School for Young Scientists
"Modelling and forecasting of river flows and managing hydrological risks: Towards a new generation of methods"
Moscow State University (20-23 November, 2017)

Hydrologists against the terrifying uncertainty: Is the beast invincible?

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The presentation is available at: http://www.itia.ntua.gr/1756/

Many "important" persons (particularly politicians and economists) are very certain about the future

GDP long-term forecast

Related topics

Economy

Trend gross domestic product (GDP), including long-term baseline projections (up to 2060), in real terms. Forecast is based on an assessment of the economic climate in individual countries and the world economy, using a combination of model-based analyses and expert judgement. The indicator is measured in USD at 2010 Purchasing Power Parities.

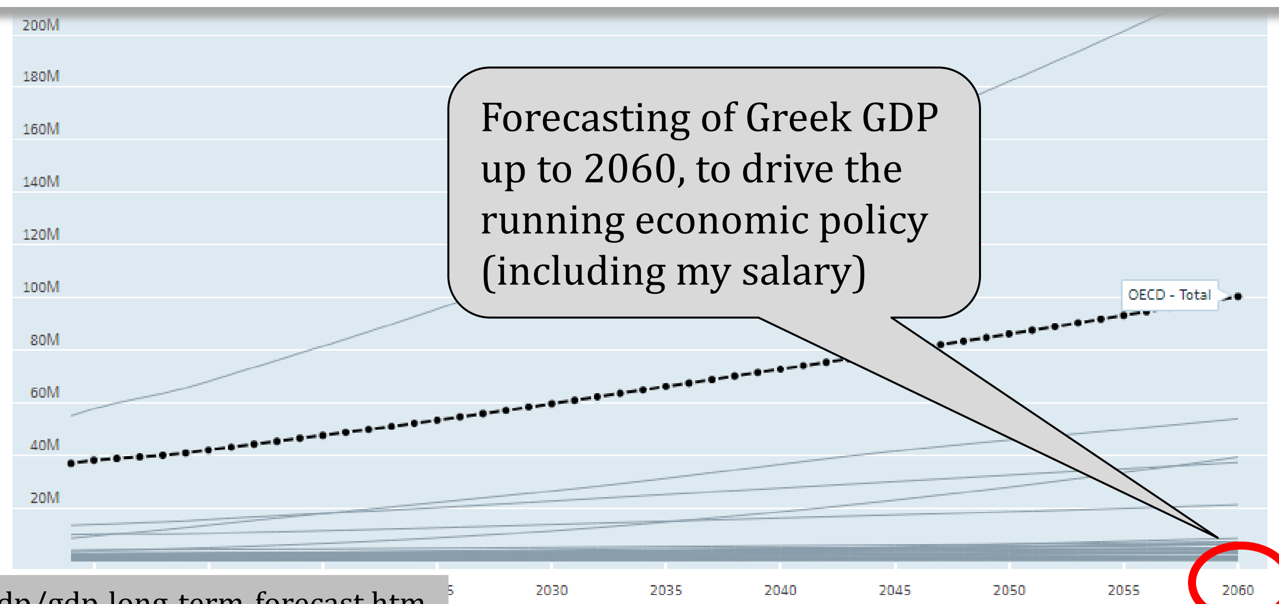
Latest publication

National Accounts at a Glance

PUBLICATION (2015)

Trend gross domestic product (GDP), including long-term baseline projections (up to 2060), in real terms. Forecast is based on an assessment of the economic climate in individual countries and the world economy, using a combination of model-based analyses and expert judgement. The indicator is measured in USD at 2010 Purchasing Power Parities.

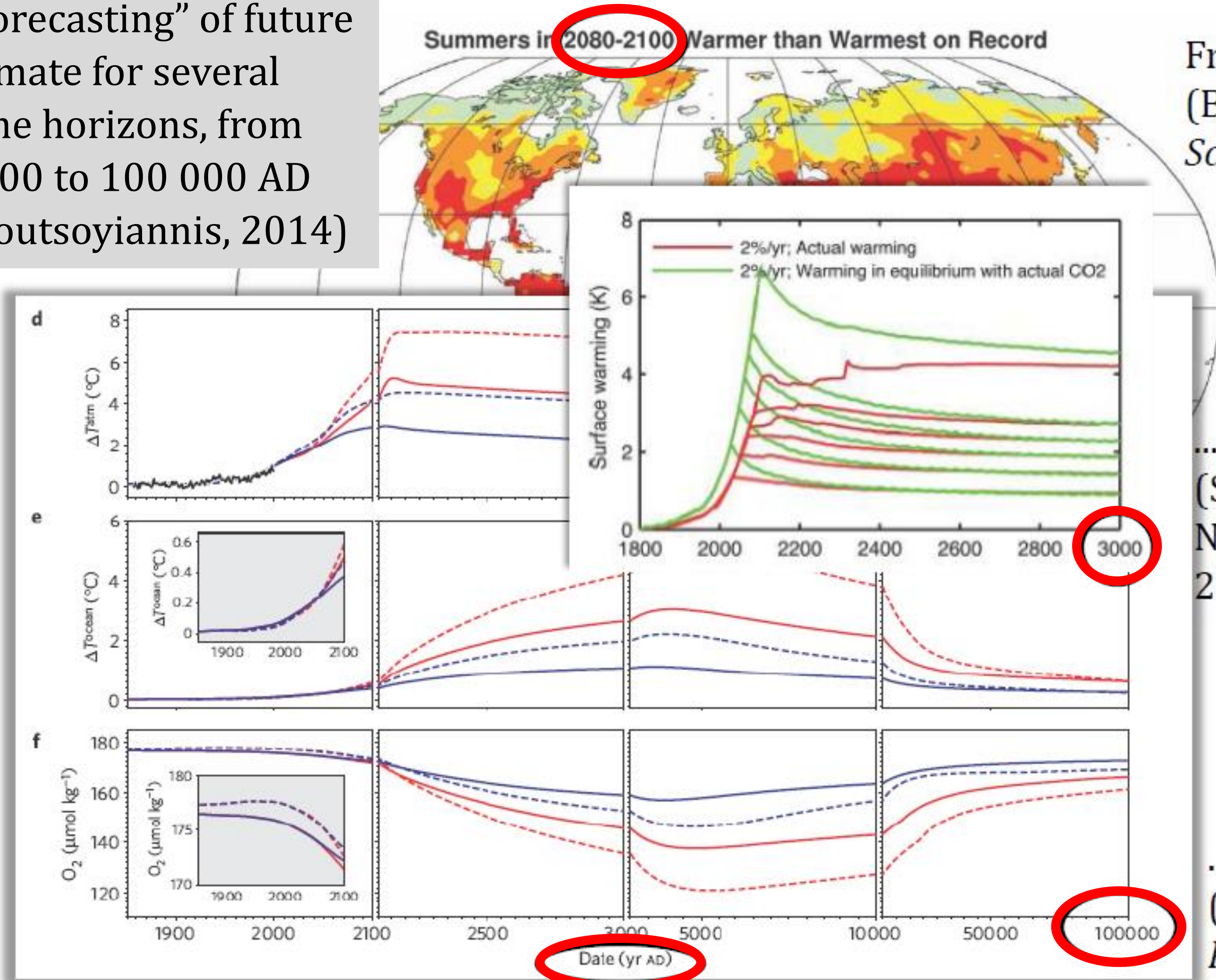
- Nominal GDP forecast
- GDP long-term forecast
- Quarterly GDP
- Investment (GFCF)
- Investment forecast
- Investment by asset
- Investment by sector
- Domestic demand forecast



Source: https://data.oecd.org/gdp/gdp-long-term-forecast.htm

Some scientists (?) are very certain as well

"Forecasting" of future climate for several time horizons, from 2100 to 100 000 AD (Koutsoyiannis, 2014)



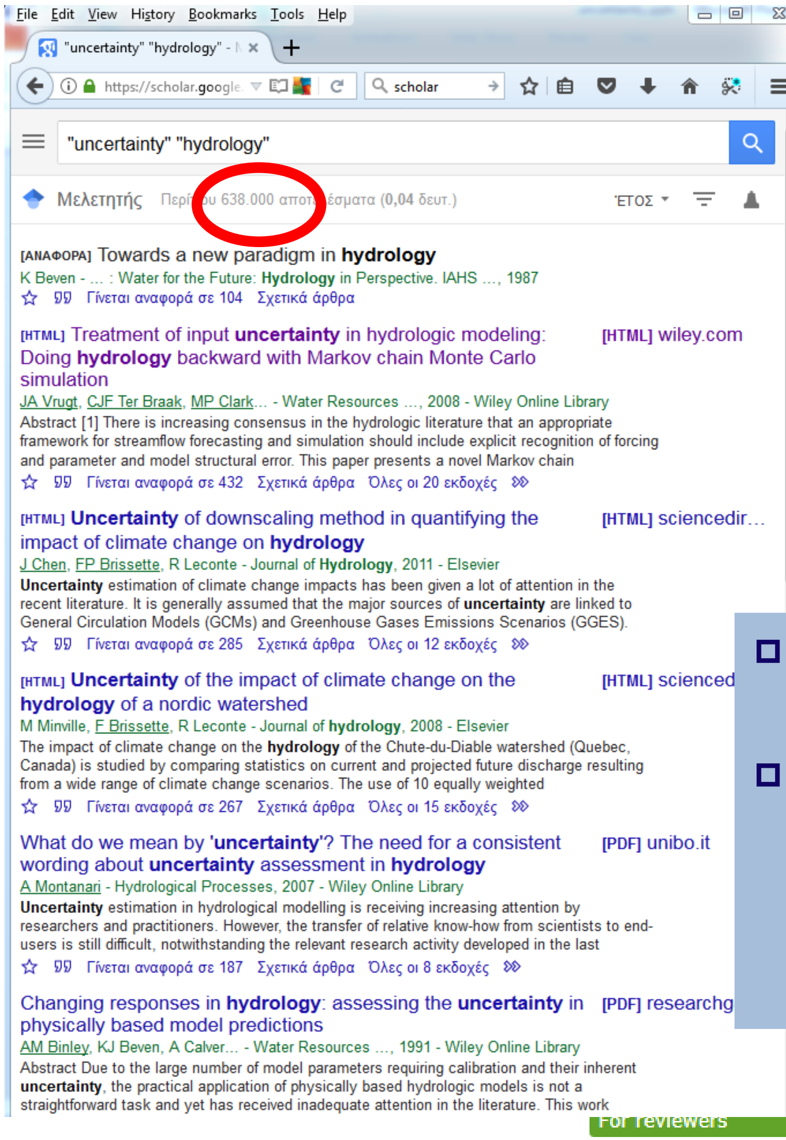
From 2100 AD (Battisti and Naylor, *Science*, 2009)...

