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## Scaling, Similarity, and the Fourth Paradigm for Hydrology

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### Abstract

In this synthesis paper addressing hydrologic scaling and similarity, we posit that roadblocks in the search for universal laws of hydrology are hindered by our focus on computational simulation (the third paradigm), and assert that it is time for hydrology to embrace a fourth paradigm of data-intensive science. Advances in information-based hydrologic science, coupled with an explosion of hydrologic data and advances in parameter estimation and modelling, have laid the foundation for a data-driven framework for scrutinizing hydrological scaling and similarity hypotheses. We summarize important scaling and similarity concepts (hypotheses) that require testing, describe a mutual information framework for testing these hypotheses, describe boundary condition, state/flux, and parameter data requirements across scales to support testing these hypotheses, and discuss some challenges to overcome while pursuing the fourth hydrological paradigm. We call upon the hydrologic sciences community to develop a focused effort towards adopting the fourth paradigm and apply this to outstanding challenges in scaling and similarity.

## 1 Introduction

This synthesis paper is an outcome of the “Symposium in Honor of Eric Wood: Observations and Modeling across Scales”, held June 2–3, 2016 in Princeton, New Jersey, USA. The focus of this contribution is the heterogeneity of hydrological processes, their organization, scaling and similarity, and the impact of the heterogeneity on water and energy states and fluxes (and vice versa). We argue here that the growth of hydrologic science, from empiricism (1<sup>st</sup> paradigm), via theory (2<sup>nd</sup> paradigm), to computational simulation (3<sup>rd</sup> paradigm) has yielded important advances in understanding and predictive capabilities – yet

we argue that accelerating advances in hydrologic science will require us to embrace the 4<sup>th</sup> paradigm of data-intensive science, to use emerging datasets to synthesize/scrutinize theories and models, and improve the data support for the mechanisms of Earth System change.

The Fourth Paradigm is a concept that focuses on how science can be advanced by enabling full exploitation of data via new computational methods. The concept is based on the idea that computational science constitutes a new set of methods beyond empiricism, theory, and simulation, and is concerned with data discovery in the sense that researchers and scientists require tools, technologies, and platforms that seamlessly integrate into standard scientific methodologies and processes. By integrating these tools and technologies for research, we provide new opportunities for researchers and scientists to share and analyze data and thereby encourage new scientific discovery. As shown in Figure 1, the scientific method applied to hydrology is not a linear process—rather, because hydrology is already in the 3<sup>rd</sup> paradigm, empiricism (the 1<sup>st</sup> paradigm) and theoretical development (the 2<sup>nd</sup> paradigm) both lead to new theories and hypotheses that are embodied in computational models. These hypotheses may not be rigorously tested with many datasets, either because the datasets have not been gathered into an effective, accessible platform, or because the datasets require additional processing and information theoretic techniques to apply them to the model predictions for hypothesis testing. Further, as noted by Pfister and Kirchner (2017), hypothesis testing with models is fraught with challenges that require not only consideration of the data required to test a given hypothesis, but also careful consideration of how to encode hypotheses as uniquely falsifiable predictions (Figure 1). Advances in data science now allow the 4<sup>th</sup> paradigm to inject “big data” into the scientific method using rigorous information theoretic methods without eliminating the other parts of the scientific method.

Our focus here on scaling and similarity directs attention to one of the most challenging problems in the hydrologic sciences. As defined by Blöschl and Sivapalan (1995), scale is a “characteristic length (or time) of process, observation, model” and scaling is a “transfer of information across scales” (see also Bierkens et al., 2000; Grayson and Blöschl, 2000). Functional relationships between hydrologic variables may also exist and these may be scale-independent (or scale-invariant). Similarity is present when characteristics of one system can be related to the corresponding characteristics of another system by a simple conversion factor, called the scale factor. We should note that the terms ‘scaling’ and ‘similarity’ used here are specific to the hydrology literature and distinct from the general notions of self-similarity, fractals, and emergent behavior in the nonlinear dynamics literature. Classic examples of similarity include the ratio of catchment areas (Willgoose et al., 1991; Smith, 1992), and the topographic index  $\ln(a/\tan\beta)$  (Beven and Kirkby, 1979) that are used for relating flows of two catchments and relating the topographic slopes and contributing areas to water table depths, respectively. Another example is the hillslope Péclet number (Berne et al., 2005; Lyon and Troch, 2007). Heterogeneity or variability in hydrology manifests itself at multiple spatial scales (e.g., Seyfried and Wilcox, 1995; Blöschl and Sivapalan, 1995), from local ( $O(1\text{ m})$ ; e.g., macropores) to hillslope ( $O(100\text{ m})$ ; e.g., preferential flowpaths) to catchment ( $O(10\text{ km})$ ; e.g., soils) and regional ( $O(1000\text{ km})$ ; e.g., geology). Similarly, temporal variability is reflected on event, seasonal and decadal time scales (e.g., Woods, 2005). Understanding scaling and similarity requires understanding how the interactions among multiple processes across scales affect the (emergent)

hydrologic behaviour at other space-time scales; such understanding underpins methods for computational simulation.

The scaling and similarity problem is nevertheless very difficult. As asserted by Dooge (1986), “within the physical sciences and the earth sciences there is and can be no universal model for water movement.” Despite numerous attempts at integrating local models across soils (e.g. Kim et al., 1997), hillslopes (Troch et al., 2015) and watersheds e.g., (Reggiani et al., 1998, 1999, 2000, 2001), universal laws in hydrology and the required closure relations remain elusive because the physics are likely scale-dependent (e.g. Bierkens, 1996) and the data required to test these hypotheses are either not readily available or not easily synthesized, or, even worse, would never be observable (Beven, 2006). Further, computational advances have enabled so-called “hyper-resolution” or, using an alternative term that is not necessarily equivalent, “hillslope-resolving” modelling (e.g. Chaney et al., 2016; Wood et al., 2011), but as noted in the discussion between Beven and Cloke (2012) and Wood et al. (2012), and later discussed in Beven et al. (2015), the ability to provide meaningful information from hillslope-resolving models is limited both by a lack of tested parameterizations at a given model scale as well as by lack of data for model evaluation (e.g. Melsen et al., 2016a).

In principle, moving to finer spatial and temporal resolutions may improve accuracy simply by reducing the truncation error in the numerical solution of the system of partial differential equations. In an analogy with fluid mechanics and the atmospheric sciences where “large eddy simulations” are designed to capture the most energetic motions and thereby reduce the sensitivity to turbulence closure, one might ask whether “hillslope-resolving” models might resolve the most energetic components (in an information theoretic/entropy sense) of the terrestrial water storage spectrum such that the closure problem may be simplified. As discussed in many of the studies cited above, topography is fractal and this, combined with scaling between the pedon and the hillslope, drives much of the scaling behavior seen in hydrology. Most of the apparent fractal nature in relation to hydrology has been demonstrated at the scale of river networks (e.g. Tarboton et al, 1988), so a hypothesis that could be tested with data following the 4<sup>th</sup> paradigm is to what extent resolving these river networks in models reduces the information loss. Further, proposed scaling relationships may be appropriate above a given scale, but as we move downward in scales from watershed to hillslope to local, these relationships may break down.

These current tactics in the hydrologic sciences are representative of the third paradigm of scientific investigation (Hey et al., 2009), characterized by applying computational science to simulate complex systems. The so-called third paradigm builds on the earlier first (empirical) and second (theoretical) paradigms. As discussed by Clark et al., (this issue), computational science approaches to modeling hydrologic systems have been discussed for decades. With the advent of high-resolution earth observing systems (McCabe et al., this issue), proximal sensing (Robinson et al., 2008), sensor networks (Xia et al., 2015), and advances in data-intensive hydrologic science (e.g., Nearing and Gupta, 2015), there is now an opportunity to recast the hydrologic scaling problem into a data-driven hypothesis testing framework e.g., (Rakovec et al., 2016a). By embracing such a framework, hydrologic

analysis can become explicitly “scale-aware” by testing specific parameterizations at a given model scale. Now is the time for a fourth paradigm in hydrologic science.

With this goal in mind, this paper addresses the following questions:

1. What are the key scaling and similarity concepts (hypotheses) that require testing?
2. What framework could we use to test these hypotheses?
3. What are the data requirements to test these hypotheses? and
4. What are the model requirements to test these hypotheses?

## 2 Scaling and similarity hypotheses

Most scaling work to date has built on the Representative Elementary Area (REA) concept (Wood et al., 1988), and extensions to the Representative Elementary Watersheds (REW) introduced by Reggiani et al. (1998, 1999, 2000, 2001) – the REA/REW concept seeks to define physically meaningful control volumes for which it is possible to obtain simpler descriptions of the rainfall-runoff process (i.e., simpler than those at the point scale). An alternative, but related, concept is the Representative Hillslope (RH; Troch et al., 2003; Berne et al., 2005; Hazenberg et al., 2015). The REA/REW approach is conceptually similar to Reynolds averaging, and relies on the fundamental assumption that the physics are known at the smallest scale considered (e.g. Miller and Miller, 1956). Critically, the fluxes at the boundaries of the model control volumes require parameterization (the so-called “closure” relations). These closure assumptions are typically ad-hoc, and include sub-grid probability distributions, scale-aware parameters, or new flux parameterizations. Fundamentally, these approaches conform to the third paradigm, in the sense that they take as given a set of conservation equations that govern behaviour at the fundamental (patch, tile, grid, hillslope, or REW) scale (Figure 2). Testing both the scaling and closure assumptions as hypotheses using data would move hydrology towards the fourth paradigm.

