and wetland health (Singh and Sinha 2021), among other ecosystem functionalities.

Building on the early work of Onstad and Brakensiek (1968), Moore et al. (1988) applied digital terrain analysis to develop a contour line-based method (TAPES-C) that subdivides the catchment into irregular polygons bounded by digitized contour lines and adjacent streamlines, thus capturing the effects of complex topography and the connectivity of upslope to downslope elements on flowpaths (Moore and Grayson 1991). While most of the early applications were for surface processes (Hortonian and saturation overland flow), later developments using TAPES-C were used to model the temporal and spatial dynamics of shallow groundwater response in slope stability and sediment routing simulations (Wu and Sidle 1995; Dhakal and Sidle 2004). A later adaptation of this contour-based topographic approach (TOPOTUBE), which included spatial heterogeneity of infiltration capacity based on ground cover, simulated the distributed partitioning of Hortonian overland flow, saturation overland flow, and saturated soil matrix flow, providing reasonable predictions of storm runoff from a small forest catchment (Gomi et al. 2013; Miyata et al. 2019). Nevertheless, the main benefit of such contour-based models appears to be achieving more spatially and temporally explicit representation of internal catchment hydrological and associated material transport processes.

Other studies have focused on how catchment wetness or shallow groundwater depth assessed by indicators such as the topographic index in TOPMODEL (i.e. ln $(a/\tan\beta)$, where a is the upslope contributing area and $\tan\beta$ is the local slope gradient) inform hydrologic connectivity and nutrient transport across hillslopes and into the riparian zone (e.g., Stieglitz et al. 2003; Detty and McGuire 2010). Later studies have incorporated vegetation patterns and topographic attributes into similar modelling approaches to assess connectivity of both surface and subsurface flow (e.g., Hwang et al. 2012; Hallema et al. 2016).

Several empirical approaches have been developed to assess connectivity of surface runoff within catchments (Bracken and Croke 2007; Borselli et al. 2008; Lane et al. 2009; Reaney et al. 2014). One of the mostly commonly used is the index of runoff and sediment connectivity (IC) developed by Borselli et al. (2008) and later modified and tested for assessing hydrological connectivity at catchment scales (Cavalli et al. 2013; Crema et al. 2015; López-Vicente et al. 2017; Koci et al. 2020). The IC is quantified as a function of average slope gradient, contributing area, and a weighting factor based on the relative 'resistance' of each cell against runoff and sediment flow derived from the C-factor in the Revised Universal Soil Loss Equation (RUSLE) (Borselli et al. 2008). This relatively simple algorithm has been applied in numerous studies, but improvements can be made by considering parameters like an index of infiltration capacity, vegetation cover indices, and/or remotely sensed antecedent soil moisture within the weighting factor.

Another approach to quantify hydrologic and associated sediment connectivity is derived from graph theory or its derivative, network theory, in which hydrologic systems are depicted as a collection of nodes that are linked to one another via threshold behaviour (e.g., Halverson and Fleming 2015; Cossart and Fressard 2017). Such network system approaches appear to rely heavily on earlier concepts developed from studies on soil moisture thresholds that control hydrological response and connectivity in catchments (e.g., Sidle et al. 2000; Western et al. 2001). Attempts have also been made to partition water fluxes using stable isotopes to examine the hydrologic connectivity of bound soil water with more mobile surface water (e.g., Good et al. 2015); however, such approaches are based on conservation of flow paths, which are often violated in the complex field systems as previously noted (e.g., Luxmoore and Ferrand 1993), and the findings are difficult to translate into catchment models.

Utilizing flexible model structure

Typically, trade-offs exist between predicting the timing of the discharge hydrograph and flow volume. Generally, it is very difficult to calibrate both timing and volume of flow in hydrological models. Combined hydrologic–hydrodynamic models can fill this gap by increasing the accuracy of the hydrograph routing while producing acceptable flow volume estimates. For example, TUFLOW employs a rainfall–runoff module for runoff generation and 2-dimensional hydrodynamic equations to route runoff to the catchment outlet. More recent advances in these types of models include the incorporation of a flexible mesh that allows for finer resolution proximate to areas with more complex hydrodynamics (e.g., woody debris in channels, rough channel banks, reaches with high topographic roughness) (Teng et al. 2017). Earlier theoretical research that extended the concept of smoothed particle hydrodynamics (SPH) to deal with free surface incompressible flows (Monaghan 1992) has advanced hydrodynamic modelling as have 3D fluid simulators, which can maximize the relative advantages of using Eulerian and Lagrangian frameworks (Sulsky et al. 1994).

