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Debates—The future of hydrological sciences: A (common) path forward? Using models and data to learn: A systems theoretic perspective on the future of hydrological science

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Key Points:

- Discovery can be advanced by taking a perspective based in Information Theory
- Much can be gained by focusing on the a priori role of Process Modeling
- System Parameterization can result in information loss

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1. Introduction

"Question Everything."

We suggest a systems theoretic framework for improving our ability to inform the discovery/learning process (and hence hydrologic science) from the juxtaposition of models and data, by taking a *perspective* based in *Information Theory*. We suggest that much can be gained by focusing more directly on the a priori role of *Process Modeling* (particularly System Architecture) while de-emphasizing detailed *System Parameterizations* or, framed as a question, "How can we generate input-state-output simulations without explicitly using the kinds of strong parameterizations (equations) commonly applied"? Stated simply, we anticipate a shift in the emphasis of modeling to the more creative aspects of scientific investigation.

2. Models and System Identification

Important aspects of any field of science include (1) acquiring ***observations***, (2) conducting ***process studies***, (3) proposing ***hypotheses***/*theories* to explain and generalize beyond what has been learned/observed, and (4) creating ***models*** that codify those hypotheses/theories into tools that can facilitate *understanding* and enable *testable predictions*. Here we focus on the role of modeling in the development of hydrological science. In doing so, we confess to being more interested in the specific value of models to developing ***understanding*** about the dynamics/behavior of a system (e.g., regarding the water balance dynamics of a catchment), and less so in their use for ***prediction*** at a specific time and place (e.g., streamflow volumes or levels). While it may be argued that all modeling is ultimately in support of prediction (i.e., and therefore decision making in an applied sense), we will take the view that "understanding" is primary. Accordingly, we comment on what role we think systems theory can play in advancing the hydrological sciences and, in particular, how systems theory and methods *can inform the discovery process* (Systems theory is the interdisciplinary study of systems in general, with the goal of elucidating principles that can be applied to all types of systems at all nesting levels in all fields of research. The term "systems theory" does not have a well established, precise meaning, but can reasonably be considered a specialization of systems thinking, a generalization of systems science, a systems approach (source Wikipedia)). To this end, we focus specifically on "System Identification" and have little or nothing to say about the (also important) role of systems analysis in problems of optimal resource allocation (e.g., dynamic programming for reservoir operation etc).

3. Brief Historical Perspective

The importance of systems theory to hydrology dates back to at least the 1950s and 1960s when computer-based modeling became possible. This gave rise to various generic models of catchment behavior, and much effort has been devoted to adjusting model parameters to "optimize" the match between model response and available observations. While this history has been well documented elsewhere [see e.g., *Gupta et al*., 2005], it is notable that *Johnston and Pilgrim*'s [1976] report of being ". . . unable to confidently

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claim to have discovered the optimum" to their watershed calibration problem "in over two years of extensive investigation," helped spawn more than three decades of interest.

By the 1990s, the optimization problem was largely well understood, and the focus began to shift away from "optimality," toward *characterizing and reducing uncertainty* [e.g., *Beven and Binley*, 1992; *Thiemann et al*., 2001] and *achieving consistency between the model and the system* [*Gupta et al*., 1998, 2008; *Martinez and Gupta*, 2011]. A simple empirical observation that many different parameter sets, widely distributed across the parameter space, often provide similar model performance in terms of particular evaluation metrics led to at least three complementary philosophical responses (and related strategies of investigation): "Parsimony," "Equifinality," and "Power" [*Wagener and Gupta*, 2005]. In essence, the Parsimony view advocates building models that are no more complex than can be identified from available data, the Equifinality view advocates that we should account for available data being insufficiently informative to distinguish between alternative model hypotheses as a source of uncertainty, and the Power view advocates a need to develop better methods for characterizing and extracting information from data—in other words that conclusions regarding parsimony and equifinality can be premature if the information (in both the model and the data) has not been properly characterized and extracted.