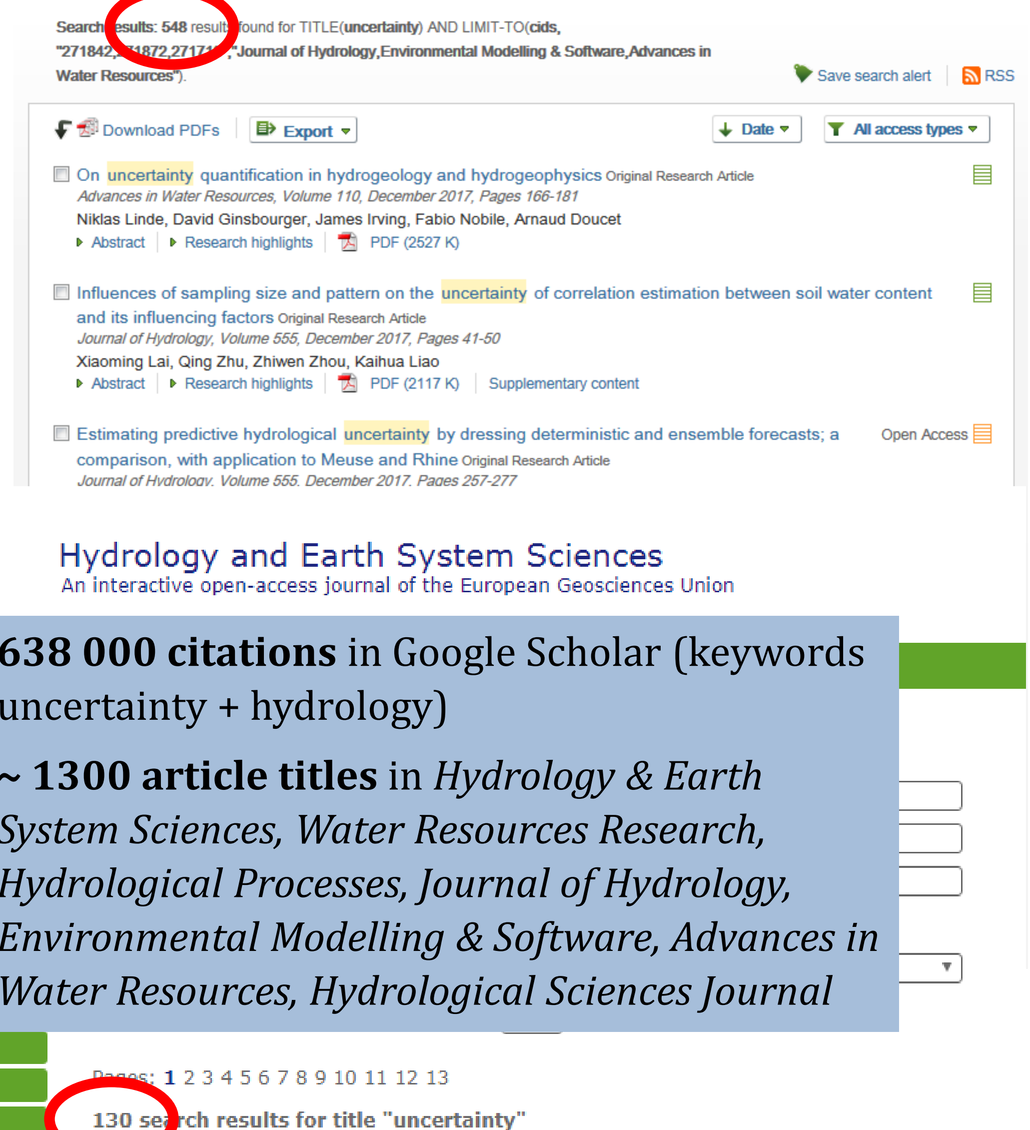
... to 3000 AD (Solomon et al., Nature Geoscience, 2009)

...to 100 000 AD (Shaffer et al., *PNAS*, 2009)

The fallacy of climate models and predictions: Koutsoyiannis *et al.*, 2007; 2008; Anagnostopoulos *et al.*, 2011

Good news: Hydrologists are aware of uncertainty (and they write a lot about it)





- **638 000 citations** in Google Scholar (keywords uncertainty + hydrology)
- **~ 1300 article titles** in *Hydrology & Earth System Sciences, Water Resources Research, Hydrological Processes, Journal of Hydrology, Environmental Modelling & Software, Advances in Water Resources, Hydrological Sciences Journal*

Widely used (sometimes uncertain) terms in hydrological literature associated with uncertainty

- Prior/posterior distribution
- Forecasting
- Change
- Deterministic
- Error
- Monte Carlo
- GLUE
- Information
- Confidence
- Reliability
- Estimator
- Likelihood
- Memory
- Entropy
- Bayesian
- Behavioral
- Prediction
- **Aleatory/epistemic/ semantic/ontological/ structural uncertainty**
- Randomness
- Risk
- Hypothesis testing
- Return period
- Noise
- Stochastic process
- Stationarity vs. non-stationarity
- Equifinality
- Dynamic systems
- Bias
- Hurst
- Variability
- Persistence
- Projection
- Dependence

The hydrological community does not provide a commonly accepted interpretation for uncertainty. Which is **your interpretation**?

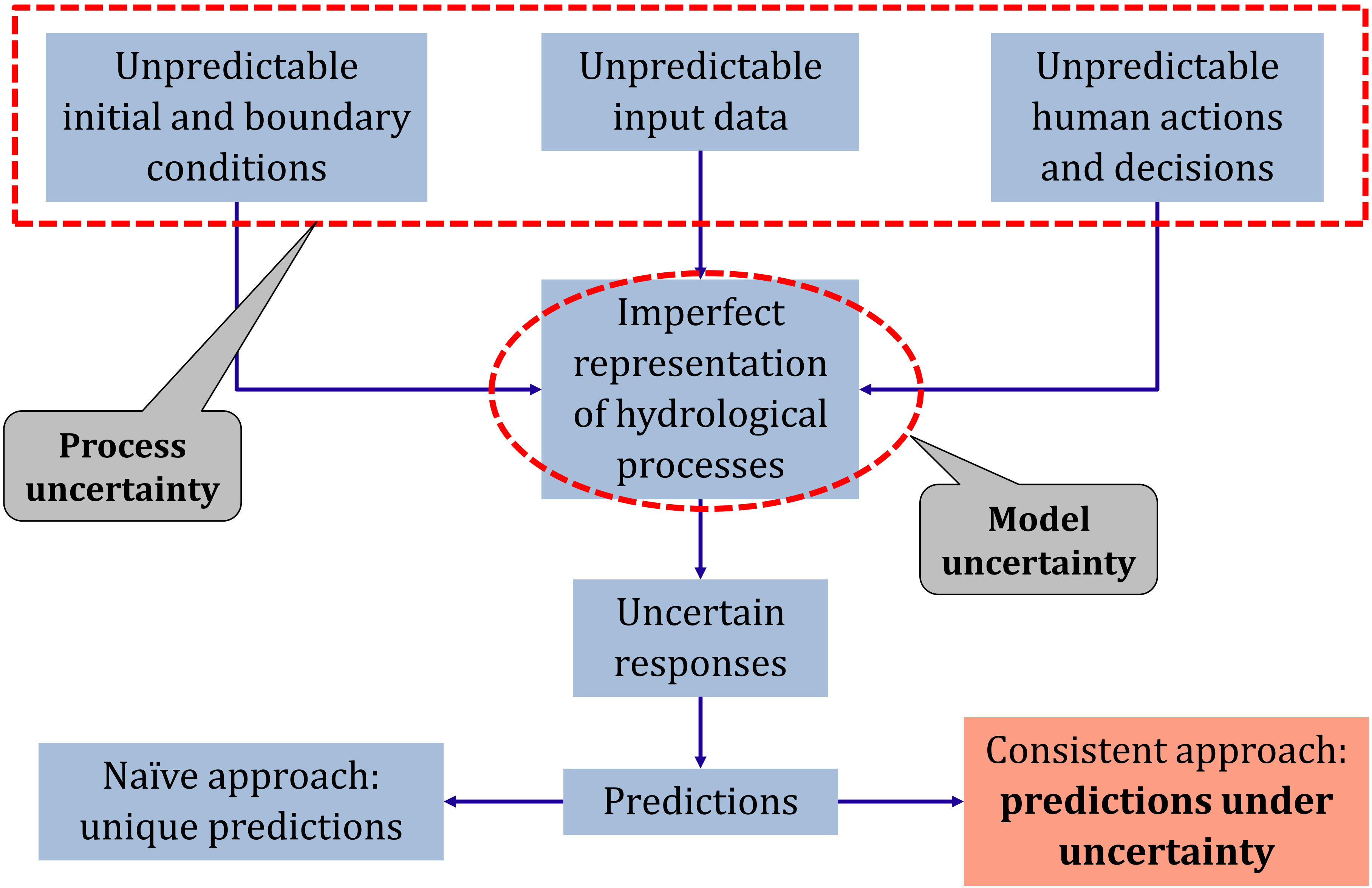
The origins of uncertainty in hydrology (and nature, in general): change, predictability, randomness

- “**Panta rhei**” = everything flows (Heraclitus of Ephesus, 535-475 BC; Pre-Socratic Greek philosopher) – motto of the **IAHS Scientific Decade 2013–2022**.
- A **change** may be either **predictable** or not; **uncertainty is associated with changing systems that are not predictable**.
- By definition, predictable changes follow **deterministic** laws
- In hydrology, determinism originates from the **daily and annual cycles** of the Earth (remark: these cycles are also varying, at extremely large temporal scales).
- **Hydrological systems** are mainly (but not solely) driven by meteorological processes that are not predictable, thus such systems are **intrinsically uncertain**.
- They are also affected by **unpredictable exogenous processes**, e.g. anthropogenic interventions, natural hazards, etc., causing non-systematic changes.
- As the responses of hydrological systems are combined effects of multiple drivers, **determinism and randomness cannot be handled separately** (processes are not the sum of a deterministic and a random component).
- Uncertainty is intrinsic property of perpetually **changing hydrological systems**.
- **Process uncertainty** substantially increases when represented by approximate simulators, i.e. **models**.

