

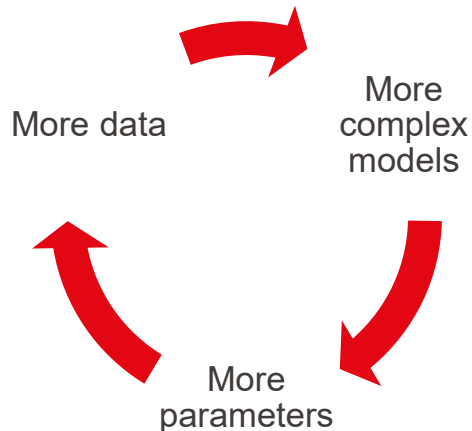
Env-411 (Ecohydrological Modeling)

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"We forget that the water cycle and the life cycle are one"
(Jacques Yves Costeau)

- Mathematical models are key to guiding decision making
- Always approximations and simplifications of real systems (models are not reality: this is perhaps an obvious point, but it is regularly ignored)
- Physically-based VS data-driven
- Spatially distributed VS lumped
- Early physically based models were simple (mostly dictated by the limited computational resources) VS nowadays (hundreds of terabytes of memory needed to run certain models)
- Major limitations, nowadays, stem from the difficulty to obtain enough detailed data to characterize all variables that are involved in the system (more than by computational resources)
- Increasing data availability -> does not necessarily make model development easier

WATER RESOURCES RESEARCH, VOL. 42, W03S04, doi:10.1029/2005WR004362, 2006



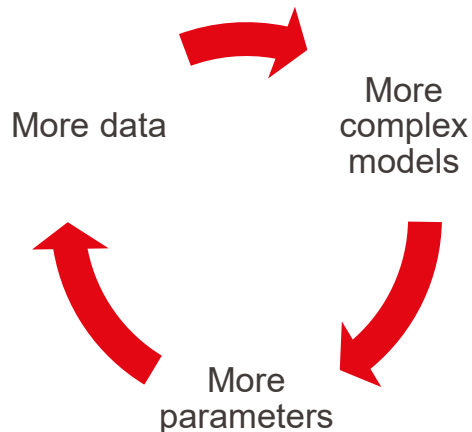
Getting the right answers for the right reasons: Linking measurements, analyses, and models to advance the science of hydrology

James W. Kirchner¹

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[1] The science of hydrology is on the threshold of major advances, driven by new hydrologic measurements, new methods for analyzing hydrologic data, and new approaches to modeling hydrologic systems. Here I suggest several promising directions forward, including (1) designing new data networks, field observations, and field experiments, with explicit recognition of the spatial and temporal heterogeneity of hydrologic processes, (2) replacing linear, additive “black box” models with “gray box” approaches that better capture the nonlinear and non-additive character of hydrologic systems, (3) developing physically based governing equations for hydrologic behavior at the catchment or hillslope scale, recognizing that they may look different from the equations that describe the small-scale physics, (4) developing models that are minimally parameterized and therefore stand some chance of failing the tests that they are subjected to, and (5) developing ways to test models more comprehensively and incisively. I argue that scientific progress will mostly be achieved through the collision of theory and data, rather than through increasingly elaborate and parameter-rich models that may succeed as mathematical marionettes, dancing to match the calibration data even if their underlying premises are unrealistic. Thus advancing the science of hydrology will require not only developing theories that get the right answers but also testing whether they get the right answers for the right reasons.

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"I remember my friend Johnny von Neumann used to say, with four parameters I can fit an elephant, and with five I can make him wiggle his trunk."

E. Fermi (1953)

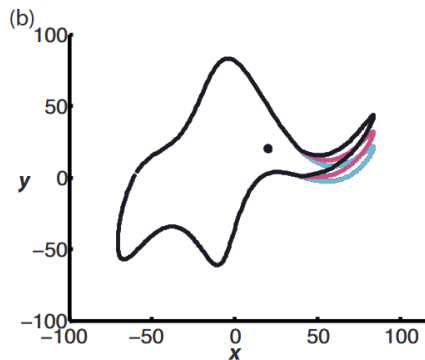


Fig. 1. (a) Outline of an elephant. (b) Three snapshots of the wiggling trunk.