The examples above represent the classic “Newtonian” approach in hydrology, but the 4<sup>th</sup> paradigm advocated here is not specific to testing hypotheses derived from that approach, and as shown in Figure 1, represents an augmentation to the scientific method in hydrology. Foundational (Sivapalan, 2005; McDonnell et al., 2007) and more recent work (Thompson et al., 2011; Harman and Troch, 2014) on “Darwinian” hydrology has used scale and similarity concepts to synthesize catchments across scales, places and processes. As noted in McDonnell et al., (2007) there has been a call for a reconciliation of the Newtonian and Darwinian approaches, starting first in the ecology community (Harte, 2002), and we believe that moving to a 4<sup>th</sup> paradigm with the augmented scientific method depicted in Figure 1 will embody the wishes of Darwin from his “Structure of Coral Reefs” as quoted in Harman and Troch (2014):

“... In effect, what an immense addition to our knowledge of the laws of nature should we possess if a tithe of the facts dispersed in the Journals of observant travellers, in the Transactions of academies and learned societies, were collected together and judiciously

arranged! From their very juxtaposition, plan, co-relation, and harmony, before unsuspected, would become instantly visible, or the causes of anomaly be rendered apparent; erroneous opinions would at once be detected; and new truths – satisfactory as such alone, or supplying corollaries of practical utility – be added to the mass of human knowledge. A better testimony to the justice of this remark can hardly be afforded than in the work before us.”

An important avenue to advance hydrologic understanding and predictive capabilities is through attention on hypotheses of hydrologic scaling and similarity, i.e., different ways to relate processes and process interactions across spatial scales. One of the foundational works in hydrologic similarity is the topographic index (Beven and Kirkby, 1979) – the topographic index defines local areas of topographic convergence, and is used to relate the probability distribution of local water table fluctuations to catchment-average surface runoff and sub-surface flow. Building on this topographic similarity, this index was expanded to include soils and study runoff production (Sivapalan et al., 1987; Sivapalan et al., 1990), and further applied to examine scaling of evaporation (Famiglietti and Wood, 1994) and soil moisture (Wood, 1995; Peters-Lidard et al., 2001). Such controls of water table depth on runoff production and evapotranspiration at catchment scales represent just one hypothesis of similarity and scaling behaviour – an example alternative hypothesis, used in the VIC model (Liang et al., 1994), is the description of how sub-element variability in soil moisture affects the development of saturated areas in a catchment and the partitioning of precipitation into surface runoff and infiltration (Moore and Clarke, 1981; Dümenil and Todini, 1992; Wood et al., 1992; Hagemann and Gates, 2003). Other scaling hypotheses are used for other physical processes, for example, how small-scale variability in snow affects large-scale snow melt (Luce et al., 1999; Liston, 2004; Clark et al., 2011a), and how energy fluxes for individual leaves scale up to the vegetation canopy (de Pury and Farquar, 1997; Wang and Leuning, 1998).

The critical issue here is the interplay between the scale of the model elements and the choice of the closure relations: As computational resources permit higher resolution simulations across larger domains (Wood et al., 2011), more physical processes can be represented explicitly, and the closure relations must be tailored to fit the spatial scale of the model simulation. To some extent such “hyper-resolution” approaches abandon the quest for physically meaningful control volumes that characterizes the REA and REW concepts, and the representation of sub-element processes in fully 3-D simulation of watersheds (e.g., Kollet and Maxwell, 2008; Maxwell and Miller, 2005) is becoming less and less obvious, and perhaps less and less necessary. A key question now is whether “hyper-resolution” applications through explicit 3-D models, or (at least for some variables) with clustered 2-D simulations (e.g., the HydroBlocks of Chaney et al., 2016), provide reasonable representations of scaling and similarity. Considering infiltration excess and saturation excess runoff generation processes, high resolution numerical studies indicate that excess infiltration doesn’t appear to have an ergodic limit (e.g. Maxwell and Kollet (2008), while excess saturation processes scale with the geometric of subsurface saturated hydraulic conductivity (e.g. Meyerhoff and Maxwell, 2011). Similarly, one might imagine different scaling relations for evapotranspiration depending on the nature of controls due to radiation (topography), vegetation, and/or soil moisture (e.g., Rigden and Salvucci, 2015). For example, as recently shown by Maxwell and Condon (2016), the interplay of water table

depths with rooting depths along a given hillslope exerts different controls on evaporation and transpiration, which links the water table dynamics with the land surface energy balance, even at continental scales. This finding is based on limited data, and would benefit from formal hypothesis testing in an information-based framework, as described in the next section.

### 3 A hypothesis testing framework for hydrologic scaling and similarity

As demand increases for hillslope-resolving or “hyper-resolution” modelling (e.g., Beven et al., 2015; Beven and Cloke, 2012; Bierkens et al., 2015; Wood et al., 2011, 2012), the question arises as to whether the physics in our models, the parameters that are used in the models, and the input data (e.g., “forcings”) are adequate to support such endeavours (e.g. Melsen et al., 2016b). Following from Nearing and Gupta (2015), we can formulate a framework for testing hypotheses based on measuring information provided by a model (e.g., parameterizations based on similarity concepts) as distinct from information provided to a model (e.g., forcing data or parameters). We should note that this is not hypothesis testing in the traditional sense, but rather a framework for scrutinizing hydrological scaling and similarity hypotheses with data. This concept was demonstrated by Nearing et al. (2016), who evaluated the information loss due to forcing data, parameters, and physics in the North American Land Data Assimilation System (NLDAS) model ensemble. In this example, information was first measured using point data for soil moisture and evaporation, and compared to regressions that are kernel density estimators of the conditional probability densities and represent the upper bound of information available on a given variable from the forcing data alone and given the forcing data and parameters. As shown in Figure 2, we can measure the total information about a given variable  $z$  contained in observations ( $H(z)$ , left bar), and then measure the information about that variable provided by a given model simulation ( $I(z; y^M)$ , right bar). The intermediate bars represent losses of information due to forcing data (boundary conditions) and due to parameters.

If we take this example, and expand it to conceptualize a framework for hypothesis testing in hydrology, we can imagine multiple instances of  $H(z)$  computed at different spatial scales, as well as multiple instances of mutual information  $I(z, y^M)$ , computed for models employing different representations of processes at that scale. One concrete example hypothesis described in the previous section is the use of TOPMODEL parameterizations for groundwater, versus representative hillslopes, versus “HydroBlocks” (Chaney et al., 2016) versus explicit 3-D modeling.

Critical to this exercise is the availability of forcing data, such as precipitation, radiation, humidity, temperature and wind speed, that have sufficient information content at the scale being evaluated such that it can adequately characterize the variable (e.g., soil moisture) or process (e.g., evapotranspiration; runoff) being studied (e.g. Berne et al., 2004). Similarly, the parameters provided to the model must also contain information about the variable or process being studied at a particular spatial and temporal scale. The Nearing and Gupta approach provides a framework for explicitly measuring the information available from observations, comparing that to information provided by a model, and attributing lost information to forcings, parameters and physics, and hence provides a rigorous method to

test our physics assumptions by confronting them with observations. Clearly, this leads to requirements for data that can support such framework.

## 4 Data requirements

As shown in Figure 1, the 4<sup>th</sup> paradigm for hydrology is characterized by the rigorous application of large datasets towards testing hypotheses as encapsulated in models. The process of constructing models requires observations both as input data, and for model and process validation or hypotheses testing. A distinguishing characteristic of data for model and process validation will be that we are observing spatial and temporal patterns of fluxes and states represented in our modeling framework, for example, soil moisture, snow pack or evapotranspiration. As discussed by McCabe et al. (this issue), there has been a dramatic increase in the type and density of hydrologic information that is becoming available at multiple scales, from point- to meso-scale and regional to global. For example, the number of remote sensing missions dedicated to observing the water cycle, allows further development of (large scale) hydrological models and data assimilation frameworks for more accurate soil moisture, evaporation, and streamflow prediction. In particular, there are exciting developments in meso-scale (i.e. hillslope to catchment) observations, which are critical for testing hypotheses about scaling (REA, RH, REW) by connecting point measurements, hydrological models, and remote sensing observations. Examples include recent advances in cosmic ray neutron sensors (Franz et al., 2015; Köhli et al., 2016; Zreda et al., 2008), distributed temperature sensing (DTS; Steele-Dunne et al., 2010; Bense et al., 2016; Dong et al., 2016), soil moisture observations, the use of crowd-sourcing (De Vos et al., 2016) and microwave signal propagation from telecommunications towers for precipitation (Leijnse et al., 2007), to the rise in the use of unmanned autonomous vehicles to characterize the landscape at centimeter scale (Vivoni et al., 2014). These alternative data sources enhance our ability to observe, understand, and simulate the hydrological cycle. Advances in citizen science (Buytaert et al., 2014; Hut et al., 2016) and the use of so-called “soft” data for hydrological modeling (Van Emmerik et al., 2015; Seibert and McDonnell, 2002) show that even though these new data are collected on nontraditional spatiotemporal scales, they might give us new insights in how processes at different scales are coupled.