Why physical uncertainty is amplified through models?

- Models are essential on order to substitute the **missing information** about the system behavior and its responses (otherwise there is any need to use models).
- Models are built upon **deduction** and **induction**:
  - Deductive reasoning ("top-down"), works from the more general to the more specific. Its starts from a **theory**, to be finally confirmed from observations;
  - Inductive reasoning ("bottom-up") uses **observations** to establish broader generalizations and theories.
- Models are mainly employed for **"predicting" the future** – more precisely, for assessing the system response under hypothetical future scenarios, in order to support **planning** and **decision-making**.
- Less often, models are exclusively applied for **reproducing the past**, although the reproduction of the past is essential step of any modelling procedure, in order to **validate** the model performance against observed data.
- Models are (and they will always be) **imperfect**:
  - Due to **assumptions** and **simplifications** (**model = working hypothesis**);
  - Due to the use of **finite** and **inaccurate data**.
- The deviation from perfectness is the **model uncertainty**.
- The combined effects of **process** and **model uncertainty** may be terrifying!

Hydrological predictions under uncertainty



From certainty to uncertainty

- All **past realizations** of a process are certain (because they happened!).
- All **future realizations** of a process are uncertain (definition of process = a randomly changing quantity).
- All **observed past realizations** of a process are uncertain (because observations are subject to uncertainties).
- All **modelled past realizations** of a process are uncertain (because models, either calibrated or not, are subject to uncertainties).
- All **modelled future realizations** of a process are uncertain (because forecasting is subject to combined uncertainties).

Let agree that:

- Modelled processes are more uncertain than observations.
- Models with empirically-derived parameters are more uncertain than calibrated models, i.e. fitted on observations.
- Forecast models are more uncertain than past simulation models.
- Long-term forecast models are more uncertain than short-term models.

The role of information in process representation

- **Knowledge-based (deduction, logic)**
  - Theoretical description of the process (establishment of physical laws, based on deterministic cause-effect relationships);
  - Approximate description based on empirically-derived laws;
  - Understanding of macroscopic physical behaviors (evidence, experience);
- **Data-based (induction, inference)**
  - Direct measurements of the process at the field (raw data);
  - Evaluation of the process of interest based on the observed data of relevant processes (e.g., stage → discharge);
  - Any other type of qualitative or proxy information (soft data);

- Hydrological models are built upon **both** types of information (purely "physically-based" and "data-driven" models do not exist!).
- **Full** knowledge or full data do not exist, thus **perfect** models cannot exist.
- The **more** the knowledge and data, the **less** the model uncertainty.

Greek-Russian example on modelling and information (Olympiacos Pireus vs. CSKA Mockow; Euroleague Final Four Madrid 2015, Semifinal B)

- **Question**: Which will be the outcome of this 3-pt shoot attempt by Vasilis Spanoulis (last shoot of the game)?
- **Information hints**:
  - The trajectory of the shot is governed by well-known physical laws, i.e. Newtonian mechanics;
  - Spanoulis' average career 3-pt shoot percentage exceeds 35%;
  - Spanoulis is a top player, one of the best guards of Euroleague history;
  - Last years, Spanoulis statistics are getting worse;
  - Until this shoot, Spanoulis has only 2 out of 7 successful 3-pt attempts;
  - Spanoulis scored two subsequent 3-pt shots in last minutes;
  - Voronchevic is much taller and he will probably stop the shot;

Contrasting a basketball shot with river flows

The trajectory of the shot is governed by well-known physical laws, i.e. Newtonian mechanics	The river dynamics is governed by well-known physical laws, i.e. Saint-Venant equations
Spanoulis' average career 3-pt shoot percentage exceeds 35%	The mean annual flow of the river exceeds 100 m^3/s
Spanoulis is a top player, one of the best guards of Euroleague history	This river produces large floods, some of the most hazardous ever observed
Last years, Spanoulis statistics are getting worse	Last years, the river flows seems being systematically decreasing
Until this shoot, Spanoulis has only 2 out of 7 successful 3-pt attempts	This year, only two out of seven months produced larger flow than their average
Spanoulis scored two subsequent 3-pt shots in last minutes	Last two subsequent months produced the larger flows of this year
Voronchevic is much taller and he will probably stop the shot	There is a major reservoir upstream that will probably store the high flows

Lessons learned from basketball and rivers

- Both systems are governed by physical laws, fully **deterministic**.
- A summary, long-term information about the systems' behavior is provided by the **statistical characteristics** of the observed data.
- **Qualitative information** ("soft" data) about the macroscopic behavior of the two systems may also be provided by human experience.
- Medium-term observations may indicate a systematically changing pattern, i.e. a decreasing **trend**.
- Short-term statistical information may indicate a significant **shift** from the observed mean.
- Clusters of high and low values appear at multiple scales, thus indicating the existence of both **long-term and short-term dependencies**.
- **Human-induced interventions** may dramatically affect the actual dynamics of the system.

- Can we model the **past**, and next use the model for **future** predictions?
- How can these **knowledge** and **data** be accounted for in predictions?
- How much informative (or misleading) is the **statistical information**?

The ultimate medicine for uncertainty estimation: Monte Carlo & stochastics

- **Theoretical** relationships for uncertainty assessment are restricted to very few cases (e.g., confidence limits for normally-distributed variables).
- **Monte Carlo** approaches = **computer experiments** based on random numbers that are generated from given statistical distributions.
- For **dependent** processes:
  - Stochastic models (representing linear correlations)
  - Copulas (representing complex dependencies)
  - Ensembles (change of initial conditions)

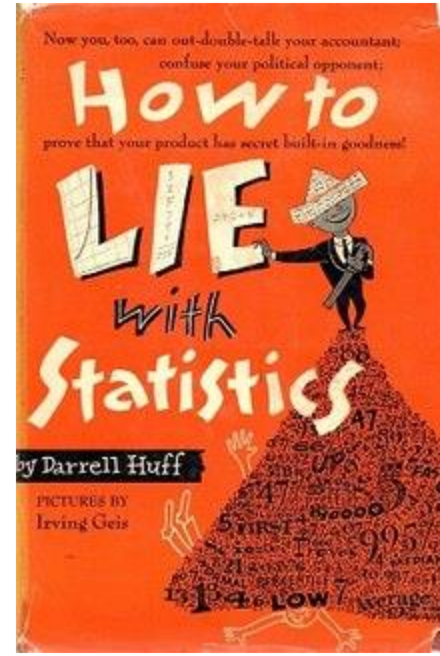
Uncertainties within uncertainty assessment

- The theoretical model for random number generation is manually selected and assigned a priori → Which is the “true” theoretical model?
- The parameters of theoretical distributions are extracted from sample data, using estimators → Which data? Which estimators?
- Monte Carlo methods make use of several algorithmic inputs → Which inputs?

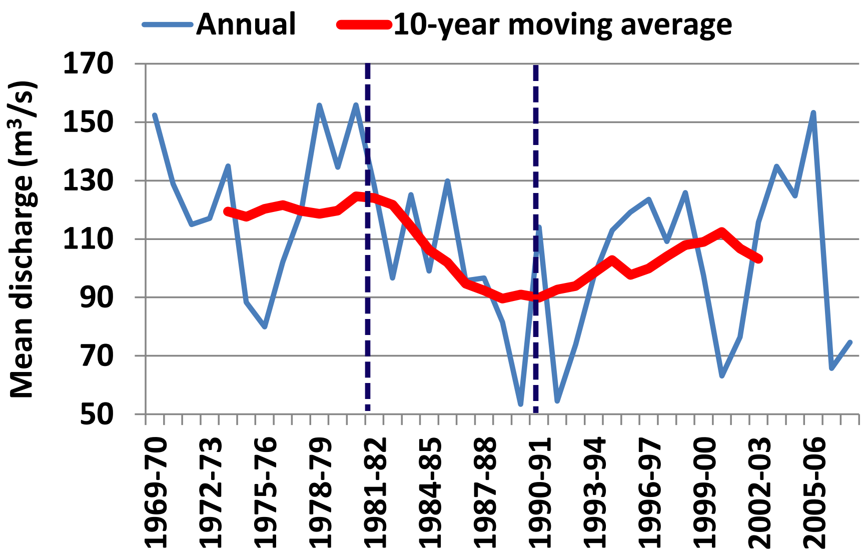
On the selection of distributions to be reproduced within stochastic modelling: Tsoukalas *et al.*, 2017

Be aware of statistics!

- Statistical information that is forced to be reproduced in stochastic models is exclusively **data-driven**.
- Observed hydrological samples are generally **too short** to capture with satisfactory accuracy the actual statistical behavior of the process.
- Uncertainty increases as moving from **low-order** to **high-order** statistics (mean → variance → skewness).
- Significantly important statistical characteristics, associated with the representation of **dependencies** and the **extremes** are very uncertain.