It has been the contention of the lead author that the hydrological community has done an inadequate job of figuring out how to learn from attempts to reconcile models with observational data [*Gupta and Sorooshian*, 1983; *Gupta et al*., 1998, 2008, 2009, 2012; *Martinez and Gupta*, 2011]. In this regard, we feel that (a) attempts to achieve better characterization of *predictive uncertainty*, and (b) a perspective of *model rejection*, are ultimately less interesting and productive than a focus on attempting to *learn* from the model-data encounter so as to achieve improvements in model structural adequacy [*Gupta et al*., 2012].

4. Models as Representations of Information

It is useful to revisit the progressive *formal* steps in model building, *with a view to being clear about the kinds of information embedded in the model through each step*. We modify the general perspective advanced in *Gupta et al*. [2012] to better suit this discussion, and skip the *informal* preliminary step of "perceptual-conceptual" modeling that (by definition) cannot be codified, while noting that this step acts as a strong prior (in the Bayesian sense) on everything that follows. In contrast with previous presentations, we discuss the nature and value of the *information* introduced at each *formal* step of the modeling process, these being:

1. Process Model (conceptual representation)

a) System Diagram (relevant physical principles)

b) Directed Graph (subsystem architecture)

2. Parameterized Model (System Parameterization)

3. Computational Model (numerical interpolation and integration).

In this characterization, the overall model hypothesis is composed of *three distinct types of hypotheses* arranged in a hierarchy of "fundamentalness," with each step strongly conditioning the next. Note that we lump physical, process and spatial variability structures [see *Gupta et al*., 2012] into the *Process Model*, to distinguish it from the system parameterization step that results in the *Parameterized Model*. The reasons for this will later become clear.

4.1 Process Model

The "System Diagram" provides a fundamental high-level hypothesis regarding the *major processes* believed to govern the behavior of the system, and specifically tells us:

1. The major *dynamical processes* to be simulated

2. The relevant *control volume* and *system boundary*

3. The relevant *conservation principles* and *boundary fluxes*

Importantly, since conservation principles explicitly express the *physical* nature of the dynamics by which the state variables evolve in time, all such models can be considered "physics-based," in contrast with regression type models (e.g., statistical time series models) that may not be constructed to obey such

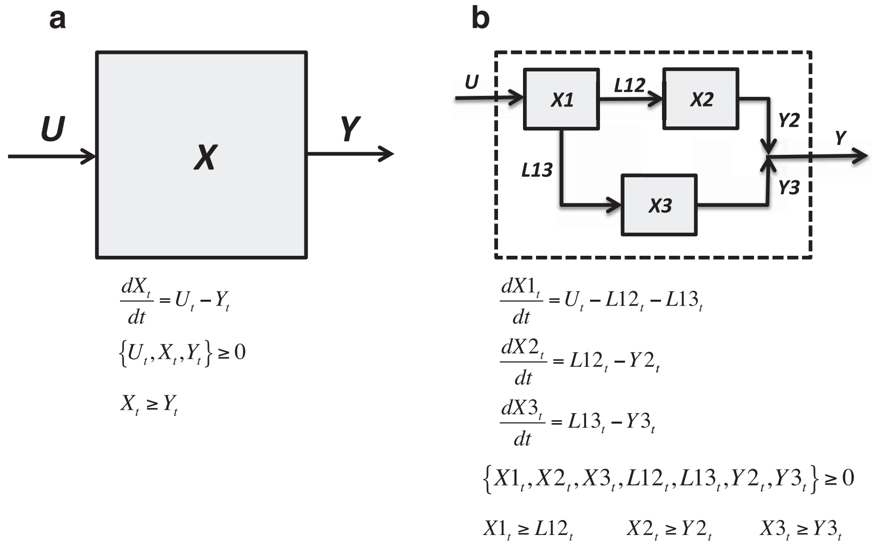

Figure 1. (a) Simple conceptual System Diagram, (b) simple conceptual Directed Graph.

constraints. The resulting conceptual System Diagram (e.g., Figure 1a) informs us about the *relevant physical principles* governing *overall behavior* of the system. If the main conservation principle is mass balance, it is expressed via the following equation, which makes explicit our assumptions regarding the major input fluxes $\boldsymbol{U}$ and output fluxes $\boldsymbol{Y}$ crossing the system boundaries, the state variables $\boldsymbol{X}$ of the system (in an abstract sense), and the conditions at the control volume boundary (e.g., constant or time-variable flux or pressure-head, etc.):

$$\frac{\boldsymbol{dX}}{\boldsymbol{dt}}=\boldsymbol{U_t}-\boldsymbol{Y_t} \tag{1}$$