Advances in hydrogeophysical characterization of the subsurface (Binley et al., 2015), such as electrical methods, ground penetrating radar and gravimetry, offer non-invasive meso-scale information that can be used to provide parameters or to infer boundary conditions, states or fluxes. Recently, Christensen, et al. (2017) demonstrated that dense airborne electromagnetic data can be used to map hydrostratigraphic zones, which is an encouraging capability. Imaging the subsoil may be feasible at local scales, but it is a challenge at river basin or continental scales. Hence, we encourage more joint efforts in hydrogeophysical imaging for integrated characterization of the subsurface.

Combined, these observations may be used in a benchmarking exercise similar to Nearing et al. (2016). Synthesizing hydrogeophysical methods with point observations and laboratory/field techniques for estimating “effective” soil hydraulic functions/parameters is a challenging opportunity (e.g. Kim et al., 1997), but one which might be tractable using a data-driven hypothesis testing framework. These new data sources allow us to understand

and apply scaling between data sources (point scale to remotely sensed data) and between model scales; and provide the critical data required to test alternative scaling hypotheses.

Beyond the new meso-scale observations, extensive catchment databases now exist to support hypothesis testing including the TERENO (Zacharias et al., 2011), MOPEX (Duan et al., 2006), CONUS benchmarking (Newman et al., 2015a), GRDC ([http://www.bafg.de/GRDC/EN/01\\_GRDC/13\\_dtbse/database\\_node.html](http://www.bafg.de/GRDC/EN/01_GRDC/13_dtbse/database_node.html)) and EURO-FRIEND databases (Stahl et al., 2010). Recent similarity studies (Sawicz et al., 2011) have systematically analyzed large numbers of catchments focusing on streamflow-oriented signatures such as the runoff coefficient, baseflow index and slope of the flow duration curve, and then have explored relationships between these signatures and model process time scales (Carrillo et al., 2011). Coopersmith et al. (2012) generalized this work with four nearly orthogonal signatures that included aridity, seasonality of rainfall, peak rainfall, and peak streamflow, and demonstrated that 77% of MOPEX catchments can be described by only six classes defined by combinations of the four signatures. Clearly there is information contained in these catchment databases about not just the coevolution of climate (forcing) and landscape properties (parameters), but also the physics of the catchment responses. Comparative hydrology (e.g., Kovács, 1984; Falkenmark and Chapman, 1989; Gupta et al., 2014) takes a first needed step in the direction of the fourth paradigm, and following the framework described above, we can explicitly quantify the mutual information in the signatures, parameters and forcings to help elucidate these connections beyond classification. One of the crucial factors that complicate scaling is the anthropogenic effect on catchments. Recent advances in modeling the co-evolution of the human-water system (see e.g. Troy et al., 2015; Ciullo et al., 2017) focused on identifying generic key processes and relations. Yet, it is unknown how these relate to systems on larger (and smaller) scales. To arrive at new understandings of scaling and similarities in human-influenced catchments, studying these issues from a socio-hydrological point of view should be an integrated part of the way forward (e.g. Van Loon et al., 2016).

## 5 Modeling framework requirements

Embracing the fourth paradigm in hydrology will face several challenges. First, it is necessary to implement/extend a hydrologic modelling framework with sufficient flexibility to evaluate competing hypotheses of similarity and scaling behavior (Clark et al., 2011b). One possible framework is the Structure for Unifying Multiple Modeling Alternatives (SUMMA), recently introduced by Clark et al. (2015), which has the capability to incorporate alternative spatial configurations and alternative flux parameterizations. Frameworks like SUMMA, which pursue the method of multiple working hypotheses, enable decomposing complex models into the individual decisions made as part of model development, and focusing attention on specific decisions (e.g., related to scaling and similarity) while keeping all other components of a model constant, hence enabling users to isolate and scrutinize specific hypotheses. One confounding issue is that models with parameterizations designed to represent sub grid processes may not add information in a manner proportional to increased information in the inputs, while models that have a single column tile/subtile form may show a more direct relationship between information in inputs and information in outputs. Similarly, integrated models with lateral flow of water in surface



and subsurface systems that generate runoff directly will have a different spatial sensitivity to the resolution of the input data than more traditional land surface models with no lateral flow and a parameterized runoff generation. Hence, the modeling framework must be able to isolate the role that surface and subsurface connectivity play in processing information at different scales.

A second challenge consists of understanding how to deal with different uncertainties/errors of different observational products and hydrologic models when comparing them for studying the scaling behavior. Several papers have highlighted the problem of different climatologies or sensitivities of remote sensing products (e.g. Albergel et al., 2012; Brocca et al., 2011), gridded meteorological products (Clark and Slater, 2006; Newman et al., 2015b), and streamflow observations (Di Baldassarre and Montanari, 2009; McMillan et al., 2010). A true correspondence of these remotely sensed variables with model results is often hampered, due to vertical mismatches in the soil column between the different products (Wilker et al., 2006), approximations in the structure of the hydrological model used, its parameterization and discretization, the initial conditions, and errors in forcing data (De Lannoy et al., 2007). Because of this, modeled variables often do not correspond well to observations; nevertheless, similar trends and dynamics between the different products are found (Koster et al., 2009).

In several data assimilation studies, the problem of differences in climatologies is resolved by bias-correcting the observations towards the model (e.g. Crow et al., 2005; Kumar et al., 2014; Lievens et al., 2015a, 2015b; Martens et al., 2016; Reichle and Koster, 2004; Sahoo et al., 2013; Verhoest et al., 2015). Yet, such (statistical) operations may not be appropriate for scaling studies. First of all, these methods only rescale the remotely sensed value, yet the uncertainties in these products need rescaling as well. Second, depending on the bias-corrections method used (ranging from only correcting for the first moment to full CDF matching) different scaling relations may be found. Ideally, multiscale data should be used in a way that best demonstrates the ability of the models to reproduce processes at the scales at which those data are available, particularly with respect to reproducing attributes of dynamics, such as the time rate of decorrelation using an information metric, and the mutual information across variables, space and time.

Testing hypotheses with multiple scale information also require assimilation/modeling frameworks that allow integrating data into models at their native resolution so that simulations and observations can be compared without the need of introducing ad-hoc downscaling/upscaling rules. One such framework has recently been proposed by Rakovec et al. (2016b). This framework uses the multiscale parameter regionalization (MPR) (Samaniego et al., 2010) technique to link the resolutions of the various data sources with the target modeling resolution and keeping a single set of model transfer parameters that are applicable to all scales. As a result, seamless, flux-matching simulations can be obtained. The MPR-based assimilation framework proposed by Rakovec et al. (2016b) is general and can be used within any land surface or hydrologic model. This framework was originally tested with mesoscale hydrological model (mHM) (Kumar et al., 2013; Samaniego et al., 2010) in order to test hypotheses related to model transferability across scale and locations as well as process description. This data assimilation approach is general and can be used—

for example within the SUMMA (Clark et al., 2015) modeling framework—to test hypothesis related with the appropriate model complexity at a given scale. A model agnostic MPR system called MPR-flex has been recently applied to the Variable Infiltration Capacity (VIC) model to estimate seamless parameter and flux fields over CONUS (Mizukami, N., Clark, M., Newman, A., Wood, A., Gutmann, E., Nijssen, B., Samaniego, L. Rakovec, under review). This symbiosis of model parameterization (MPR-Flex) and simulation frameworks (e.g., SUMMA, mHM, etc.) is a very promising avenue to test scaling laws as well as the uncertainty decomposition described above. Finally, the issue of subjective modeling decisions (e.g. the choice of time step, spatial resolution, numerical scheme, study region, time period for calibration/validation, performance metrics, etc.) and associated uncertainties is an issue that requires further attention (e.g. Krueger et al., 2012).

## 6 Summary and Next Steps

In this paper we review advances in hydrologic scaling and similarity. Beginning with the challenge of Dooge (1986), we posit that roadblocks in the search for universal laws of hydrology are hindered by our third-paradigm approach, and assert that it is time for hydrology to embrace a fourth paradigm of data-intensive science. Building on other synthesis papers in this issue (Clark et al., McCabe et al.), advances in data-intensive hydrologic science (e.g., Nearing and Gupta, 2015) have laid the foundation for a data-driven hypothesis testing framework for scaling and similarity. To achieve this goal, we have (1) summarized important scaling and similarity concepts (hypotheses) that require testing; (2) described a mutual information framework for testing these hypotheses; (3) described boundary condition, state/flux, and parameter data requirements across scales to support testing these hypotheses, and (4) discussed some challenges to overcome while pursuing the fourth hydrological paradigm.

Figure 1 illustrates the concept that embracing a 4<sup>th</sup> paradigm in hydrology where we enable a rigorous confrontation of our hypotheses embodied within our models with a range of data types across many locations and spatial-temporal scales. This paradigm represents a union and extension of previous scientific methods within a formal hypotheses driven framework. Models are a synthesis of all what we have learned (e.g., conservation equations; constitutive relationships for soil infiltration) and data, particularly through first paradigm examples like comparative hydrology, yields empirical relationships, signatures, fingerprints that helps lead to new understanding and theory (2<sup>nd</sup> paradigm). By coupling traditional (e.g., in situ) and new data sources (e.g., satellites) we can use the power of information theory and rigorous hypothesis testing to elucidate the causes for behaviours that may not be evident in the analysis of individual sites or catchments. In this sense, a move to the 4th paradigm means that we seek modelling-driven monitoring, and simultaneously, monitoring-driven modelling. The formal hypotheses driven framework will indicate where we have weak processes understanding because we cannot explain the data obtained at high resolution. In other cases, comprehensive integrated simulations and big-data relationships would allow the identification of where the measurement errors are too large (i.e. data has little information content, entropy) and point out what kind of sensors or new measurements/sensors are needed to improve our physical understanding. These are the feedback loops in

Figure 1, and these represent two important paths to optimizing the use of models and data to enhance hydrologic science.