Employing flexible model structure also increases the applicability of models to a broader range of applications. Some modelling approaches provide the user a choice of different processes and modules based on the environment, objectives, and data availability. Moreover, open-source models also provide opportunities for modellers to modify the model structure based on their modelling requirements. For example, the relatively new Wflow model produced by Deltares' (http://www.openstreams.nl) facilitates fully distributed inputs of precipitation, interception, soil water, evapotranspiration, snow accumulation and melt, surface water, and groundwater recharge and uses a kinematic wave routing function. Wflow utilizes open earth observation data and can calculate hydrological fluxes at any geographic location within the model domain for any time step. The structure of the model is transparent and can easily be changed.

To address more complex environmental problems that involve holistic system thinking within the context of environmental decision-making, including socioeconomic activities and policy development, integrated environmental modelling has emerged as a science-based structure to organize transdisciplinary knowledge (Laniak 2013). Integrated environmental modelling involves a systems-based approach to environmental modelling that includes multiple models, data bases, and assessment methods that form the basis for constructing a complex simulation system that addresses real-world environmental problems. This system allows for various models to communicate with one another in a 'plug and play' manner whilst embracing the challenge of interoperability, which involves data standardization (Laniak et al. 2013; Whelan 2014a). This approach is far broader in scope than hydrological models per se, but catchment hydrology and related sediment, nutrient, and contaminant transport processes and pathways are typically incorporated—often across the source-to-receptor spectrum (Whelan 2014b). As such, many applications involve water as a primary vector for the fate, transport, and exposure of pollutants.

An example of an integrated modelling application involves the use of the FRAMES (Framework for Risk Analysis in Multi-media Environmental Systems) platform (Gaber et al. 2008) to assess the source, fate, and transport of mercury, as well as the exposure to fish (including bioaccumulation of mercury) within the Albemarle–Pamlico drainage basins in eastern USA (Johnston 2011). FRAMES is linked to Data for Environmental Modeling (D4EM; Wolfe et al. 2014) software that obtains and processes data sets that can be seamlessly used in the integrated modelling exercise. In this application, FRAMES linked five environmental models, including SWAT for catchment runoff, Watershed Mercury Model for mercury runoff and loading to streams, WASP to assess water quality dynamics within the stream system, Habitat Suitability Index model to predict habitat quality for various fish species, and BASS to predict bioaccumulation of mercury and its effect on fish growth and production. Such system-based approaches are very useful, albeit time consuming and complex, to inform regulatory policy and decision-making on complex environmental issues.

Prognosis and summary

Clearly, the selection of the most appropriate hydrological model depends on the problem at hand and the level of complexity needed to satisfactorily address this. Aside from a purely research approach, to be useful for managers, regulators, and other practitioners, the selected hydrological model should be as parsimonious as possible. In some cases, simple empirical, statistical, or conceptual models may be appropriate and sufficient, particularly when only catchment outflow needs to be predicted and where sufficient parameterization data from proximate catchments are available or where "training" data within the designated catchment can be relied on. Herein, the focus is on more complex scenarios where catchment hydrology is affected by spatially and temporally variable water inputs, climate, land use, and demographics where such simple models are of limited relevance. Addressing these more complex effects and interactions may, but does not necessarily, imply a highly sophisticated hydrological model. While the complexity of the hydrological processes and the scaling effects need to be understood, translating these into informative but reasonably simple model algorithms remain the primary challenge. A flow diagram is presented (Fig. 2) that illustrates major data requirements for robust hydrological process representation (blue boxes), broad assessment objectives (white boxes), decision points (green boxes), and key areas for model improvement (yellow boxes) that lead to the selection of the optimal and most parsimonious catchment model (pink boxes). Initially evaluating and understanding the dominant water sources and