This equation can be used to compute the trajectory of $\boldsymbol{X_t}$ conditional on an estimate of the initial state $\boldsymbol{X_o}$ and data regarding the time history of input and output fluxes $\{\boldsymbol{U_t}, \boldsymbol{Y_t}\}$ over some period $\{\boldsymbol{t}=\boldsymbol{1},\ldots,\boldsymbol{T}\}$. However, if data regarding $\{\boldsymbol{Y_t}\}$ are not available, we have two unknowns $\{\mathbf{X_t}, \mathbf{Y_t}\}$ and only one equation, and therefore additional information is needed before the corresponding trajectories can be computed.

Next, the "Directed Graph," provides a fundamental high-level hypothesis regarding the *Subsystem Architecture* (believed to be) necessary to represent *internal* system dynamics with sufficient detail to reproduce both the internal and the trans-boundary system dynamics. Specifically, it tells us:

1. What level of internal decomposition into subsystem components is necessary; this determines the dimensionality of each of the state variables $\boldsymbol{X}$ of the system

2. How subsystem components are linked to each other and to the system inputs and outputs, and the directionality of these links (links can be bidirectional)

The internal decomposition can be zero-dimensional (treating the system as lumped with no explicit representation of spatial organization), one-dimensional (treating the system as a one-directional flow), two-dimensional (e.g., vertical 2-D cross-section or horizontal 2-D map), three-dimensional, or some other conceptually useful architecture. Note that the *relevant conservation principles* specified via the System Diagram are also applicable at each of the nodes, and that each component-to-component link represents an internal process within the system, generating a flux between those components.

The result is an explicit representation of the major processes (considered to be) occurring *within* the system, and their structural organization (architecture), and results in a conceptual Directed Graph (such as illustrated in Figure 1b). If the main conservation principle is mass balance, the associated conservation equations related to Figure 1b are:

$$\frac{d\boldsymbol{X1}_t}{dt}=\boldsymbol{U}_t-\boldsymbol{L12}_t,\boldsymbol{L13}_t \tag{2}$$

$$\frac{d\boldsymbol{X2}_t}{dt}=\boldsymbol{L12}_t-\boldsymbol{Y2}_t \tag{3}$$

$$\frac{d\boldsymbol{X3}_t}{dt}=\boldsymbol{L13}_t-\boldsymbol{Y3}_t \tag{4}$$

where the numbers 1, 2, and 3 are used to "label/index" each node, and the internal fluxes between nodes are indicated as $\boldsymbol{L12}_t$ and $\boldsymbol{L13}_t$. In addition, we have the conservation constraint $\boldsymbol{Y}_t=\boldsymbol{Y2}_t+\boldsymbol{Y3}_t$. In this case, we now have eight unknowns {$\boldsymbol{X1}_t$, $\boldsymbol{X2}_t$, $\boldsymbol{X3}_t$, $\boldsymbol{L12}_t$, $\boldsymbol{L13}_t$, $\boldsymbol{Y2}_t$, $\boldsymbol{Y3}_t$, $\boldsymbol{Y}_t$} and only four equations, and therefore additional information is needed before the corresponding trajectories can be computed.

4.2. System Parameterization

The second formal step is specification of the "System Parameterization," which consists of an *assemblage of hypotheses* [*Clark et al*., 2008] regarding the *mathematical forms* of the *Process Equations* (believed to) describe the physical processes linking the subsystem components. Upon completion of this step, the resulting set of equations can be solved (either explicitly or via numerical integration) to compute the input-state-output evolution of the system.