As a next step, we propose a focused community effort to shape the development of the fourth paradigm for hydrology. To this end, a workshop following the publication of this special issue would be a good first step.

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## References

- Albergel C, de Rosnay P, Gruhier C, Muñoz-Sabater J, Hasenauer S, Isaksen L, Kerr Y, Wagner W. Evaluation of remotely sensed and modelled soil moisture products using global ground-based in situ observations, *Remote Sens. Environ.* 2012; 118:215–226. DOI: 10.1016/j.rse.2011.11.017
- Bense VF, Read T, Bour O, Le Borgne T, Coleman T, Krause S, Chalari A, Mondanos M, Ciocca F, Selker JS. Distributed Temperature Sensing as a downhole tool in hydrogeology. *Water Resour Res.* 2016; 52(12):9259–9273. DOI: 10.1002/2016WR018869
- Berghuijs WR, Sivapalan M, Woods RA, Savenije HHG. Patterns of similarity of seasonal water balances: A window into streamflow variability over a range of time scales. *Water Resour Res.* 2014; 50(7):5638–5661. DOI: 10.1002/2014WR015692
- Berne A, Delrieu G, Creutin JD, Obled C. Temporal and spatial resolution of rainfall measurements required for urban hydrology. *J Hydrol.* 2004; 299(3–4):166–179. DOI: 10.1016/j.jhydrol.2004.08.002
- Berne A, Uijlenhoet R, Troch PA. Similarity analysis of subsurface flow response of hillslopes with complex geometry. *Water Resour Res.* 2005; 41(9):W09410.
- Beven K. Searching for the Holy Grail of scientific hydrology:  $Q_t = (S, R, t)A$  as closure, *Hydrol. Earth Syst Sci.* 2006; 10(5):609–618. DOI: 10.5194/hess-10-609-2006
- Beven K, Cloke H, Pappenberger F, Lamb R, Hunter N. Hyperresolution information and hyperresolution ignorance in modelling the hydrology of the land surface. *Sci China-Earth Sci.* 2015; 58(1):25–35. DOI: 10.1007/s11430-014-5003-4
- Beven KJ, Cloke HL. Comment on “Hyperresolution global land surface modeling: Meeting a grand challenge for monitoring Earth’s terrestrial water” by Eric F. Wood et al. *Water Resour Res.* 2012; 48(1):W01801.
- Beven KJ, Kirkby MJ. A physically based, variable contributing area model of basin hydrology. *Hydrol Sci Bull.* 1979; 24(1):43–69. DOI: 10.1080/02626667909491834
- Beven KJ, Wood EF, Sivapalan M. On hydrological heterogeneity — Catchment morphology and catchment response. *J Hydrol.* 1988; 100(1):353–375. DOI: 10.1016/0022-1694(88)90192-8
- Bierkens MFP. Modeling Hydraulic Conductivity of a Complex Confining Layer at Various Spatial Scales. *Water Resour Res.* 1996; 32(8):2369–2382. DOI: 10.1029/96WR01465
- Bierkens, MFP, Finke, PA., de Willigen, P. *Upscaling and Downscaling Methods for Environmental Research.* Springer; Netherlands: 2000.
- Bierkens MFP, Bell VA, Burek P, Chaney N, Condon LE, David CH, de Roo A, Döll P, Drost N, Famiglietti JS, Flörke M, Gochis DJ, Houser P, Hut R, Keune J, Kollet S, Maxwell RM, Reager JT, Samaniego L, Sudicky E, Sutanudjaja EH, van de Giesen N, Winsemius H, Wood EF. Hyper-resolution global hydrological modelling: What is next?: “Everywhere and locally relevant” M. F. P. Bierkens et al. Invited Commentary. *Hydrol Process.* 2015; 29(2):310–320. DOI: 10.1002/hyp.10391
- Binley A, Hubbard SS, Huisman JA, Revil A, Robinson DA, Singha K, Slater LD. The emergence of hydrogeophysics for improved understanding of subsurface processes over multiple scales. *Water Resour Res.* 2015; 51(6):3837–3866. DOI: 10.1002/2015WR017016 [PubMed: 26900183]

- Blöschl G, Grayson RB, Sivapalan M. On the representative elementary area (REA) concept and its utility for distributed rainfall-runoff modelling. *Hydrological Processes*. 1995; 9:313–330.
- Blöschl G, Sivapalan M. Scale issues in hydrological modelling: A review. *Hydrol Process*. Sep.1994 9:251–290. 1995. DOI: 10.1002/hyp.3360090305
- Brocca L, Hasenauer S, Lacava T, Melone F, Moramarco T, Wagner W, Dorigo W, Matgen P, Martínez-Fernández J, Llorens P, Latron J, Martin C, Bittelli M. Soil moisture estimation through ASCAT and AMSR-E sensors: An intercomparison and validation study across Europe. *Remote Sens Environ*. 2011; 115(12):3390–3408. DOI: 10.1016/j.rse.2011.08.003
- Buytaert W, Zulkafli Z, Grainger S, Acosta L, Alemie TC, Bastiaensen J, De Bièvre B, Bhusal J, Clark J, Dewulf A, Foggin M, Hannah DM, Hergarten C, Isaeva A, Karpouzoglou T, Pandeya B, Paudel D, Sharma K, Steenhuis T, Tilahun S, Van Hecken G, Zhumanova M. Citizen science in hydrology and water resources: opportunities for knowledge generation, ecosystem service management, and sustainable development. *Front Earth Sci*. Oct.2014 2:1–21. DOI: 10.3389/feart.2014.00026
- Carrillo G, Troch PA, Sivapalan M, Wagener T, Harman C, Sawicz K. Catchment classification: Hydrological analysis of catchment behavior through process-based modeling along a climate gradient. *Hydrol Earth Syst Sci*. 2011; 15(11):3411–3430. DOI: 10.5194/hess-15-3411-2011
- Chaney NW, Metcalfe P, Wood EF. HydroBlocks: a field-scale resolving land surface model for application over continental extents. *Hydrol Process*. 2016; 30(20):3543–3559. DOI: 10.1002/hyp.10891
- Christensen NK, Minsley BJ, Christensen S. Generation of 3-D hydrostratigraphic zones from dense airborne electromagnetic data to assess groundwater model prediction error. *Water Resour Res*. 2017; 53(2):1019–1038. DOI: 10.1002/2016WR019141
- Clark MP, Bierkens MFP, Samaniego L, Woods RA, Uijenoet R, Bennet KE, Pauwels VRN, Cai X, Wood AW, Peters-Lidard CD. The evolution of process-based hydrologic models: Historical challenges and the collective quest for physical realism. *Hydrol Earth Syst Sci Discuss*. 2017 in review.
- Clark MP, Hendriks J, Slater AG, Kavetski D, Anderson B, Cullen NJ, Kerr T, Örn Hreinsson E, Woods RA. Representing spatial variability of snow water equivalent in hydrologic and land-surface models: A review. *Water Resour Res*. 2011a; 47(7):W07539.
- Clark MP, Kavetski D, Fenicia F. Pursuing the method of multiple working hypotheses for hydrological modeling. *Water Resour Res*. 2011b; 47(9):W09301.
- Clark MP, Nijssen B, Lundquist JD, Kavetski D, Rupp DE, Woods RA, Freer JE, Gutmann ED, Wood AW, Brekke LD, Arnold JR, Gochis DJ, Rasmussen RM. A unified approach for process-based hydrologic modeling: 1. Modeling concept. *Water Resour Res*. 2015; 51(4):2498–2514. DOI: 10.1002/2015WR017198
- Clark MP, Schaeffli B, Schymanski SJ, Samaniego L, Luce CH, Jackson BM, Freer JE, Arnold JR, Moore RD, Istanbuloglu E, Ceola S. Improving the theoretical underpinnings of process-based hydrologic models. *Water Resour Res*. 2016; 52(3):2350–2365. DOI: 10.1002/2015WR017910
- Clark MP, Slater AG. Probabilistic Quantitative Precipitation Estimation in Complex Terrain, J. *Hydrometeorol*. 2006; 7(1):3–22. DOI: 10.1175/JHM474.1
- Coopersmith E, Yaeger MA, Ye S, Cheng L, Sivapalan M. Exploring the physical controls of regional patterns of flow duration curves - Part 3: A catchment classification system based on regime curve indicators. *Hydrol Earth Syst Sci*. 2012; 16(11):4467–4482. DOI: 10.5194/hess-16-4467-2012
- Crow WT, Koster RD, Reichle RH, Sharif HO. Relevance of time-varying and time-invariant retrieval error sources on the utility of spaceborne soil moisture products. *Geophys Res Lett*. 2005; 32(24): 1–5. DOI: 10.1029/2005GL024889
- Ciullo A, Viglione A, Castellarin A, Crisci M, Di Baldassarre G. Socio-hydrological modelling of flood-risk dynamics: comparing the resilience of green and technological systems. *Hydrol Sci J*. 2017; 62(6):880–891. DOI: 10.1080/02626667.2016.1273527
- De Lannoy GJM, Houser PR, Pauwels VRN, Verhoest NEC. State and bias estimation for soil moisture profiles by an ensemble Kalman filter: Effect of assimilation depth and frequency. *Water Resour Res*. 2007; 43(6):1–15. DOI: 10.1029/2006WR005100 [PubMed: 20300476]