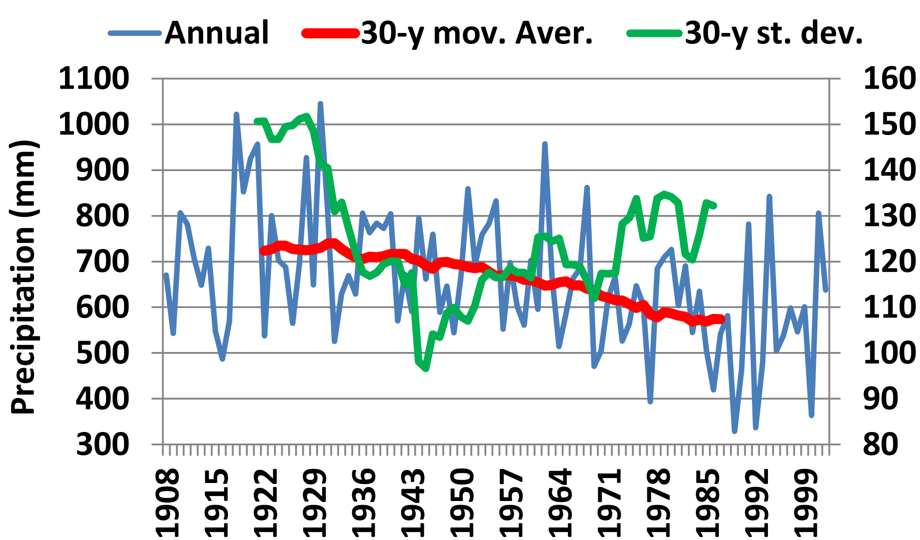


The curse of small samples (and rolling statistics)

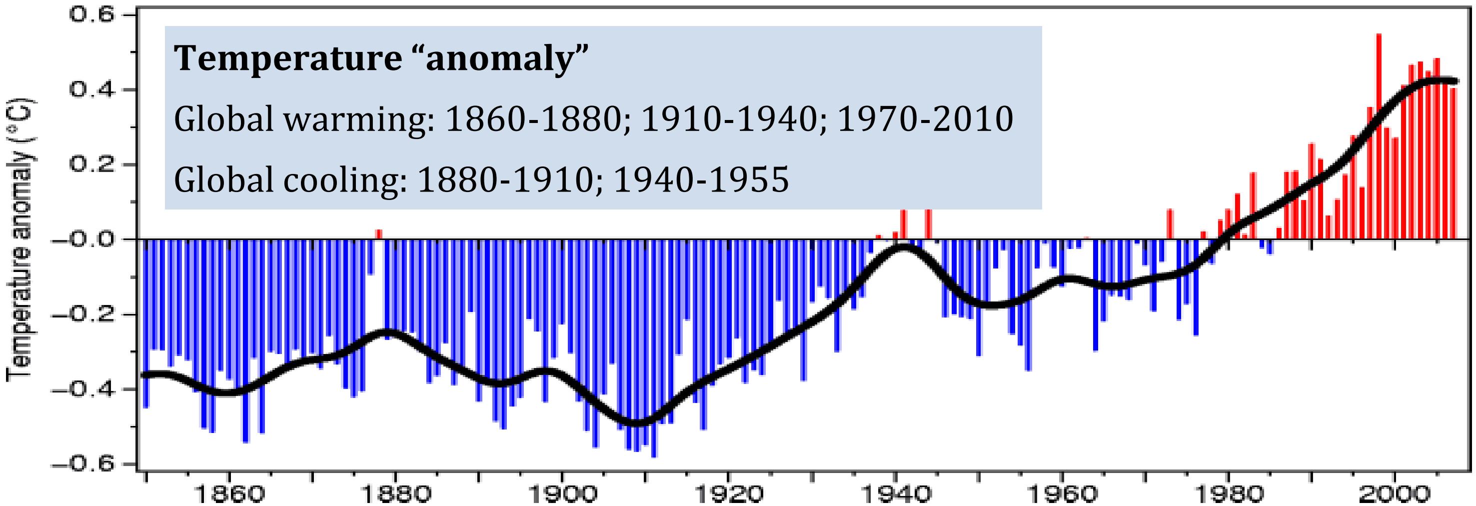


- Acheloos river at Kremasta dam (the largest river in Greece and the largest reservoir, with 4200 hm^3 capacity).
- 40 years of inflow data, comprising systematically dry and systematically wet periods.
- Random fluctuations at the annual scale, "structured" randomness at coarser scales.

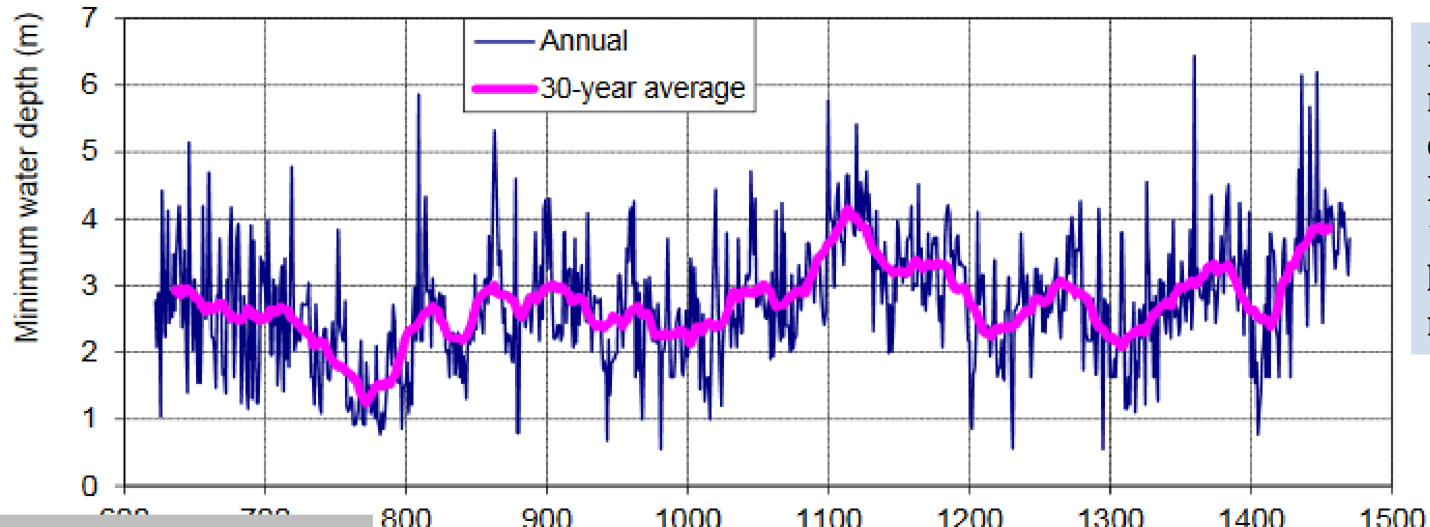
- Precipitation at Aliartos station, one of the oldest in Greece.
- 30-year moving average (climate scale) indicates a negative trend.
- 30-year standard deviation (measure of uncertainty) exhibits significant fluctuations.
- Which statistical characteristics should be applied for simulations?



The time window matters!



Source: Climatic Research Unit (www.cru.uea.ac.uk/cru/info/warming)



Nile River annual minimum water depth at Roda Nilometer (650 to 1450 AC; longest hydrological record so far)

Source: Koutsoyiannis (2013)

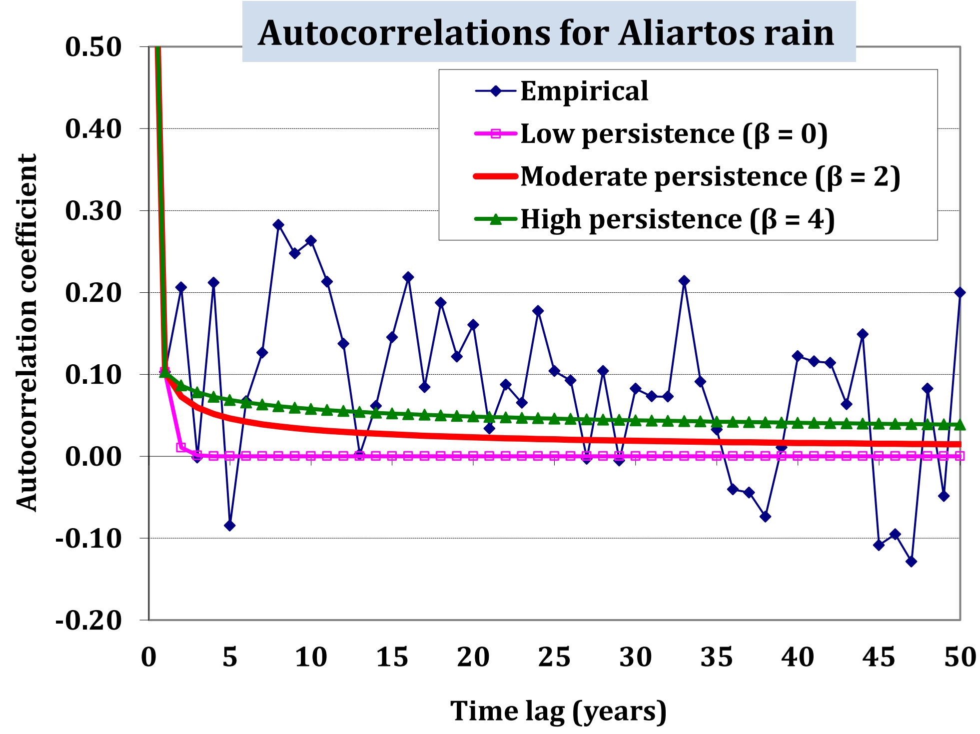
Embedding Hurst-Kolmogorov dynamics within stochastics