Mayer et al. (2010), *Am. J. Phys.* 78(6)

essay turning points

A meeting with Enrico Fermi

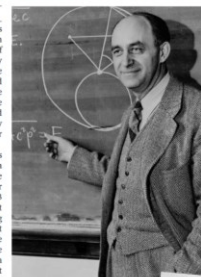
How one intuitive physicist rescued a team from fruitless research.

Freeman Dyson

One of the big turning points in my life was a meeting with Enrico Fermi in the spring of 1953. In a few minutes, Fermi politely but ruthlessly demolished a programme of research that my students and I had been pursuing for several years. He probably saved us from several more years of fruitless wandering along a road that was leading nowhere. I am eternally grateful to him for destroying our illusions and telling us the bitter truth.

Fermi was one of the great physicists of our time, outstanding both as a theorist and as an experimenter. He led the team that built the first nuclear reactor in Chicago in 1942. By 1953 he was head of the team that built the Chicago cyclotron, and was using it to explore the strong forces that hold nuclei together. He made the first accurate measurements of the scattering of mesons by protons, an experiment that gave the most direct evidence then available of the nature of the strong forces.

At that time I was a young professor of theoretical physics at Cornell University, responsible for directing the research of a small army of graduate students and postdocs. I had put them to work calculating meson-proton scattering, so that their theoretical calculations could be compared with Fermi's measurements. In 1948 and 1949 we had made similar calculations of atomic processes, using the theory of quantum electrodynamics, and found spectacular agreement between experiment and theory. Quantum electrodynamics is the theory of electrons and photons interacting through electromagnetic forces. Because the electromagnetic forces are weak, we could calculate the atomic processes precisely. By 1951, we had triumphantly finished the atomic calculations and were looking for fresh fields to conquer. We decided to use the same techniques of calculation to explore the strong nuclear forces. We began by calculating meson-proton scattering, using a theory of the strong forces known as pseudoscalar meson theory. By the spring of 1953, after heroic efforts, we had plotted theoretical graphs of meson-proton scattering. We joyfully observed that our calculated numbers agreed pretty well with Fermi's measured numbers. So I made an appointment to meet with Fermi and show him our results. Proudly, I rode the Greyhound bus from Ithaca to Chicago with



Crossed paths: A discussion with Enrico Fermi (above) made Freeman Dyson (right) change his career direction.



little bags of quarks. Before Murray Gell-Mann discovered quarks, no theory of the strong forces could possibly have been adequate. Fermi knew nothing about quarks, and died before they were discovered. But somehow he knew that something essential was missing in the meson theories of the 1950s. His physical intuition told him that the pseudoscalar meson theory could not be right. And so it was Fermi's intuition, and not any discrepancy between theory and experiment, that saved me and my students from getting stuck in a blind alley.

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A model should be:

- **Reliable**: it gives approximately correct predictions under most circumstances.
- **Robust**: whose results do not depend sensitively on the specification of quantities that are poorly known.
- **Realistic**: it includes sufficient processes, represented in adequate detail, to allow simulation of the system's response to a change in all of the external variables of interest.

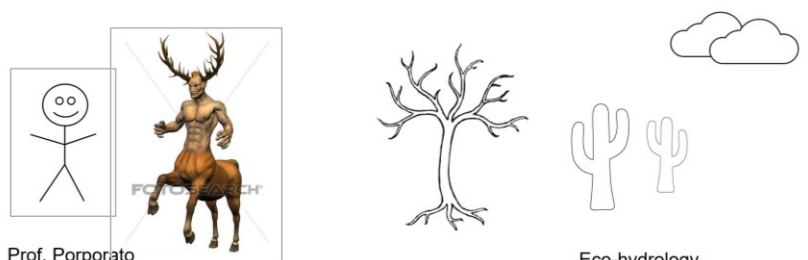
Possession of one feature above does not by any means guarantee the rest.

"We will argue that the dominant paradigm in land-surface modelling focusses too heavily on realism at the expense of the other two R's" (Prentice et al., 2015)

Although it seems reasonable to expect that a model including a larger subset of processes that are known to be important should be more realistic than a simpler model, increases in reliability and robustness by no means automatically follow.