For the simple case of equation (1), we can proceed by making a *hypothesis* of the parameterized form $Y_t=f(X_t|\theta_{XY})$, where $f(.|\theta)$ is a conditional probability distribution (generally assumed time-invariant) that can be adjusted by altering the values assigned to its parameters θ; all such parameterizations are fundamentally probabilistic, with deterministic parameterizations simply being Dirac distributions [*Montanari and Koutsoyiannis*, 2012]. By substituting the parameterization into the conservation equation (1), we obtain the implicit form of the state transition equation from which the (probabilistic) trajectory of {$\boldsymbol{X}_t$, $\boldsymbol{Y}_t$} can be computed:

$$\frac{d\boldsymbol{X}_t}{dt}=\boldsymbol{U}_t-f(X_t|\theta_{XY}) \tag{5}$$

For the more detailed case expressed by equations (2–4), we need an assemblage of parameterized hypotheses such as $L12_t=f(X1_t|\theta_{X_1L_{12}})$, $L13_t=f(X1_t|\theta_{X_1L_{13}})$, $Y2_t=f(X2_t|\theta_{X_2Y_2})$, and $Y3_t=f(X3_t|\theta_{X_2Y_3})$. Now having eight equations, the (probabilistic) trajectory of the eight unknowns {$X1_t$, $X2_t$, $X3_t$, $L12_t$, $L13_t$, $Y2_t$, $Y3_t$, Y_t} can be computed.

The result is a *Parameterized Model*, in which the concept of a model "parameter" has been introduced, arising as an artifact of the *specific hypotheses* regarding the System Parameterization. Since these parameters are largely abstractions related to the specific mathematical forms chosen, it may be possible to specify *feasible* ranges for their values, but "correct" values are not a meaningful concept. Therefore, it is common to select parameter estimates that enable the model to "adequately" track the observed input-state-output behavior of the real system. When this selection is done by calibration, it is justifiably referred to as model "tuning."

4.3. Numerical Interpolation and Integration (Computational Model)

To compute the coupled input-state-output trajectory of the entire system, some scheme for solving the equations of the Parameterized Model is necessary. In simple cases, it may be possible to explicitly solve the equations. In general, however, we proceed via numerical interpolation and integration. As has been discussed elsewhere [e.g., *Clark et al*., 2011], additional hypotheses (in the form of simplifying assumptions or approximations) may be introduced to facilitate efficient solution.

5. Information Coded Into the Model at Each Modeling Step

The two steps that make up the *Process Model* (*System Diagram* and *Directed Graph*) are largely *conceptual*, in that they specify the dominant system processes and architectures to be represented. The only mathematical forms (*equations*) involved are:

1. The equality constraints used to compactly notate the conservation laws (at the overall system and its subcomponent levels), these being derived directly from application of Newton's second law of motion, and typically taking the form of (deterministic or stochastic, ordinary or partial) differential equations describing the associated space-time dynamics.

Table 1. Information Coded Into the Model During Each Step of the Modeling Process

Modeling Step	Information Introduced
System Diagram	*Primary* (i) Processes to be considered/ignored (ii) Physical laws/principles governing overall system behavior (usually equality constraints) (iii) Nature of boundary conditions (iv) Specific input and output fluxes and state variables (U, Y, X) to be represented *Additional* (v) Positivity restrictions (usually inequality constraints) on fluxes and state variables ($U \geq 0$, $Y \geq 0$, $X \geq 0$) (vi) Magnitude and relativity restrictions (usually inequality constraints) on the fluxes and state variables (e.g., $X \geq Y$)
Directed Graph	*Primary* (i) Subsystem processes to be considered/ignored (ii) Physical laws/principles governing internal system behavior (usually equality constraints) (iii) Architecture of the flow of mass, energy, and/or information through the system (iv) Internal fluxes and state variables to be represented *Additional* (v) Positivity restrictions on all subcomponent flux and state variables (vi) Magnitude and relativity restrictions on the subcomponent fluxes and state variables
System Parameterization	*Primary* (i) Functional parametric relationships linking outputs of each system subcomponent to the state variables (usually deterministic equality constraints) *Additional* (ii) Restrictions on feasible values for the parameters (iii) Magnitude and relativity restrictions on the parameters
Numerical Interpolation & Integration	(i) Computational implementation

2. The *positivity, magnitude*, and *relativity restrictions* on all flux and state variables, these being based on requirements for physical realism of the system (i.e., that the model components isomorphically relate to aspects of the real world system).