- Hurst-Kolmogorov (HK) dynamics are present in all hydroclimatic and geophysical processes, and they are associated with **long-term persistence, scaling peculiarities and structured changes** (e.g., trends, shifts).
- HK implies the existence of a **heavy-tail autocorrelation structure**, which can be modelled through a generalized autocovariance function of the form:

$$\gamma_j = \gamma_0\, [1 + \kappa\, \beta\, j]^{-1/\beta}$$

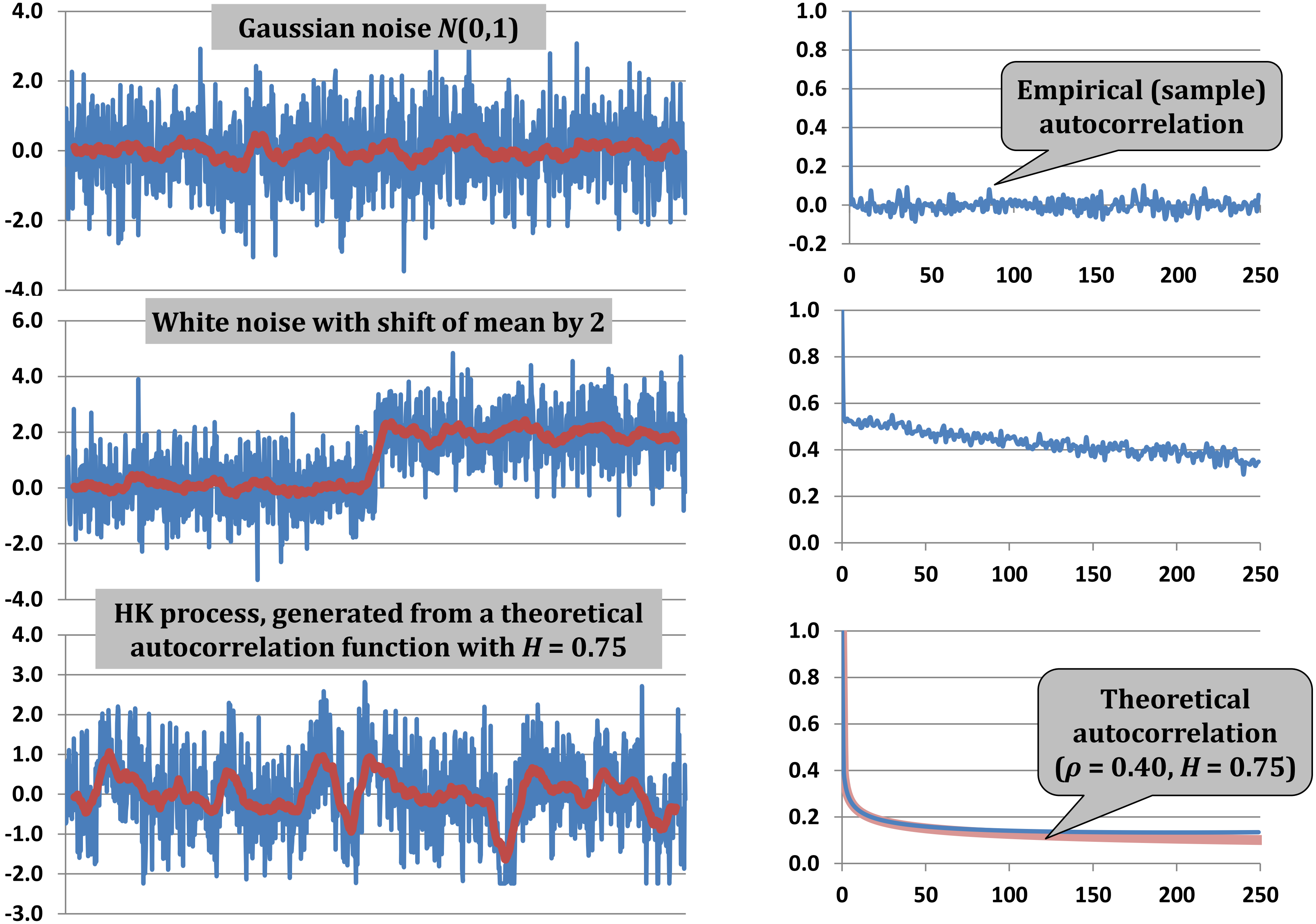
where γ_0 is the variance and κ, β are shape and scale parameters, respectively,

- By adjusting κ and β, one can take a wide range of feasible autocovariance structures (e.g., for $\beta = 0$ we obtain an ARMA-type structure).
- The autocovariances γ_j can be easily reproduced through typical stationary stochastic models (e.g. moving average).



On the HK dynamics and its modelling implementation: Koutsoyiannis, 2000; 2002; 2011; Efstratiadis *et al.*, 2014

Stochastic processes vs. autocorrelation structures



Sample uncertainty + HK dynamics = terrifying uncertainty

- Let $(x_1, \dots, x_n)$ is a sample of n realizations of the random process X, with mean μ and standard deviation σ. The simpler statistical characteristic that can be estimated from the sample is the average, with standard estimator:

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} x_i$$

- According to classical statistics, assuming that X is an iid process (independent identically distributed), the variance of $\bar{X}$ is:

$$\mathrm{Var}[\bar{X}] = \sigma^2 / n$$

- If X is a Markovian process with first-order autocorrelation ρ, the variance of $\bar{X}$ is:

$$\mathrm{Var}[\bar{X}] = \frac{\sigma^2}{n} \frac{(1-\rho^2) - 2\rho(1-\rho^n)/n}{(1-\rho)^2}$$

- If X is a Hurst-Kolmogorov process with exponent $H > 0.5$, the variance of the sample average becomes:

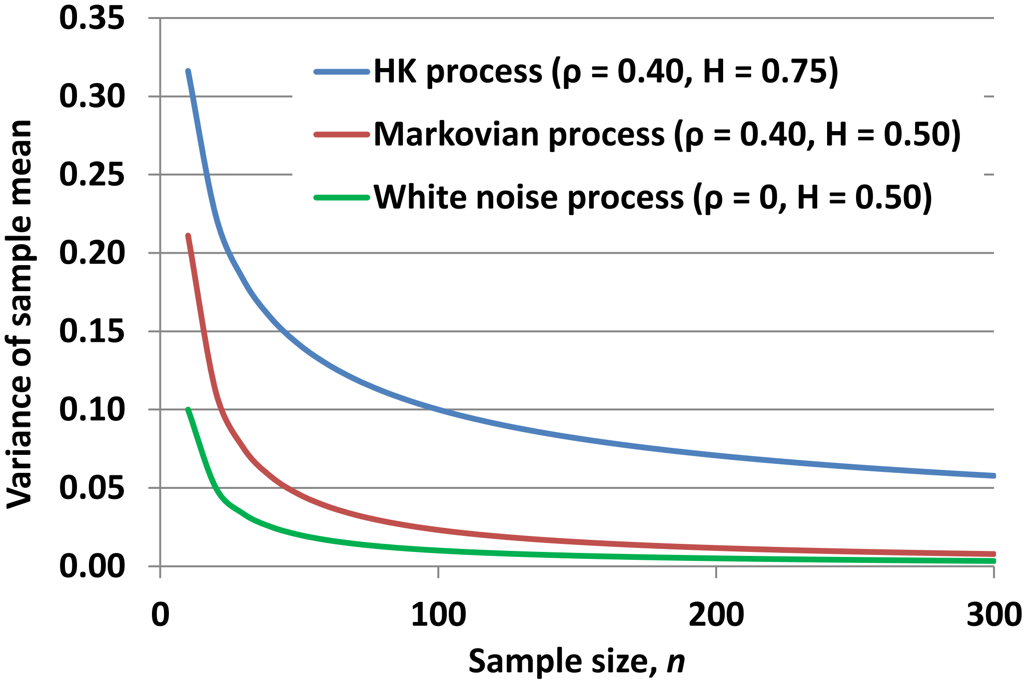
$$\mathrm{Var}[\bar{X}] = \frac{\sigma^2}{n^{2(1-H)}}$$

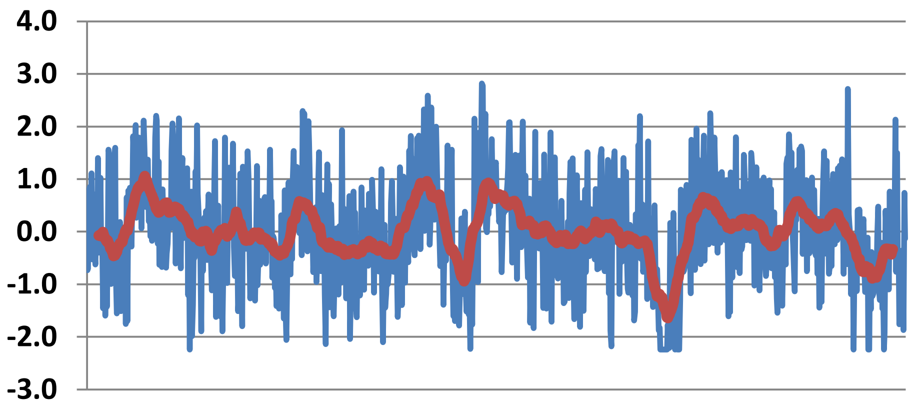
Uncertain (depend on sample and estimation procedure)

- The variance of the sample mean $\bar{X}$ depends on the sample size, the variance of the random process X, and the Hurst exponent.
- Both statistics are highly uncertain; parameter H is practically impossible to be derived from an observed time series (needs very long data).

How many data is needed to provide reliable estimations of the “true” statistics?

- The answer **depends on the model** – but the model is **just a hypothesis** (uncertainty!).
- Theoretical relationships are only valid for **Gaussian distributions** and the **specific correlation structures** (white noise, Markovian, HK).
- For any other case, please employ the ultimate medicine, i.e. **Monte Carlo simulation**.