- De Pury DGG, Farquhar GD. Simple scaling of photosynthesis from leaves to canopies without the errors of big-leaf models, *Plant. Cell Environ.* 1997; 20(5):537–557. DOI: 10.1111/j.1365-3040.1997.00094.x
- Di Baldassarre G, Montanari A. Uncertainty in river discharge observations: a quantitative analysis, *Hydrol. Earth Syst Sci.* 2009; 13(6):913–921. DOI: 10.5194/hess-13-913-2009
- De Vos L, Leijnse H, Overeem A, Uijlenhoet R. The potential of urban rainfall monitoring with crowdsourced automatic weather stations in Amsterdam, *Hydrol. Earth Syst Sci.* 2017; 21:765–777. DOI: 10.5194/hess-21-765-2017
- Dong J, Steele-Dunne SC, Ochsner TE, Hatch CE, Sayde C, Selker J, Tyler S, Cosh MH, van de Giesen N. Mapping high-resolution soil moisture and properties using distributed temperature sensing data and an adaptive particle batch smoother. *Water Resour Res.* 2016; 52(10):7690–7710. DOI: 10.1002/2016WR019031
- Dooge JCI. Looking for hydrologic laws. *Water Resour Res.* 1986; 22(9S):46S–58S. DOI: 10.1029/WR022i09Sp0046S
- Duan Q, Schaake J, Andréassian V, Franks S, Goteti G, Gupta HV, Gusev YM, Habets F, Hall A, Hay L, Hogue T, Huang M, Leavesley G, Liang X, Nasonova ON, Noilhan J, Oudin L, Sorooshian S, Wagener T, Wood EF. Model Parameter Estimation Experiment (MOPEX): An overview of science strategy and major results from the second and third workshops. *J Hydrol.* 2006; 320(1–2): 3–17. DOI: 10.1016/j.jhydrol.2005.07.031
- Dümenil L, Todini E. A rainfall-runoff scheme for use in the Hamburg climate model, in *Advances in Theoretical Hydrology - A Tribute to James Dooge*. 1992:129–157.
- Van Emmerik T, Mulder G, Eilander D, Piet M, Savenije H. Predicting the ungauged basin: model validation and realism assessment. *Front Earth Sci.* Oct.2015 3:1–11. DOI: 10.3389/feart.2015.00062
- Falkenmark, M., Chapman, T., editors. *Comparative Hydrology*. UNESCO; Paris: 1989.
- Famiglietti JS, Wood EF. Multiscale modeling of spatially variable water and energy balance processes. *Water Resour Res.* 1994; 30(11):3061–3078. DOI: 10.1029/94WR01498
- Fan Y, Bras RL. On the concept of a representative elementary area in catchment runoff. *Hydrol Process.* 1995; 9(7):821–832. DOI: 10.1002/hyp.3360090708
- Franz TE, Wang T, Avery W, Finkenbiner C, Brocca L. Combined analysis of soil moisture measurements from roving and fixed cosmic ray neutron probes for multiscale real-time monitoring. *Geophys Res Lett.* May.2015 :1–8. Received. DOI: 10.1002/2015GL063963
- Gao H, Wood EF, Jackson TJ, Drusch M, Bindlish R. Using TRMM/TMI to Retrieve Surface Soil Moisture over the Southern United States from 1998 to 2002. *J Hydrometeorol.* 2006; 7:23–38. DOI: 10.1175/JHM473.1
- Gupta HV, Perrin C, Blöschl G, Montanari A, Kumar R, Clark M, Andréassian V. Large-sample hydrology: A need to balance depth with breadth. *Hydrol Earth Syst Sci.* 2014; 18:463–477. DOI: 10.5194/hess-18-463-2014
- Grayson, R., Blöschl, G. *Spatial Patterns in Catchment Hydrology: Observations and Modelling*. Cambridge University Press; 2001.
- Hagemann S, Gates LD. Improving a subgrid runoff parameterization scheme for climate models by the use of high resolution data derived from satellite observations. *Clim Dyn.* 2003; 21(3–4):349–359. DOI: 10.1007/s00382-003-0349-x
- Hazenbergh P, Fang Y, Broxton P, Gochis D, Niu GY, Pelletier JD, Troch PA, Zeng X. A hybrid-3D hillslope hydrological model for use in Earth system models. *Water Resour Res.* 2015; 51(10): 8218–8239. DOI: 10.1002/2014WR016842
- Hey, T., Tansley, S., Tolle, KM. *The fourth paradigm: data-intensive scientific discovery*. Microsoft research; Redmond, WA: 2009.
- Hut R, Tyler S, Van Emmerik T. Proof of concept: Temperature-sensing waders for environmental sciences. *Geosci Instrumentation Methods Data Syst.* 2016; 5(1):45–51. DOI: 10.5194/gi-5-45-2016
- Kim CP, Stricker JNM, Feddes RA. Impact of soil heterogeneity on the water budget of the unsaturated zone. *Water Resour Res.* 1997; 33(5):991–999. DOI: 10.1029/97WR00364