However, we emphasize that (in our characterization) the specification of the Process Model *does not require the (mathematical) forms of the process equations linking the components to be known*. Further, the detailed structure of the system at scales *smaller* than the scales of the subcomponent elements is not explicitly represented. Such information is introduced either explicitly or implicitly with specification of the System Parameterization. Finally, additional mathematical concepts are introduced, via schemes for numerical interpolation and integration, to facilitate actual computation.

At each of these steps, very specific kinds of *information* are coded into the model as summarized in Table 1. Here we use the notion of *information* in the specific *Information Theoretic* sense that adding information results in a *change in our state of uncertainty* (alternatively certainty) about something. To be clear, the addition of information can result in (i) a *decrease* in magnitude of all or certain aspects of uncertainty, (ii) an *increase* in magnitude of all or certain aspects of uncertainty, (iii) a *shift* in the nature of uncertainty with magnitudes remaining the same, or (iv) any combination of the above [*Nearing*, 2013; *Nearing et al*., 2013].

In general, any new information that is "consistent" with our prior knowledge will increase our certainty, while new information that is "inconsistent" with our prior knowledge will reduce our certainty. At the same time, "good information" will shift our certainty in the direction of more accurate and precise simulations of system behavior, while "bad information" will do the converse. In regards to the latter, while *Beven and Westerberg* [2011] introduce and discuss (but do not explicitly define) the idea of "disinformation," *Nearing et al*. [2013] provide a demonstration of how the effects of good and bad information can be explicitly measured in the context of an observing system simulation experiment (OSSE).

Further, information can only be evaluated within a specific context (*information about something*). In the context of our discussion, this can take two major forms:

1. Information about the *system structure*

2. Information regarding the dynamical evolution of the *state variables and fluxes* in response to perturbations to the system (trajectory of inputs, changes in system structure, or boundary conditions, etc.)

What is important is that the amount of information introduced at each step of the modeling process outlined above is not insubstantial.

6. Implications for Learning

"Fact is solidified opinion; Facts may weaken under extreme heat and pressure; Truth is elastic" [*Bloch* 2003].

In this context of the "Debates on Water Resources," our goal is to suggest how we may better inform the discovery/learning process (and thereby improve hydrologic science) from the juxtaposition of models and data, by taking a *systems perspective* based in *Information Theory*.

In a Bayesian sense, each formal stage of the model development process (*Process Model*, *Parameterized Model*, and *Computational Model*) conditions each subsequent step. Physics is introduced at the *Process Model* stage (through hypotheses regarding the applicable conservation laws) and permeates through the remaining steps (during which additional physics may also be introduced). These conservation principles are, in general, expected to be "stationary" and therefore not affected by system changes (e.g., anthropogenic effects), except in the details of their execution. In other words, changes are more likely to occur in the System Architecture (*Directed Graph*) than in the *System Diagram* (although such may also occur in extreme situations).

In contrast, the *Model Parameterization* introduces very *specific hypotheses* regarding the behavior of each subcomponent, at which point tunable *parameters* may be introduced. These hypotheses may be explicitly derived from first principles, or may consist of semiempirical hypotheses regarding, for example, finer level (e.g., subgrid) behaviors of the system that are not explicitly resolved by the selected System Architecture (e.g., parameterization of rainfall generation in General Circulation Models).

At each stage, valuable *information* is introduced that changes (hopefully correctly reduces) our uncertainty regarding the state-output evolution of the system in response to inputs. The net result is a "Model Prior" which we then test, and try to improve, through inference. To the extent that each stage adds useful information, we can expect the accuracy of state-output simulations to improve and predictive uncertainty to diminish. The inference process, in which the Likelihood that the observed data "could have been generated by the proposed model (and measurement error) hypotheses" is examined, can be used to indirectly assess the amount of information added (reduction in uncertainty) regarding system structure.