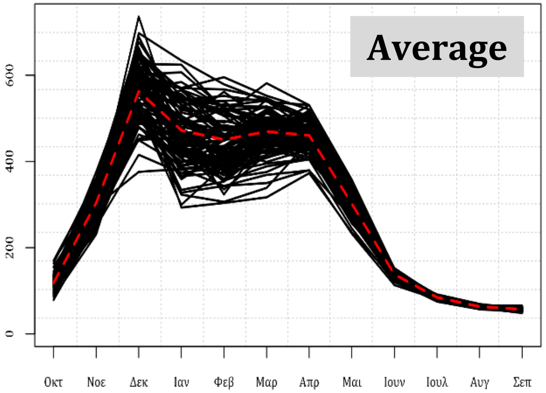


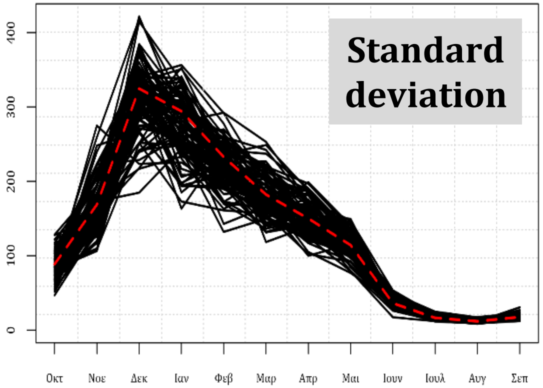


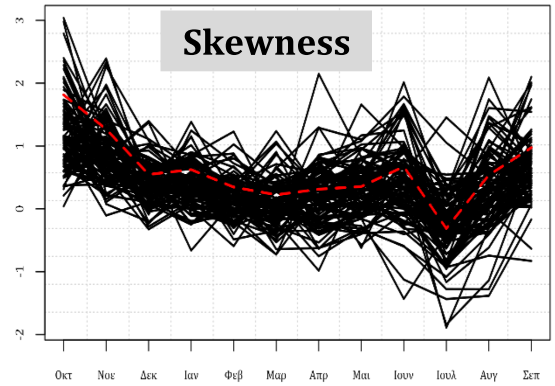
For an **HK process**, we need hundreds of years to estimate the average, with satisfactory accuracy, and thousands of years to estimate higher-order statistics.

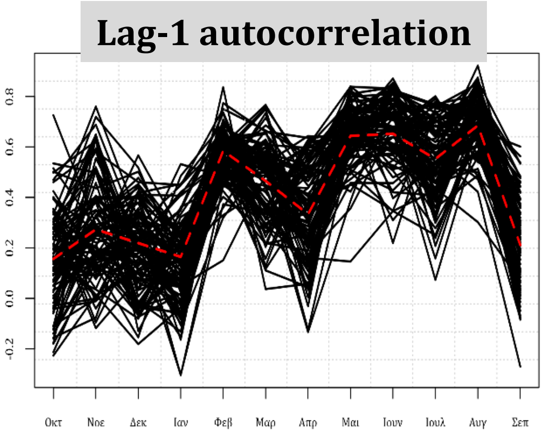
Small samples introduce substantial uncertainty, thus we use **synthetic data**.

Impacts of sample uncertainty to reservoir design and management: the capacity-yield-reliability relationship

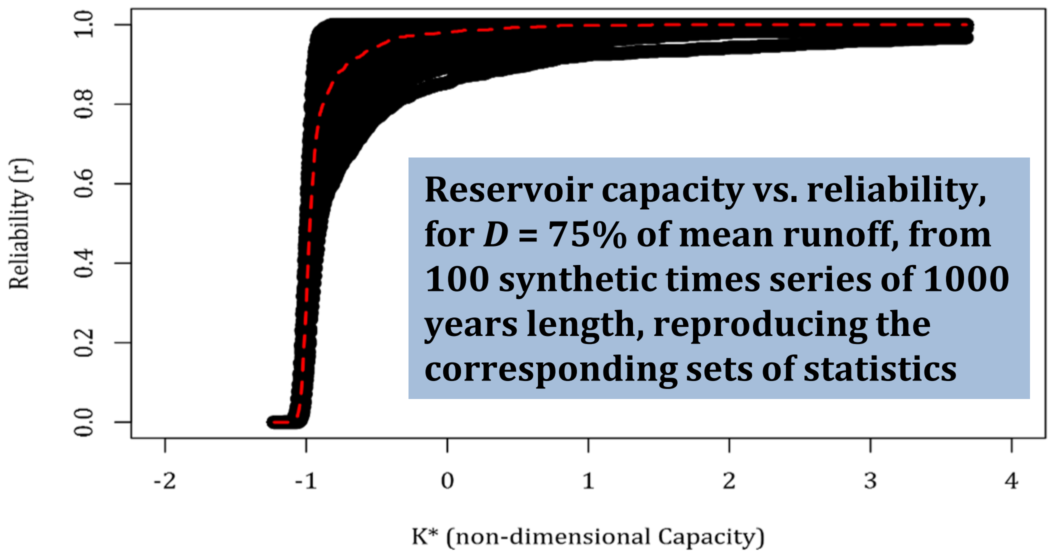








Simulated monthly statistical characteristics (100 synthetic time series of length equal to historical data, i.e. 28 years)



Impacts of inflow sample uncertainty to reservoir design and management: Zacharopoulou, 2017

Deterministic models and uncertainty

- Deterministic approaches are preferable over stochastic models for describing:
  - Cause-effect relationships, in case of **missing or inadequate response data** (thus a direct stochastic simulation of the response process is impossible);
  - Nonlinear **transformations** and complex **interactions** among processes;
  - **Storage**, **regulation**, and **timing** phenomena;
  - **Exogenous interventions** and known (or expected) **systematic changes**.
- Components of **deterministic hydrological models**:
  - Governing equations;
  - Initial and boundary conditions;
  - Input variables;
  - Numerical coefficients;
  - Properties derived from field measurements (e.g., geometrical);
  - Parameters (conceptual properties, with macroscopic physical interpretation);
  - Hyper-parameters (quantities that are functions of other parameters);
- Which of the above components are **varying**?
- Which of the above components are **uncertain**?

Model uncertainty is everywhere – even in "constants": The case of Manning's formula

- For uniform flow conditions:

$$Q = \frac{1}{n} A\, R^{2/3}\, J^{1/2}$$

The sole certain component, as derived from theoretical hydraulics

where n is a friction coefficient, A is the section area, R is the hydraulic radius, and J is the longitudinal slope; A and R are functions of section geometry and depth, y.

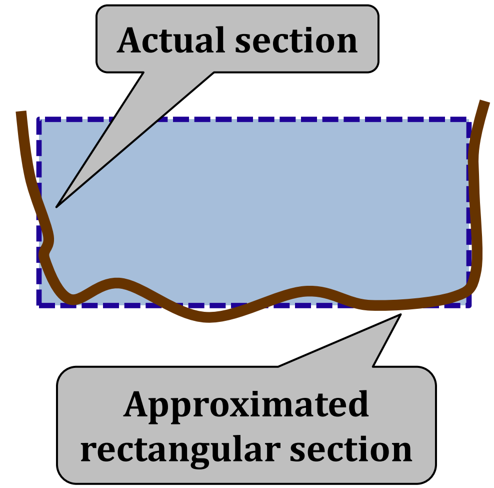
- **Traditional approach**: y is varying, all other quantities are constants.
- **Working approach**: y is varying, n is uncertain, all other quantities are constants.

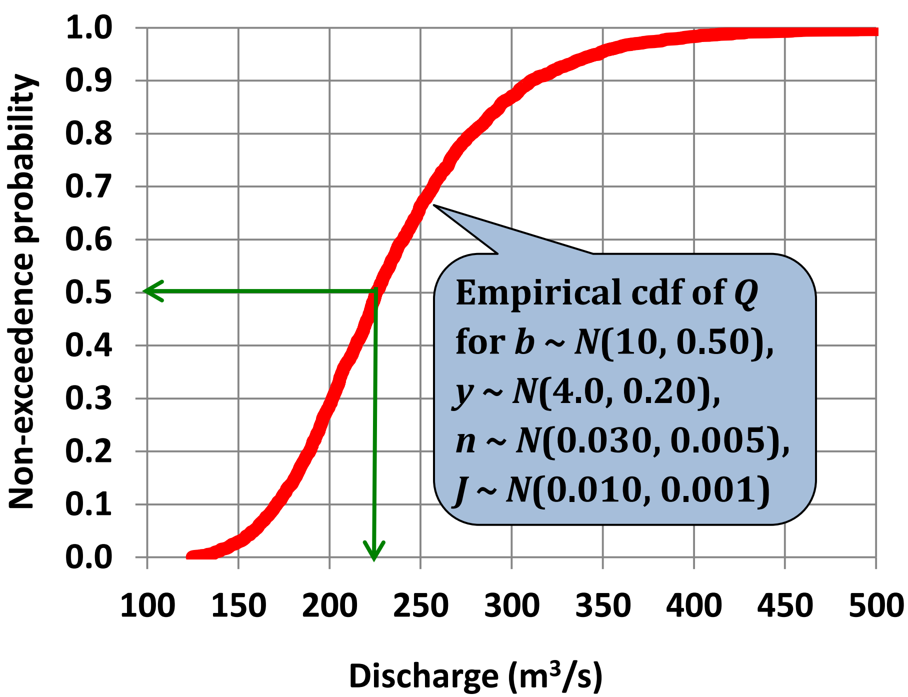
The uncomfortable reality:

- **Uniform flow** is a hypothesis.
- The **Manning's *n*** is not a physical property but a conceptual quantity, which also depends on y – thus n is actually a *random variable*, not a constant.
- The **area** and **hydraulic radius** depend on section geometry, which is usually approximated by a prismatic shape (to facilitate calculations).
- **Geometrical properties** (channel slope, bed width, bank slope, etc.) are subject to measurement errors and approximations (how is the channel slope defined?).
- **Exponent 2/3** is empirically derived, through laboratory experiments.