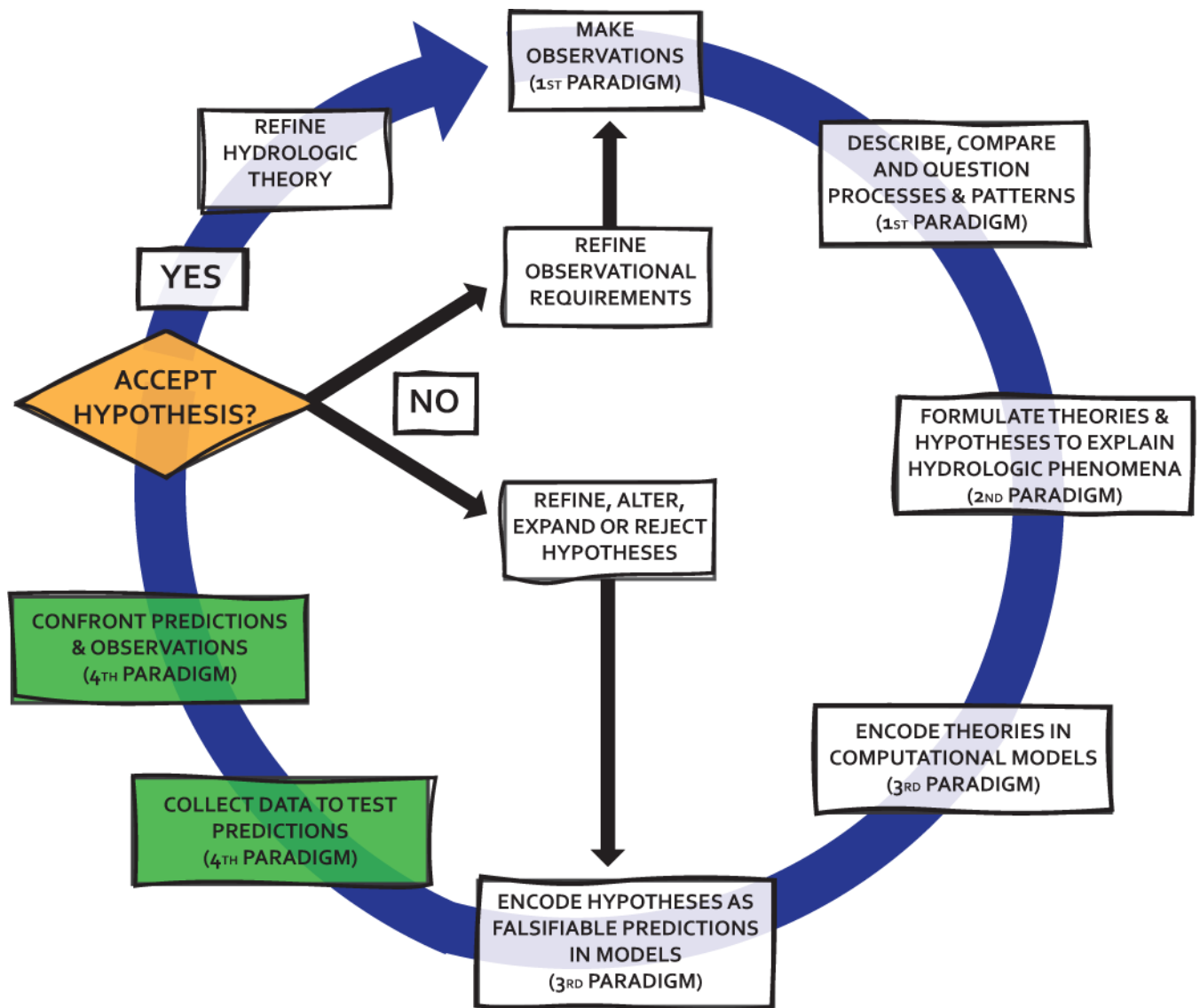
- Köhli M, Schrön M, Zreda M, Schmidt U, Dietrich P, Zacharias S. Footprint Characteristics Revised for Field-Scale Soil Moisture Monitoring with Cosmic-Ray Neutrons. 2016; 51(7):5772–5790. DOI: 10.1002/2015WR017169
- Kollet SJ, Maxwell RM. Capturing the influence of groundwater dynamics on land surface processes using an integrated, distributed watershed model. *Water Resour Res.* 2008; 44(2):W02402.
- Koster RD, Guo Z, Yang R, Dirmeyer PA, Mitchell K, Puma MJ. On the nature of soil moisture in land surface models. *J Clim.* 2009; 22(16):4322–4335. DOI: 10.1175/2009JCLI2832.1
- Kovács G. Proposal to construct a coordinating matrix for comparative hydrology. *Hydrol Sci J.* 1984; 29:435–443. DOI: 10.1080/02626668409490961
- Krueger T, Page T, Hubacek K, Smith L, Hiscock K. The role of expert opinion in environmental modelling. *Environ Model Softw.* 2012; 36:4–18. DOI: 10.1016/j.envsoft.2012.01.011
- Kumar R, Samaniego L, Attinger S. Implications of distributed hydrologic model parameterization on water fluxes at multiple scales and locations. *Water Resour Res.* 2013; 49(1):360–379. DOI: 10.1029/2012WR012195
- Kumar SV, Peters-Lidard CD, Mocko D, Reichle R, Liu Y, Arsenault KR, Xia Y, Ek M, Riggs G, Livneh B, Cosh MH. Assimilation of remotely sensed soil moisture and snow depth retrievals for drought estimation. *J Hydrometeorol.* 2014; 15(6):2446–2469. DOI: 10.1175/JHM-D-13-0132.1
- Leijnse H, Uijlenhoet R, Stricker JNM. Rainfall measurement using radio links from cellular communication networks. *Water Resour Res.* 2007; 43(3):W03201.
- Liang X, Lettenmaier DP, Wood EF, Burges SJ. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *J Geophys Res.* 1994; 99(D7):14415.
- Lievens H, De Lannoy GJM, Al Bitar A, Drusch M, Dumedah G, Hendricks Franssen HJ, Kerr YH, Tomer SK, Martens B, Merlin O, Pan M, Roundy JK, Vereecken H, Walker JP, Wood EF, Verhoest NEC, Pauwels VRN. Assimilation of SMOS soil moisture and brightness temperature products into a land surface model. *Remote Sens Environ.* 2015a; 180:292–304. DOI: 10.1016/j.rse.2015.10.033
- Lievens H, Tomer SK, Al Bitar A, De Lannoy GJM, Drusch M, Dumedah G, Hendricks Franssen HJ, Kerr YH, Martens B, Pan M, Roundy JK, Vereecken H, Walker JP, Wood EF, Verhoest NEC, Pauwels VRN. SMOS soil moisture assimilation for improved hydrologic simulation in the Murray Darling Basin, Australia. *Remote Sens Environ.* 2015b; 168:146–162. DOI: 10.1016/j.rse.2015.06.025
- Liston GE. Representing Subgrid Snow Cover Heterogeneities in Regional and Global Models. *J Clim.* 2004; 17(6):1381–1397. DOI: 10.1175/1520-0442(2004)017<1381:RSSCHI>2.0.CO;2
- Luce CH, Tarboton DG, Cooley KR. Sub-grid parameterization of snow distribution for an energy and mass balance snow cover model. *Hydrol Process.* 1999; 13(12–13):1921–1933. DOI: 10.1002/(SICI)1099-1085(199909)13:12/13<1921::AID-HYP867>3.0.CO;2-S
- Lyon SW, Troch PA. Hillslope subsurface flow similarity: Real-world tests of the hillslope Pécel number. *Water Resour Res.* 2007; 43(7)
- Martens B, Miralles D, Lievens H, Fernández-Prieto D, Verhoest NEC. Improving terrestrial evaporation estimates over continental Australia through assimilation of SMOS soil moisture. *Int J Appl Earth Obs Geoinf.* 2016; 48:146–162. DOI: 10.1016/j.jag.2015.09.012
- Maxwell RM, Condon LE. Connections between groundwater flow and transpiration partitioning. *Science (80-).* 2016; 353(6297):377–380. DOI: 10.1126/science.aaf7891
- Maxwell RM, Kollet SJ. Quantifying the effects of three-dimensional subsurface heterogeneity on Hortonian runoff processes using a coupled numerical, stochastic approach. *Adv. Water Resour.* 2008; 31(5):807–817. DOI: 10.1016/j.advwatres.2008.01.020
- Maxwell RM, Miller NL. Development of a Coupled Land Surface and Groundwater Model. *J Hydrometeorol.* 2005; 6(3):233–247. DOI: 10.1175/JHM422.1
- McCabe MF, Rodell M, Alsdorf DE, Miralles DG, Uijlenhoet R, Wagner W, Lucieer A, Houborg R, Verhoest NEC, Franz TE, Shi J, Gao H, Wood EF. The Future of Earth Observation in Hydrology. *Hydrol Earth Syst Sci Discuss.* 2017 in review.
- McDonnell JJ, Sivapalan M, Vaché K, Dunn S, Grant G, Haggerty R, Hinz C, Hooper R, Kirchner J, Roderick ML, Selker J, Weiler M. Moving beyond heterogeneity and process complexity: A new

- vision for watershed hydrology. *Water Resour Res.* 2007; 43(7):1–6. DOI: 10.1029/2006WR005467 [PubMed: 20300476]
- McMillan H, Freer J, Pappenberger F, Krueger T, Clark M. Impacts of uncertain river flow data on rainfall-runoff model calibration and discharge predictions. *Hydrol Process.* 2010; 24(10):1270–1284. DOI: 10.1002/hyp.7587
- Melsen LA, Teuling AJ, Torfs PJF, Uijlenhoet R, Mizukami N, Clark MP. HESS Opinions: The need for process-based evaluation of large-domain hyper-resolution models. *Hydrol Earth Syst Sci.* 2016; 20(3):1069–1079. DOI: 10.5194/hess-20-1069-2016
- Melsen L, Teuling A, Torfs P, Zappa M, Mizukami N, Clark M, Uijlenhoet R. Representation of spatial and temporal variability in large-domain hydrological models: case study for a mesoscale pre-Alpine basin. *Hydrol Earth Syst Sci.* 2016; 20(6):2207–2226. DOI: 10.5194/hess-20-2207-2016
- Meyerhoff SB, Maxwell RM. Quantifying the effects of subsurface heterogeneity on hillslope runoff using a stochastic approach. *Hydrogeol J.* 2011; 19(8):1515–1530. DOI: 10.1007/s10040-011-0753-y
- Miller EE, Miller RD. Physical Theory for Capillary Flow Phenomena. *J Appl Phys.* 1956; 27(4):324–332. DOI: 10.1063/1.1722370
- Mizukami N, Clark M, Newman A, Wood A, Gutmann E, Nijssen B, Samaniego L, Rakovec O. Towards seamless large domain parameter estimation for hydrologic models. *Water Resources Research.* 2017 under review.
- Moore RJ, Clarke RT. A distribution function approach to rainfall runoff modeling. *Water Resour Res.* 1981; 17(5):1367–1382. DOI: 10.1029/WR017i005p01367
- Nearing GS, Gupta HV. The quantity and quality of information in hydrologic models. *Water Resour Res.* 2015; 51(1):524–538. DOI: 10.1002/2014WR015895
- Nearing GS, Mocko DM, Peters-Lidard CD, Kumar SV, Xia Y. Benchmarking NLDAS-2 Soil Moisture and Evapotranspiration to Separate Uncertainty Contributions. *J Hydrometeorol.* 2016; 17(3):745–759. DOI: 10.1175/JHM-D-15-0063.1 [PubMed: 29697706]
- Newman AJ, Clark MP, Craig J, Nijssen B, Wood A, Gutmann E, Mizukami N, Brekke L, Arnold JR. Gridded Ensemble Precipitation and Temperature Estimates for the Contiguous United States. *J Hydrometeorol.* 2015a; 16(6):2481–2500. DOI: 10.1175/JHM-D-15-0026.1
- Newman AJ, Clark MP, Sampson K, Wood A, Hay LE, Bock A, Viger RJ, Blodgett D, Brekke L, Arnold JR, Hopson T, Duan Q. Development of a large-sample watershed-scale hydrometeorological data set for the contiguous USA: data set characteristics and assessment of regional variability in hydrologic model performance. *Hydrol Earth Syst Sci.* 2015b; 19(1):209–223. DOI: 10.5194/hess-19-209-2015
- Peters-Lidard CD, Pan F, Wood EF. A re-examination of modeled and measured soil moisture spatial variability and its implications for land surface modeling. *Adv Water Resour.* 2001; 24(9–10):1069–1083. DOI: 10.1016/S0309-1708(01)00035-5
- Pfister L, Kirchner JW. Debates-Hypothesis testing in hydrology: Theory and practice. *Water Resour Res.* 2017; 53(3):1792–1798. DOI: 10.1002/2016WR020116
- Rakovec O, Kumar R, Attinger S, Samaniego L. Improving the realism of hydrologic model functioning through multivariate parameter estimation. *Water Resour Res.* 2016a; 52(10):7779–7792. DOI: 10.1002/2016WR019430
- Rakovec O, Kumar R, Mai J, Cuntz M, Thober S, Zink M, Attinger S, Schäfer D, Schrön M, Samaniego L. Multiscale and multivariate evaluation of water fluxes and states over European river basins. *J Hydrometeorol.* 2016b; 17(1):287–307. DOI: 10.1175/JHM-D-15-0054.1
- Reggiani P, Sivapalan M, Majid Hassanizadeh S. A unifying framework for watershed thermodynamics: balance equations for mass, momentum, energy and entropy, and the second law of thermodynamics. *Adv Water Resour.* 1998; 22(4):367–398. DOI: 10.1016/S0309-1708(98)00012-8
- Reggiani P, Hassanizadeh SM, Sivapalan M, Gray WG. A unifying framework for watershed thermodynamics: constitutive relationships. *Adv Water Resour.* 1999; 23(1):15–39. DOI: 10.1016/S0309-1708(99)00005-6