However, if we do not apply sufficient care, the System Parameterization step may actually result in less information being added to the model than the potential maximum amount actually possible. This conjecture is supported by the well-reported fact that multimodel predictions (often based on multiple, appropriately weighted, alternative Parameterizations) can produce more accurate state-output simulations with reduced uncertainty. Similarly, G. S. *Nearing* and H. V. Gupta (Quantifying induction: On the amount and quality of information in a model, submitted to *Geophysical Research Letters*) demonstrate that restricting model parameter values from their entire feasible space to point values (via calibration) can result in information loss that will result in greater propensity for statistical forecast errors. More generally, one may expect information loss when working with only one Architectural Hypothesis, particularly when the hypothesis is biased in some important way (e.g., missing an important state variable/process).

To be clear, these are not arguments for *equifinality* (which primarily implies inability to distinguish alternative hypotheses) but rather for *diversity* (multiple relatively distinct alternative hypotheses). Conversely, it can be useful to know how much detail regarding system architecture is necessary; for example, in the Sacramento model, does splitting the upper and lower soil zones into "tension" and "free water" stores actually provide any measureable benefit?

Finally, one should recognize that there can (often will) be significant loss of *potential information added*, due to assumptions and expediencies introduced during the Computational Model step. As explained by *Nearing* [2013], all attempts at inference are "imperfect implementations of Bayes law." The imperfections arise from imperfect *Priors* (model and observational hypotheses), imperfect *Likelihoods* (approximations in the information extraction and transfer process), and imperfect solutions (e.g., sampling) of Bayes law. The inductive process is a progressive attempt to reduce such imperfections, through diagnostic evaluation and analysis of the juxtaposition of models and data.

A conjecture we wish to advance is that the *System Parameterization* stage may result in more information loss than is commonly recognized, and that this stage, which often involves *empiricism*, may sometimes be given far too much importance vis-a-vis the a priori role of *Process Modeling* (particularly System Architecture), which tends to be preassumed (at least by modelers) and can remain in the shadows. Support for this conjecture comes from a recent paper by *Gharari et al*. [2013], which shows convincingly (in our opinion) that when working with a "Parameterized" catchment-scale precipitation-runoff model, simply imposing *Relativity* and *Magnitude* constraints on the parameters, state variables and internal fluxes, results in sufficient reduction of parameter space uncertainty that ensemble model simulations track the observed streamflow very nicely—without any calibration to observed streamflow! Note that this is without recourse to any information from the system output data.

While the *Gharari et al*. [2013] example remains based on the use of a strongly determined System Parameterization (set of deterministic subprocess equations having a priori fixed functional form), we are suggesting (here is the possibly controversial part) that such results might actually be achievable using primarily the information introduced during the Process Model stage (System Diagram and Directed Graph; Table 1) *without* imposing strong a priori hypotheses regarding the System Parameterization. If true (investigation in progress), this could reduce the importance of knowing the precise mathematical forms of the subcomponent state-process equations, or the choice of Likelihood Measures used for extracting information from observations, thereby shifting the primary focus of investigation to proper characterization of the Process Model (particularly the System Architecture).

Further, one may argue whether imposing a limitation such as (for example) an abrupt constraint on maximum storage capacity is a *state-process constraint* or a *parameterization* (since it potentially introduces a "parameter" corresponding to maximum allowable storage capacity that may need to be tuned). We contend that such debate is pointless, as any classification system, such as ours, will be imperfect. In this regard, it is interesting to note that the shift from a *Manabe*-type bucket [*Manabe*, 1969] to a bucket with surface resistance resulted in significant improvements to Land Surface Modeling schemes (LSMs), while successive attempts to improve the characterization of the energy and water balance at the land-surface resulted in only relatively marginal improvements [*Pitman et al*., 1999].

Overall, our characterization helps to nicely frame many recent contributions to the modeling discussion, and possibly also contributes to the discussion regarding Diagnostic Evaluation [*Gupta et al*., 2008]. In regard to the former, the "Framework for Understanding Structural Errors" (FUSE) discussion explores multiple System Parameterizations within a single "master" framework so that different models can be viewed as simplifications of a more general architecture [*Clark et al*., 2008]. The "Flexible Modeling Approach" (FLEX) discussion facilitates exploration of multiple system architectures (and flexible parameterizations) based on alternative combinations of universal system subcomponents [*Fenicia et al*., 2008]. The "Bayesian Estimation of Structure" (BESt) discussion facilitates inference of the mathematical forms of a system parameterization by treating the state-process relationships as flexible marginal density functions that can be updated via Bayesian data assimilation [*Bulygina and Gupta*, 2009]. *Nearing* further develops and simplifies the BESt approach while introducing the use of *Information Theoretic* concepts to characterize and quantify the information gained during different parts of the model construction and inference process [*Nearing*, 2013; *Nearing et al*., 2013; G. S. Nearing and H. V. Gupta, 2014].