Numerical example

- Deterministic approach, assuming a rectangular section with b = 10 m, y = 4 m, n = 0.030, J = 0.01 → $\boldsymbol{Q}$ **= 227 m³/s**
- Monte Carlo approach:
  - Normally-distributed inputs, considering different coefficients of variation, σ/μ (measure of uncertainty);
  - Generation of 2000 independent b, y, n and J values and estimation of Q by the Manning's formula.





- The range of uncertainty is huge (Q_5 = 195 m³/s, Q_{95} = 345 m³/s).
- The derived distribution of Q for normally-distributed inputs is far from normal (skewness > 1.5).
- The statistical characteristics of modelled Q strongly depend on the simulation length.

Uncertainties of hydraulic models and impacts to flood mapping: Dimitriadis *et al.*, 2016

Disentangling the rational formula

- Assuming a constant rainfall intensity i, uniformly-distributed over the catchment area A, for duration d equal to the time of concentration t_c, and a constant loss ratio $\varphi = 1 - c$, the peak discharge is given by:

$$Q = c\, i\, A$$

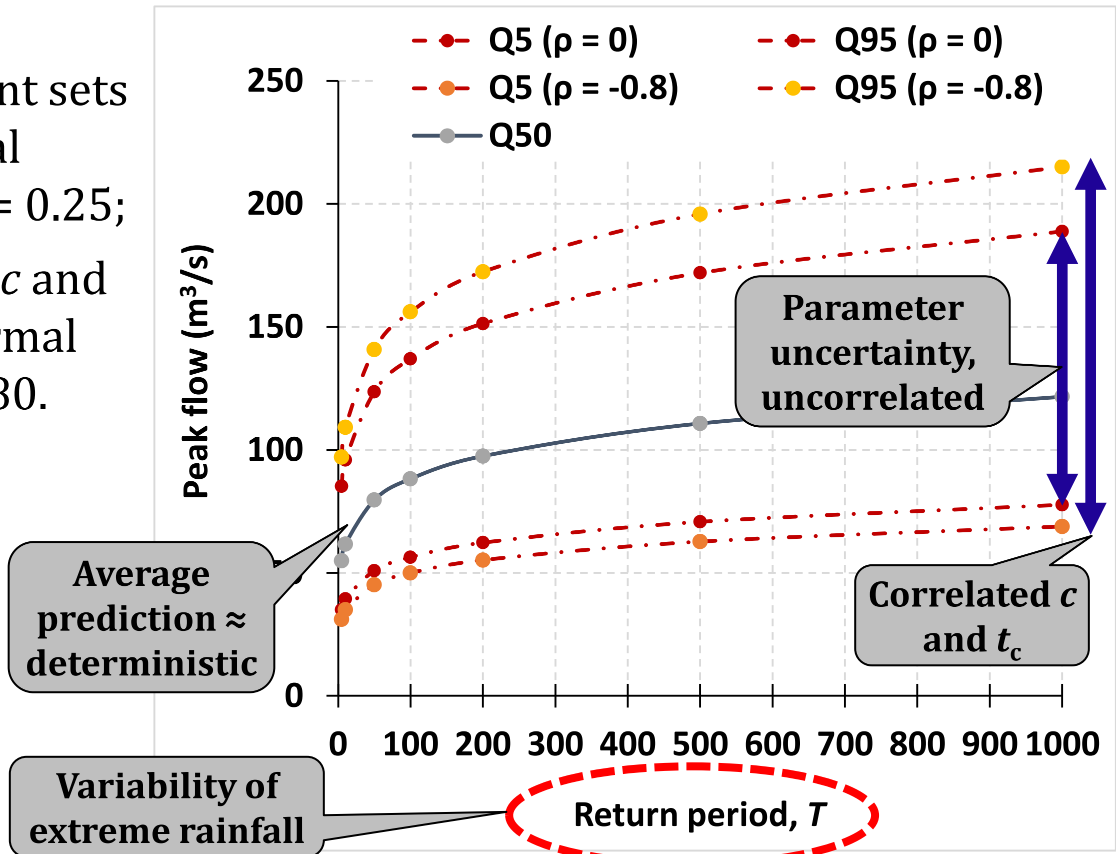
- In flood studies, the rainfall intensity is typically estimated by an idf relationship $i(d, T) = a(T)/b(d)$, where T is the return period and d the duration.
- **Traditional approach**: For a given risk, expressed by means of T, set $d = t_c$ and apply the rational formula for constants c and t_c, to obtain the design peak flow.

The uncomfortable reality:

- The **runoff coefficient**, c, is not a constant but a random variable, depending on storm profile, changing soil moisture conditions and catchment properties.
- The **time of concentration**, t_c, is not a constant but a random variable, depending on the runoff produced over the catchment and the river hydraulics.
- Both c and t_c depend on flow, thus they are (negatively) **correlated** variables.
- The **catchment area**, A, may also be varying (*partial area hypothesis*) and it is also subject to (minor) measurement uncertainties.
- The **idf relationship** is a statistical model, which is subject to sample, structural and parameter uncertainties.

Mind the correlations!

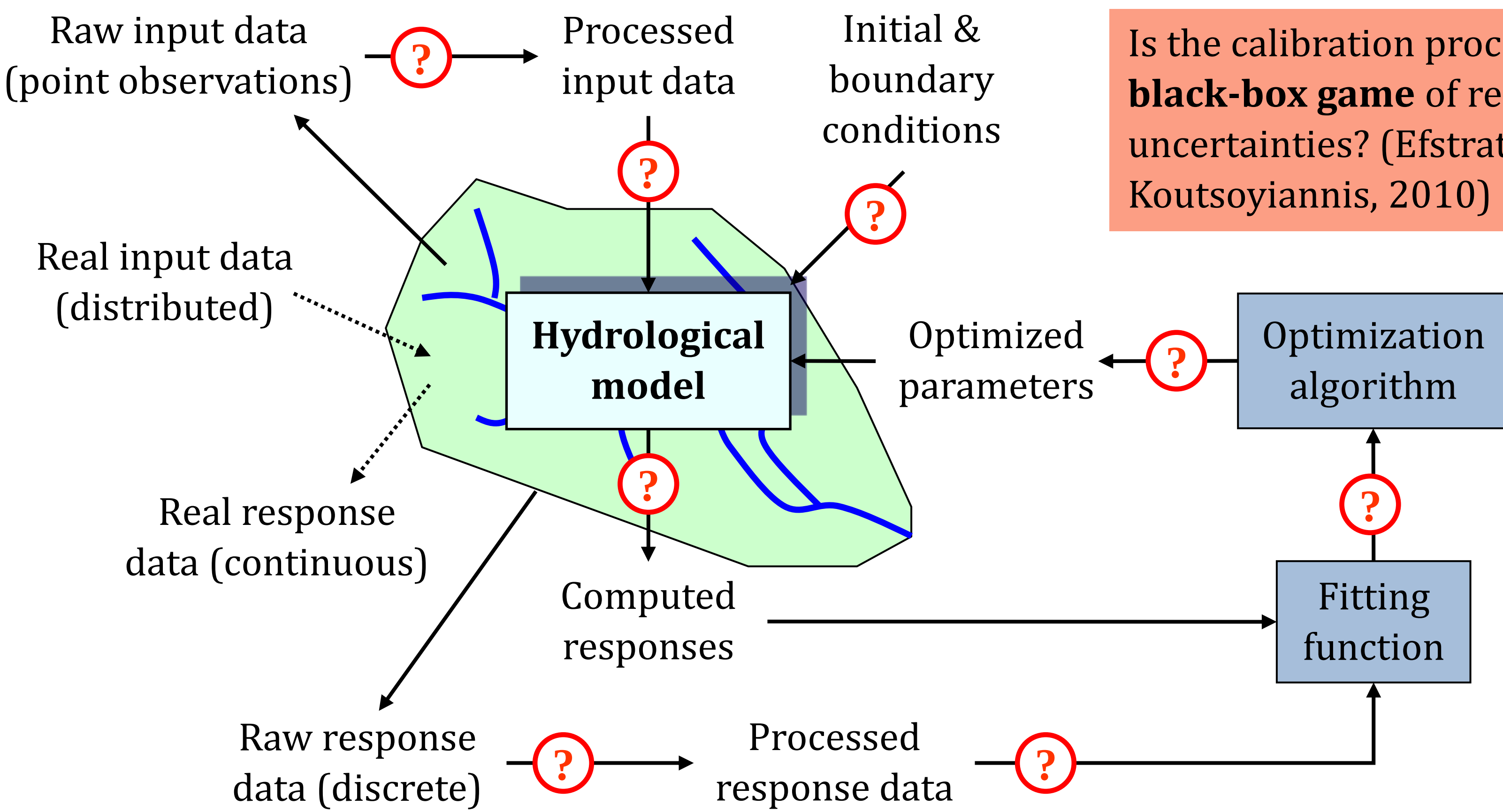
- Statistical model of extreme rainfall: $i = \lambda(T^k - \psi)/(1 + d/\theta)^\eta$, with $\lambda = 180$, $k = 0.15$, $\psi = 0.50$, $\theta = 0.30$, $\eta = 0.60$ (λ, k and ψ are scale, shape and location parameters of a GEV distribution model; cf. Koutsoyiannis *et al.*, 1998).
- Deterministic use of the rational formula to a catchment area $A = 10$ km^2, for several return periods T, with $c = 0.40$ and $t_c = 1.0$ h.
- Monte Carlo approach:
  - Generation of independent sets of c and t_c from lognormal distributions, with CVar = 0.25;
  - Generation of correlated c and t_c from a bivariate lognormal distribution, with $\rho = -0.80$.
- Remark that the uncertainty associated with rainfall (idf) is ignored (*otherwise*?).