- Reggiani P, Sivapalan M, Hassanizadeh SM. Conservation equations governing hillslope responses: Exploring the physical basis of water balance. *Water Resour Res.* 2000; 36(7):1845–1863. DOI: 10.1029/2000WR900066
- Reggiani P, Sivapalan M, Hassanizadeh SM, Gray WG. Coupled equations for mass and momentum balance in a stream network: theoretical derivation and computational experiments. *Proc R Soc A-Mathematical Phys Eng Sci.* 2001; 457(2005):157–189. DOI: 10.1098/rspa.2000.0661
- Reichle RH, Koster RD. Bias reduction in short records of satellite soil moisture. *Geophys Res Lett.* 2004; 31(19):2–5. DOI: 10.1029/2004GL020938
- Rigden AJ, Salvucci GD. Evapotranspiration based on equilibrated relative humidity (ETRHEQ): Evaluation over the continental U.S. *Water Resour Res.* 2015; 51(4):2951–2973. DOI: 10.1002/2014WR016072
- Robinson DA, Binley A, Crook N, Day-Lewis FD, Ferré TPA, Grauch VJS, Knight R, Knoll M, Lakshmi V, Miller R, Nyquist J, Pellerin L, Singha K, Slater L. Advancing process-based watershed hydrological research using near-surface geophysics: a vision for, and review of, electrical and magnetic geophysical methods. *Hydrol Process.* 2008; 22(18):3604–3635. DOI: 10.1002/hyp.6963
- Sahoo AK, De Lannoy GJM, Reichle RH, Houser PR. Assimilation and downscaling of satellite observed soil moisture over the Little River Experimental Watershed in Georgia, USA. *Adv Water Resour.* 2013; 52:19–33. DOI: 10.1016/j.advwatres.2012.08.007
- Samaniego L, Kumar R, Attinger S. Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resour Res.* 2010; 46(5):1–25. DOI: 10.1029/2008WR007327
- Sawicz K, Wagener T, Sivapalan M, Troch PA, Carrillo G. Catchment classification: Empirical analysis of hydrologic similarity based on catchment function in the eastern USA. *Hydrol Earth Syst Sci.* 2011; 15(9):2895–2911. DOI: 10.5194/hess-15-2895-2011
- Seibert J, McDonnell JJ. On the dialog between experimentalist and modeler in catchment hydrology: Use of soft data for multicriteria model calibration. *Water Resour Res.* 2002; 38(11):23, 1–14. DOI: 10.1029/2001WR000978
- Sivapalan, M. Pattern, Process and Function: Elements of a Unified Theory of Hydrology at the Catchment Scale, in *Encyclopedia of Hydrological Sciences*. John Wiley & Sons, Ltd; Chichester, UK: 2005.
- Sivapalan M, Beven K, Wood EF. On hydrologic similarity: 2. A scaled model of storm runoff production. *Water Resour Res.* 1987; 23(12):2266–2278. DOI: 10.1029/WR023i012p02266
- Sivapalan M, Wood EF, Beven KJ. On hydrologic similarity: 3. A dimensionless flood frequency model using a generalized geomorphologic unit hydrograph and partial area runoff generation. *Water Resour Res.* 1990; 26(1):43–58. DOI: 10.1029/WR026i001p00043
- Smith JA. Representation of basin scale in flood peak distributions. *Water Resour Res.* 1992; 28(11):2993–2999. DOI: 10.1029/92WR01718
- Stahl K, Hisdal H, Hannaford J, Tallaksen LM, Van Lanen HAJ, Sauquet E, Demuth S, Fendekova M, Jódar J. Streamflow trends in Europe: Evidence from a dataset of near-natural catchments. *Hydrol Earth Syst Sci.* 2010; 14(12):2367–2382. DOI: 10.5194/hess-14-2367-2010
- Steele-Dunne SC, Rutten MM, Krzeminska DM, Hausner M, Tyler SW, Selker J, Bogaard TA, van de Giesen NC. Feasibility of soil moisture estimation using passive distributed temperature sensing. *Water Resour Res.* 2010; 46(3):W03534.
- Tarboton DG, Bras RL, Rodriguez-Iturbe I. The fractal nature of river networks. *Water Resour Res.* 1988; 24(8):1317–1322. DOI: 10.1029/WR024i008p01317
- Thompson SE, Harman CJ, Schumer R, Wilson JS, Basu NB, Brooks PD, Donner SD, Hassan MA, Packman AI, Rao PSC, Troch PA, Sivapalan M. Patterns, puzzles and people: Implementing hydrologic synthesis. *Hydrol Process.* 2011; 25(20):3256–3266. DOI: 10.1002/hyp.8234
- Troch PA, Paniconi C, Emiel van Loon E. Hillslope-storage Boussinesq model for subsurface flow and variable source areas along complex hillslopes: 1. Formulation and characteristic response. *Water Resour Res.* 2003; 39(11):1316.
- Troch PA, Lahmers T, Meira A, Mukherjee R, Pedersen JW, Roy T, Valdés-Pineda R. Catchment coevolution: A useful framework for improving predictions of hydrological change? *Water Resour Res.* 2015; 51(7):4903–4922. DOI: 10.1002/2015WR017032