In regard to diagnostic evaluation, the important question is about how we can characterize and learn about model inadequacy of each type of hypothesis (Process, Parameterization, and Computation) via juxtaposition of the model against data [*Gupta et al*., 2012]

7. Conclusions

In conclusion, our two main points are as follows. First, we need to explicitly distinguish between the three major steps in the model building process: (a) conceptual representation (Process Model); (b) system parameterization (Parameterized Model); and (c) methods used for numerical interpolation and integration (Computational Model). Second, there is a formal and unifying framework that can deal with the model identification problem, within which hypothesis testing plays an important role. We suggest that much can be gained by working more directly with Process Models while de-emphasizing System Parameterization. Framed as a question, how can we generate input-state-output simulations without explicitly using the kind of strong parameterizations (equations) commonly applied? While practical computational strategies for doing this need to be developed, we contend that the aforementioned studies (and possibly others) have already demonstrated the potential for doing so. For example, *Bulygina and Gupta* [2009, 2010] demonstrated use of Monte Carlo sampling (particle tracking) to generate stochastic input-state-output simulations without imposing the form of the state-output equation. Subsequently, *Bulygina and Gupta* [2011] and *Nearing* [2013] also demonstrated that a prior model hypothesis regarding the system parameterization can be updated/corrected via data assimilation. In other words, as is well known, Monte Carlo sampling can be implemented as an alternative to *classical* numerical integration.

Stated simply, we foresee a shift in the emphasis of modeling toward the more creative aspects of scientific investigation. We argue that systems hydrology has moved beyond the stage where learning about model parameters (or even model states via data assimilation) is of primary importance. New tools are being developed to reconcile observations with parts of models that have not traditionally been considered "flexible"; specifically, the new frontier for hydrologic systems science is in ways to reconcile *Process Models* and model architectures with observations. When evaluated from the perspective of the amount of information provided by models, such methods appear to be much more valuable than those that focus on system parameterizations. The state of the science is still young, however, and the degree to which this holds true may vary with application. We look forward to discovering what is possible, and to collaborating with others in this regard.

8. Postscript: Comments on the Other Papers in the Debate

We appreciate and have enjoyed the opportunity to offer an opinion on how systems methodology can (continue to) support the developing science of hydrology, and are gratified that *Lall* [2014] concurs that pursuit of understanding should be preeminent. *Lall*'s characterization of hydromorphology as a paradigm seems consistent with our focus on the "bigger" issues of modeling.

Further, we are gratified that *McDonnell and Beven* [2014] also emphasize the role of "information" in hydrologic data as a diagnostic tool [*Gupta et al*., 2008]. While we agree that a diversity of hypotheses can lead to perceived equifinality, we *point to the important philosophical difference* ("Learning" instead of "Rejection"), and that equifinality can only be concluded if a rigorous job is done to evaluate the information content and quality of data *in the context of the hypothesis under examination* (i.e., information must be "about something"). We contend that robust strategies have not been sufficiently developed or become common practice, contributing to poor practices in model evaluation.

Most important, we particularly agree with *Lall* [2014] regarding the need to broaden discussion beyond methodological details to "appeal to the scientific and human relevance of hydrology," and that important questions currently faced by hydrological science are "peripheral to most of what is taught in a hydrology curriculum or . . . in the forefront of research published." It seems clear that for hydrology as a science to progress, the overall educational curriculum should be adapted [*Wagener et al*., 2012] to root it more firmly in the fundamental physics of water and its role as a fundamental aspect of nature, its origins and abundant presence in the universe, its intriguing fundamental properties (and so on), and ultimately its impact on our daily lives (clouds, weather, climate, water supply, etc.).

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