Porporato & Yin ©Cambridge University Press

The value of Minimalist (or Reduced Order) Models



Prof. Porporato

Eco-hydrology

- Based on different models (all consistent with observed data) predictions of future or hypothetical scenarios can vary widely.
- Uncertainty of model results refers to the potential variability of the results due to different model structure, input parameters, and forcing variables (*Beven, 1993; Montanari, 2007*)
- When models are employed to make forecasts or as a tool for decision-making processes, it is important to quantify and, if possible, reduce the uncertainty of their results.

1. Three conventional **steps to build a model**:

- A. **Conceptual** model
- B. **Mathematical** model
- C. **Evaluating solutions** (analytical, numerical)

2. Once the model is setup, a **sensitivity analysis** is performed to quantify the variations of its results due to variations of its parameters

3. Parameter **calibration** and model **validation**

ARTICLE

Verification, Validation, and Confirmation of Numerical Models in the Earth Sciences

Naomi Oreskes,* Kristin Shrader-Frechette, Kenneth Belitz

Verification and validation of numerical models of natural systems is impossible. This is because natural systems are never closed and because model results are always non-unique. Models can be confirmed by the demonstration of agreement between observation and prediction, but confirmation is inherently partial. Complete confirmation is logically precluded by the fallacy of affirming the consequent and by incomplete access to natural phenomena. Models can only be evaluated in relative terms, and their predictive value is always open to question. The primary value of models is heuristic.

puter program may be verifiable (12). Mathematical components are subject to verification because they are part of closed systems that include claims that are always true as a function of the meanings assigned to the specific symbols used to express them (13). However, the models that use these components are never closed systems. One reason they are never closed is that models

3. Parameter calibration and model ~~validation~~

Input data uncertainty	Measurements errors from sensors	Better and repeated measurements, postprocessing of data (cleaning, gap-filling)
Input data uncertainty	Spatial representativity of local observations + errors from regionalization	Statistical techniques can be used to map most probable values and their uncertainty ranges
Input data uncertainty	Climate data uncertainty (different emission scenarios, climate model structural uncertainty, chaotic nature of climate processes)	Ensembles of climate projections
Structural uncertainty	Conceptual model, mathematical model, numerical solution	Multi-model ensembles
Parameter uncertainty	Estimation of parameters	Bayesian approaches, data assimilation
Output data uncertainty	Observed outputs (used for calibration/validation) can have errors	Statistical techniques

- These uncertainties interact with (and add to) each other in complex manners
- Epistemic (due to lack of knowledge) vs. aleatoric (irreducible part of total uncertainty) uncertainty