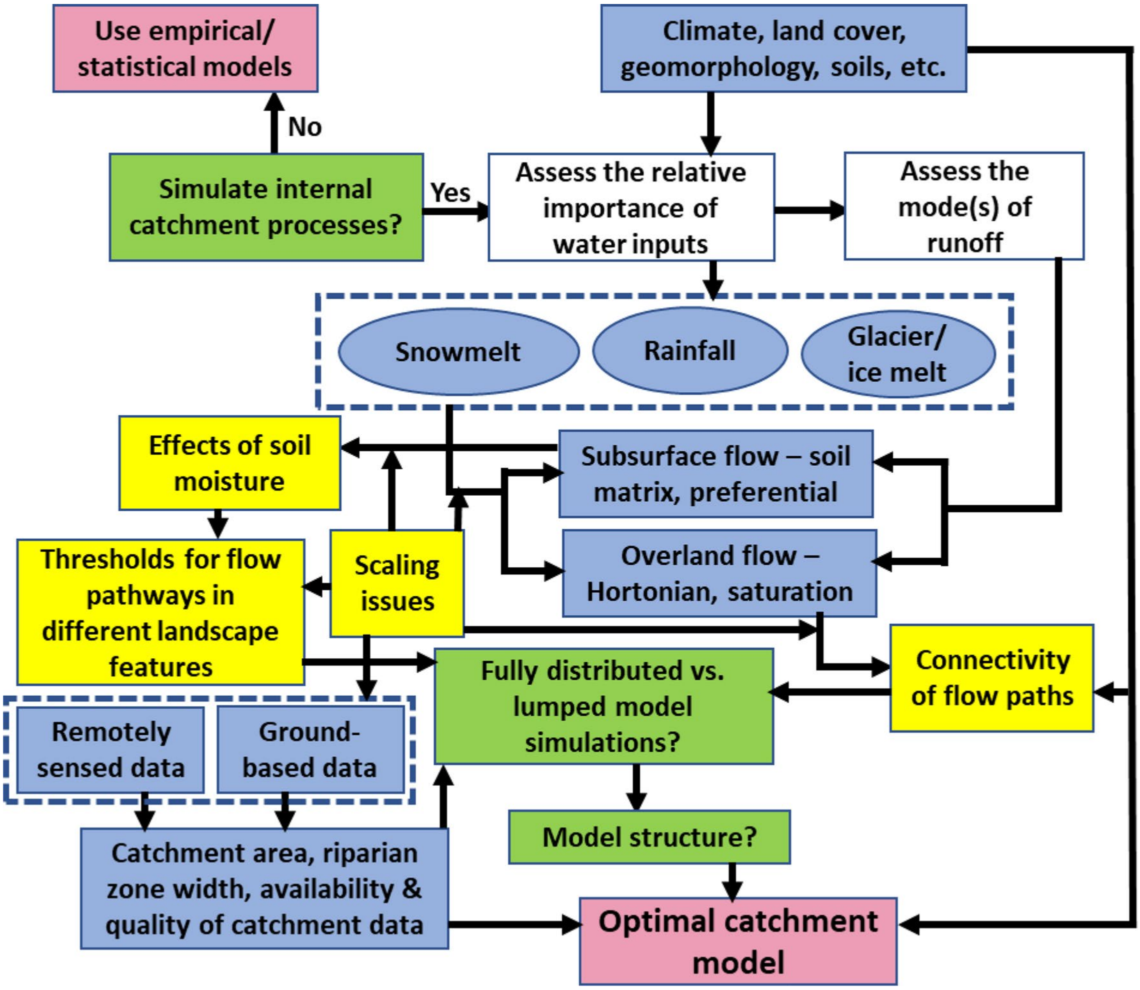

Fig. 2 A framework for illustrating where improvements (yellow boxes) can be achieved in catchment models, as well as requirements for hydrological process representation (blue boxes), broad assessment objectives (white boxes), and major decision points (green boxes) that lead to most optimal and most parsimonious model selection (pink boxes)

hydrological processes operating at different times within a catchment and then employing a flexible model structure that focuses on the most important hydrological processes is a promising approach that may avoid over parameterization (Fig. 2).

Although many technological advances have been made in the realm of hydrological modelling related to computation, remote data sources, and interoperability, there remain gaps in our ability to effectively incorporate spatial and temporal scaling of hydrological processes into models. This can partly be attributed to the ongoing evolution of concepts in streamflow and stormflow generation, including articulating thresholds for activation of various hydrologic flow paths and geomorphic features in the landscape (Fig. 2). Temporal changes in land cover, climate forcing, water sources, energy budgets, and social dynamics also present challenges for long-term hydrological simulations. Much of these hydrological dynamics have yet to be successfully incorporated into many models despite advances in process understanding. One reason for this gap between process understanding and modelling is that catchment hydrologists have typically not produced robust, scale-dependent algorithms that reflect their level of process understanding; however, another reason is that hydrological modellers continue to embrace algorithms that give reasonably good predictions at catchment outlets without concern for within-catchment processes and pathways—i.e. getting the right answer (at a fixed point) for the wrong reasons.

Advances in remote sensing in the past two decades have the potential to narrow this gap between process hydrologists and modellers. Spatially and temporally variable precipitation, other water inputs, radiation and temperature, soil moisture, and land cover are not only important hydrological controls (Fig. 2), but also affect fluxes of sediments, nutrients, and pollutants from source to sink. The concept of hydrological connectivity, supported by detailed digital elevation models and understanding of subsurface flow dynamics, can be used to better articulate flow pathways using rather simple algorithms (Fig. 2). This can help identify important focal areas for mitigation practices within catchments and thus is a potentially useful tool for managers. These and other innovations that rely on remote sensing and process representation are the best pathways forward for supporting hydrological modelling in remote regions, particularly in poor regions of the world with very limited historical hydrological data, few resources, and little access to ground-based data acquisition systems. Furthermore, to ensure the development of smarter hydrological models, modellers need to work closely with catchment hydrologists to incorporate important processes and scaling concepts.

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Declaration

Competing interests
The author declares no conflict of interest.

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