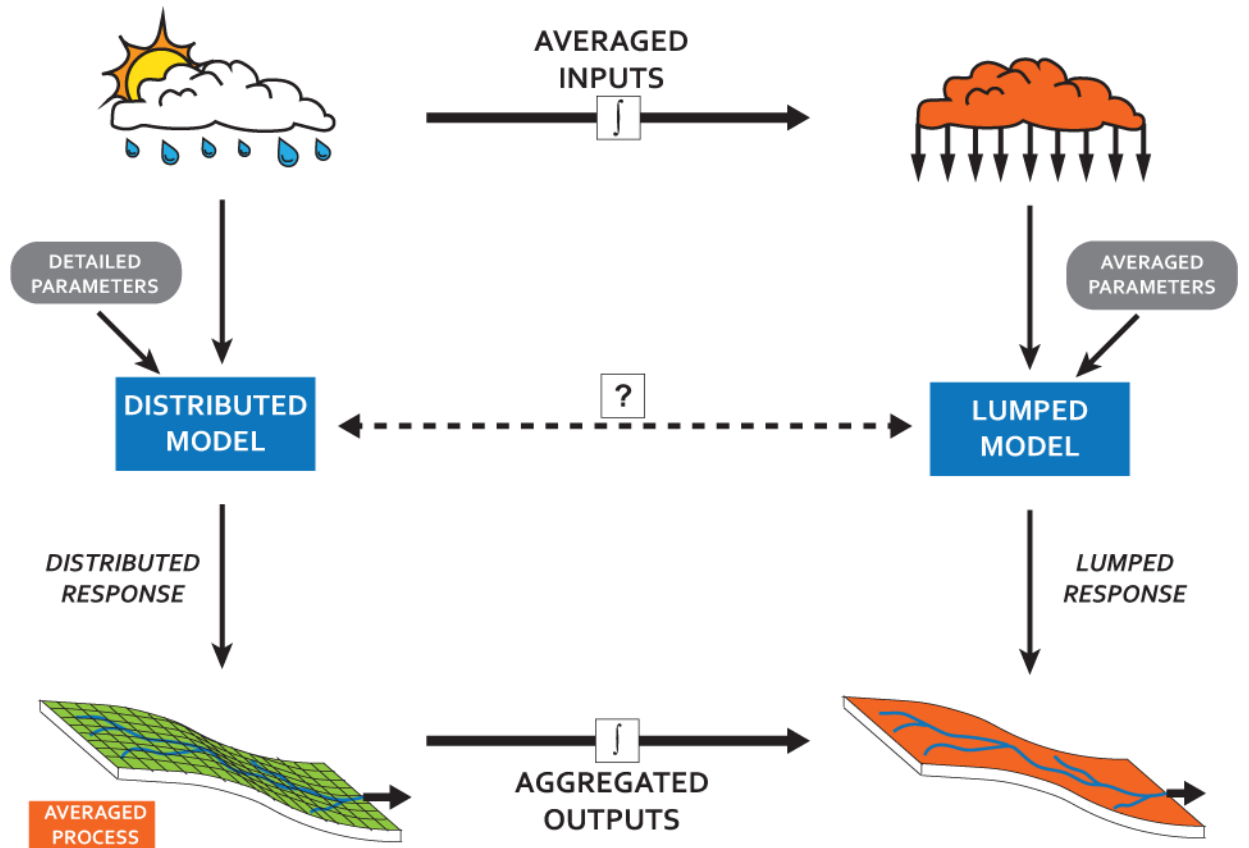


- Troy TJ, Pavao-Zuckerman M, Evans TP. Debates-Perspectives on socio-hydrology: Socio-hydrologic modeling: Tradeoffs, hypothesis testing, and validation. *Water Resour Res.* 2015; 51(6):4806–4814. DOI: 10.1002/2015WR017046
- Van Loon AF, Gleeson T, Clark J, Van Dijk AIJM, Stahl K, Hannaford J, Di Baldassarre G, Teuling AJ, Tallaksen LM, Uijlenhoet R, Hannah DM, Sheffield J, Svoboda M, Verbeiren B, Wagener T, Rangecroft S, Wanders N, Van Lanen HAJ. Drought in the Anthropocene. *Nat Geosci.* 2016; 9(2):89–91. [online] Available from: <http://dx.doi.org/10.1038/ngeo2646>.
- Verhoest NEC, Van den Berg MJ, Martens B, Lievens H, Wood EF, Pan M, Kerr YH, Al Bitar A, Tomer SK, Drusch M, Vernieuwe H, De Baets B, Walker JP, Dumedah G, Pauwels VRN. Copula-based downscaling of coarse-scale soil moisture observations with implicit bias correction, *IEEE Trans. Geosci Remote Sens.* 2015; 53(6):3507–3521. DOI: 10.1109/TGRS.2014.2378913
- Vivoni ER, Rango A, Anderson CA, Pierini NA, Schreiner-McGraw AP, Saripalli S, Laliberte AS. Ecohydrology with unmanned aerial vehicles. *Ecosphere.* 2014; 5(10) art130.
- Wang YP, Leuning R. A two-leaf model for canopy conductance, photosynthesis and partitioning of available energy I: Model description and comparison with a multi-layered model. *Agric For Meteorol.* 1998; 91(1–2):89–111. DOI: 10.1016/S0168-1923(98)00061-6
- Wilker H, Drusch M, Seuffert G, Simmer C. Effects of the Near-Surface Soil Moisture Profile on the Assimilation of L-band Microwave Brightness Temperature. *J Hydrometeorol.* 2006; 7(3):433–442. DOI: 10.1175/JHM498.1
- Willgoose G, Bras RL, Rodriguez-Iturbe I. A coupled channel network growth and hillslope evolution model: 2. Nondimensionalization and applications. *Water Resour Res.* 1991; 27(7):1685–1696. DOI: 10.1029/91WR00936
- Wood EF. Scaling behaviour of hydrological fluxes and variables: Empirical studies using a hydrological model and remote sensing data. *Hydrol Process.* 1995; 9(3–4):331–346. DOI: 10.1002/hyp.3360090308
- Wood EF, Lettenmaier DP, Zartarian VG. A land-surface hydrology parameterization with subgrid variability for general circulation models. *J Geophys Res.* 1992; 97(D3):2717.
- Wood EF, Roundy JK, Troy TJ, van Beek LPH, Bierkens MFP, Blyth E, de Roo A, Doell P, Ek M, Famiglietti J, Gochis D, van de Giesen N, Houser P, Jaffe PR, Kollet S, Lehner B, Lettenmaier DP, Peters-Lidard C, Sivapalan M, Sheffield J, Wade A, Whitehead P. Hyperresolution global land surface modeling: Meeting a grand challenge for monitoring Earth's terrestrial water. *Water Resour Res.* 2011; 47:W05301.
- Wood EF, Roundy JK, Troy TJ, van Beek R, Bierkens M, Blyth E, de Roo A, Doell P, Ek M, Famiglietti J, Gochis D, van de Giesen N, Houser P, Jaffe P, Kollet S, Lehner B, Lettenmaier DP, Peters-Lidard CD, Sivapalan M, Sheffield J, Wade AJ, Whitehead P. Reply to comment by Keith J. Beven and Hannah L. Cloke on “Hyperresolution global land surface modeling: Meeting a grand challenge for monitoring Earth's terrestrial water”. *Water Resour Res.* 2012; 48:W01802.
- Wood EF, Sivapalan M, Beven K, Band L. Effects of spatial variability and scale with implications to hydrologic modeling. *J Hydrol.* 1988; 102(1–4):29–47. DOI: 10.1016/0022-1694(88)90090-X
- Woods, RA. *Encyclopedia of Hydrological Sciences.* 1. Vol. 1. John Wiley and Sons, Inc; 2005. Hydrologic Concepts of Variability and Scale; p. 23–40.
- Xia Y, Ek MB, Wu Y, Ford T, Quiring SM. Comparison of NLDAS-2 Simulated and NASMD Observed Daily Soil Moisture. Part I: Comparison and Analysis. *J Hydrometeorol.* 2015; 16(5): 1962–1980. DOI: 10.1175/JHM-D-14-0096.1
- Zacharias S, Bogen H, Samaniego L, Mauder M, Fuß R, Pütz T, Frenzel M, Schwank M, Baessler C, Butterbach-Bahl K, Bens O, Borg E, Brauer A, Dietrich P, Hajsek I, Helle G, Kiese R, Kunstmann H, Klotz S, Munch JC, Papen H, Priesack E, Schmid HP, Steinbrecher R, Rosenbaum U, Teutsch G, Vereecken H. A Network of Terrestrial Environmental Observatories in Germany. *Vadose Zone J.* 2011; 10:955–973. DOI: 10.2136/vzj2010.0139
- Zreda M, Desilets D, Ferré TPA, Scott RL. Measuring soil moisture content non-invasively at intermediate spatial scale using cosmic-ray neutrons. *Geophys Res Lett.* 2008; 35(21):1–5. DOI: 10.1029/2008GL035655

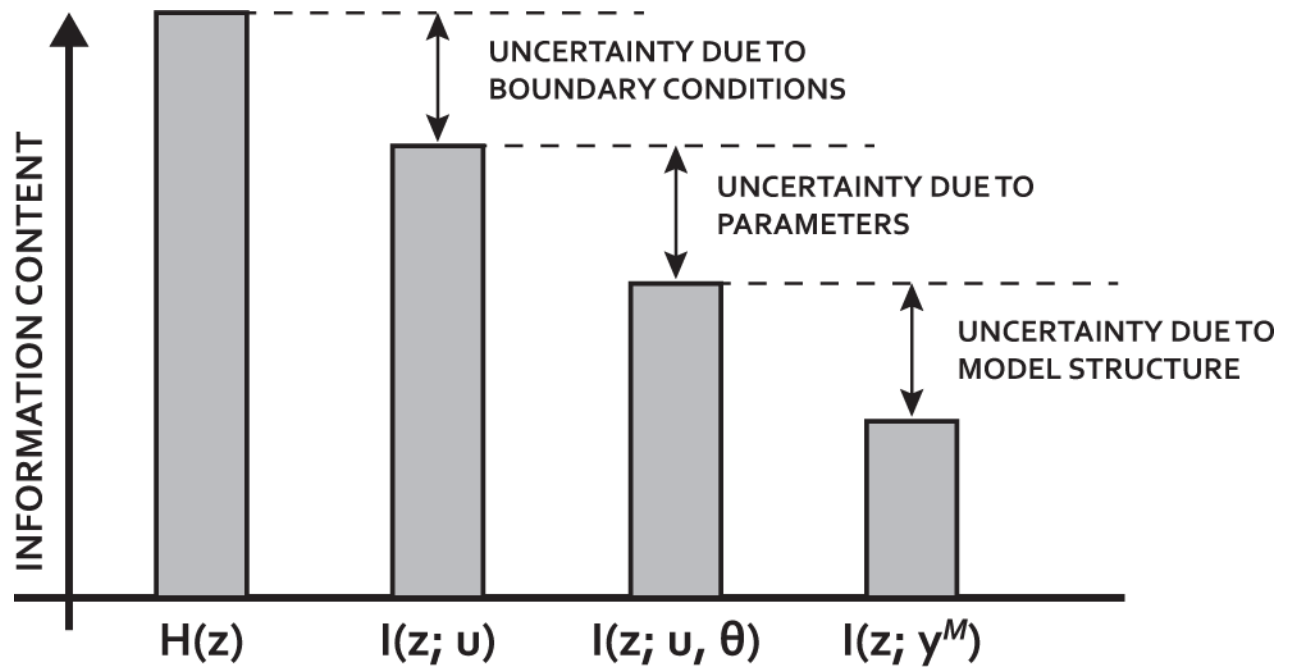


**Figure 1.**

An illustration of the scientific method in hydrology, highlighting how each component of the method reflects the various paradigms of science. The 4<sup>th</sup> paradigm is characterized by advanced data collection and analysis, as noted in the green boxes. Based on Figure 1 in Clark et al., 2016.



**Figure 2.** Aggregation and scaling schematic following Wood (1995).



**Figure 3.**

A conceptual diagram of uncertainty decomposition using Shannon information following Nearing et al., (2016). The term  $H(z)$  represents the total uncertainty (entropy) in the benchmark observations, and  $I(z; u)$  represents the amount of information about the benchmark observations that is available from the forcing data. Uncertainty due to forcing data is the difference between the total entropy and the information available in the forcing data. The information in the parameters plus forcing data is  $I(z; u, \theta)$ , and  $I(z; u, \theta) < I(z; u)$  because of errors in the parameters. The term  $I(z; y^M)$  is the total information available from the model, and  $I(z; y^M) < I(z; u, \theta)$  because of model structural error.