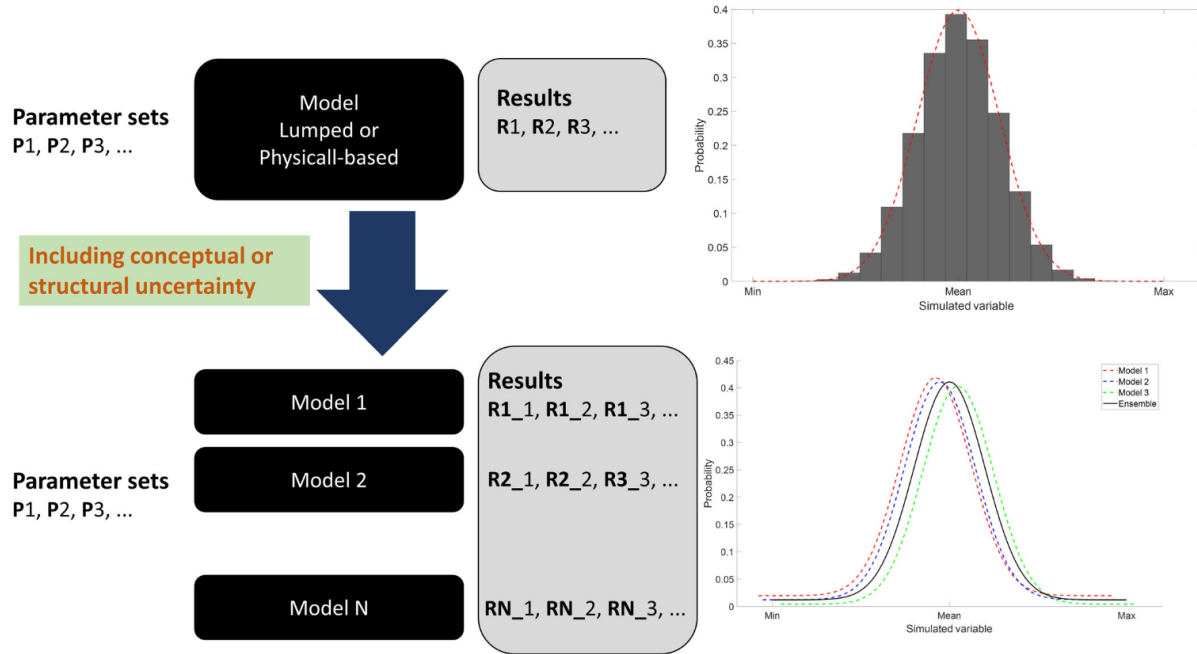


FIGURE 2 To evaluate the uncertainty of a given conceptual or structural model, it is necessary to generate many sets of input parameters that are coherent with the conceptual model. Then, the model is run many times to compute the probability distribution function (*pdf*) of the results, which allows estimating their uncertainty. If the structural uncertainty is included, then many models must be used to perform the same procedure employed for single models. The overall uncertainty can be evaluated from the ensemble *pdf* (Butts et al., 2004; Georgakakos et al., 2004; Neuman, 2003)

RESEARCH ARTICLE

10.1002/2013WR013725

Special Section:

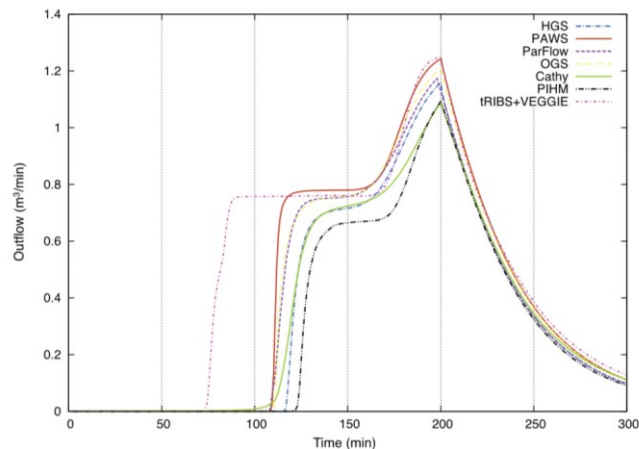
Advancing Computational
Methods In Hydrology

Key Points:

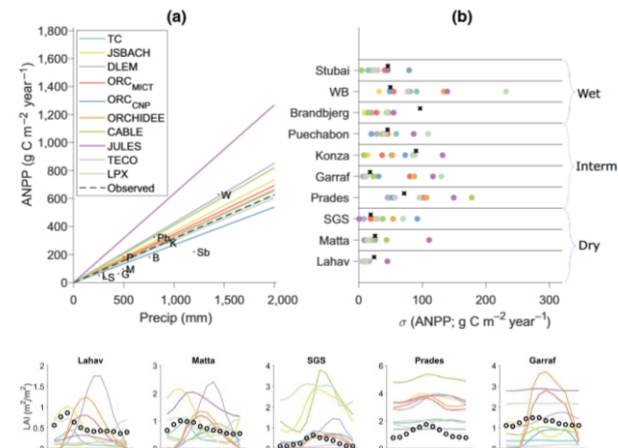
- Seven hydrologic models were intercompared on standard

Surface-subsurface model intercomparison: A first set of benchmark results to diagnose integrated hydrology and feedbacks

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■ ENV-411 | X – Model uncertainty



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PRIMARY RESEARCH ARTICLE

Global Change Biology | WILEY

Rainfall manipulation experiments as simulated by terrestrial biosphere models: Where do we stand?

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