Uncertainties and misuse of flood design recipes: Efstratiadis *et al.*, 2014

The concept of the varying time of concentration: Michailidi *et al.*, 2017

Models for ungauged basins are tremendously uncertain – but if we have data for calibration, we can beat the beast

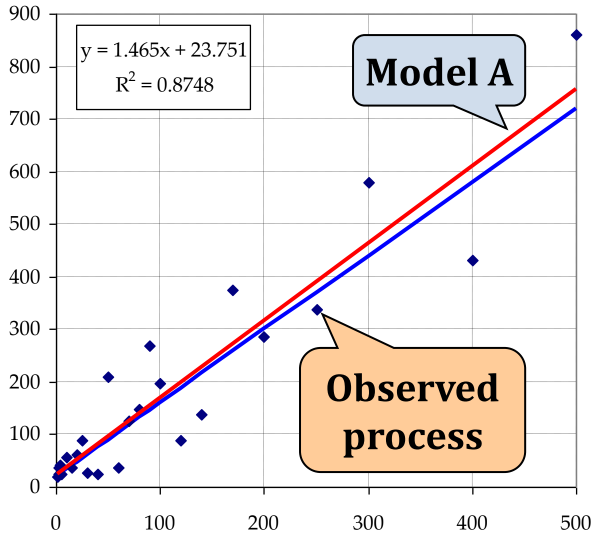


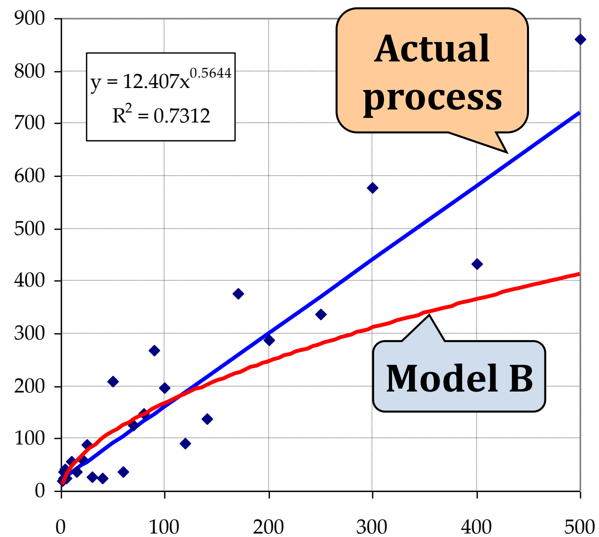
Is the calibration procedure a **black-box game** of recycling uncertainties? (Efstratiadis & Koutsoyiannis, 2010)

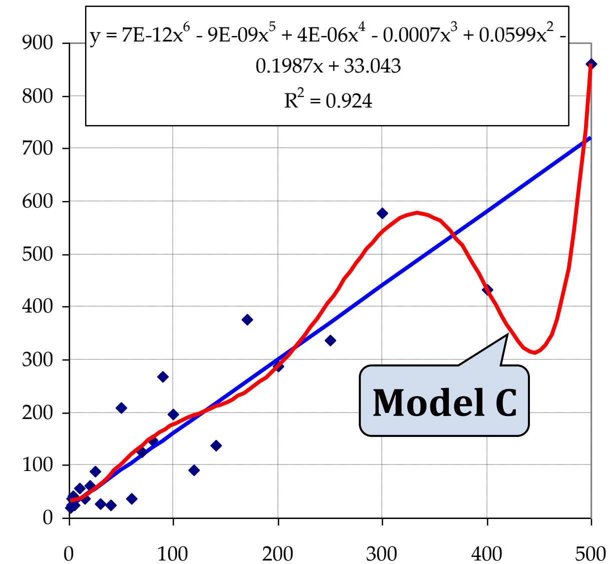
The uncomfortable reality:

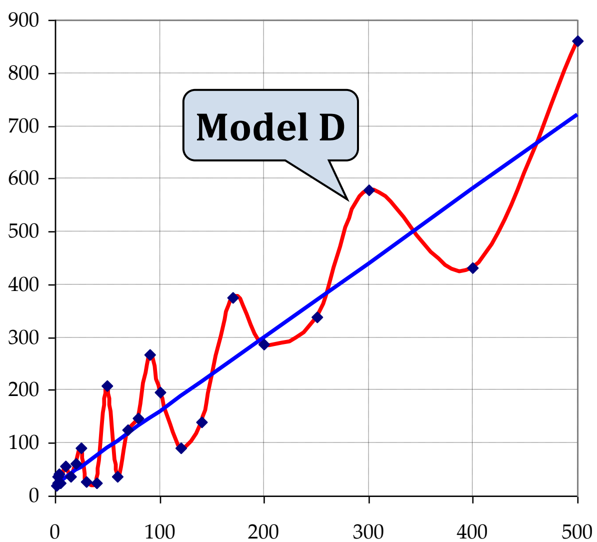
- More data → more complex models → more uncertainty (a very dangerous spiral)
- More automatizations → less hydrological judgment → more uncertainty

A small step towards reducing uncertainty: The concept of parsimony (to be as simple as possible but not simpler)









Actual process: linear law, $y = 1.4x + 20$

Observed process: $y_m = y + w$, where w is a white noise $N(0, \sigma)$ with variance σ_y^2 (measurement error, heteroscedastic)

Model A: linear, 2 parameters, $r^2 = 0.875$

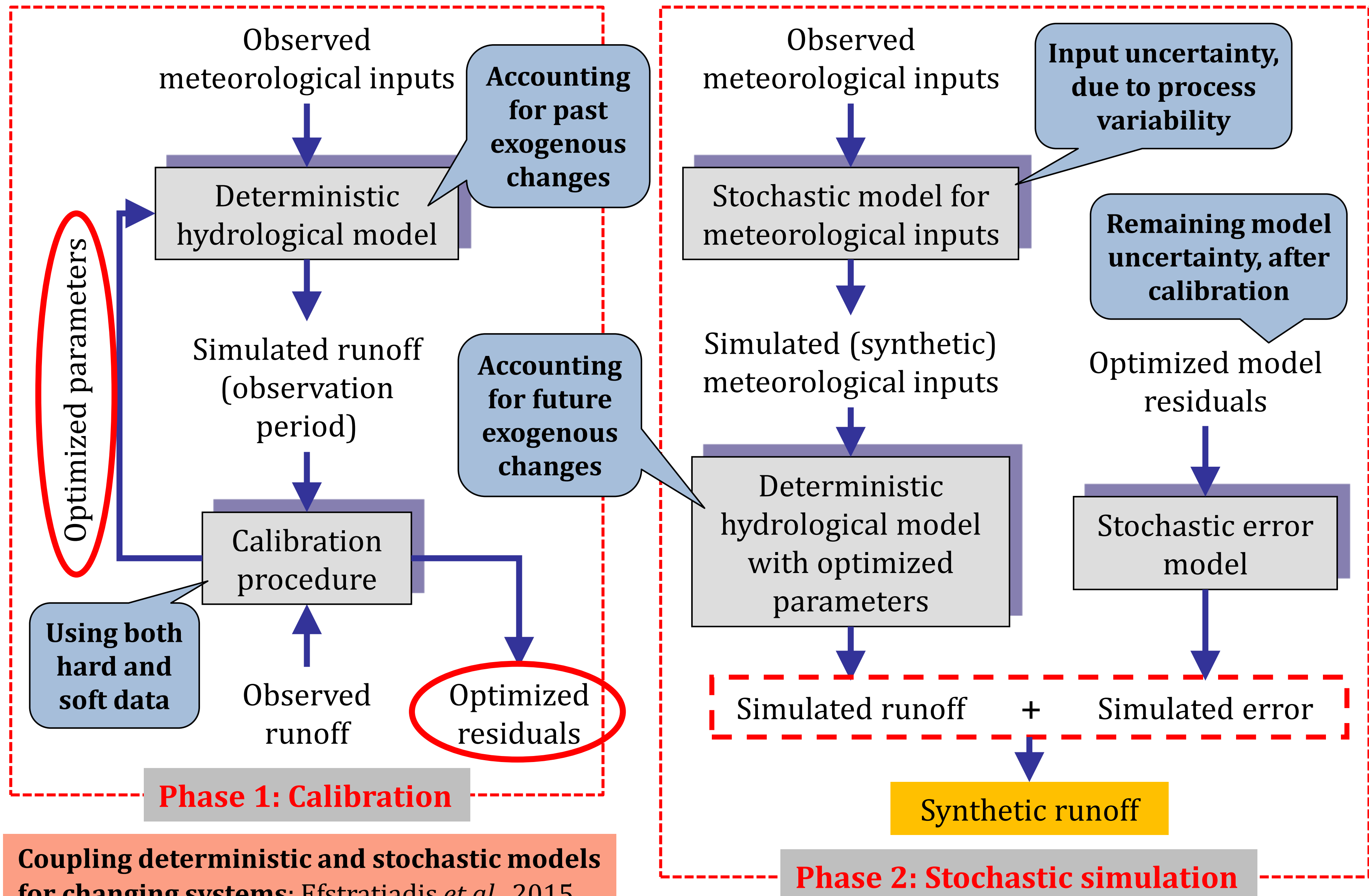
Model B: power-type, 2 parameters, $r^2 = 0.731$

Model C: polynomial 6th order, 7 parameters, $r^2 = 0.924$

Model D: highly nonlinear "caricature" model, $n + 1$ parameters for n observations, $r^2 = 1$

The value of parsimony in model configuration: Nalbantis *et al.*, 2011

The nonlinear stochastic modelling framework



Coupling deterministic and stochastic models for changing systems: Efstratiadis *et al.*, 2015

Conclusions

- In order to fight the beast of uncertainty, we have to **recognize all its facets**, instead of *sweeping the dirt under the carpet*.
- Several modelling aspects that have been traditionally handled as **certain** are actually **uncertain**.
- Several modelling aspects that have been traditionally handled as **constants** are actually **varying**, and thus **uncertain**.
- Short historical samples cannot capture the **overall changing behavior** of the observed processes.
- Ignoring **parameter dependencies** may result to significant underestimation of uncertainty.
- In order to fight the beast:
  - Distinguish **process uncertainty**, resulting from the inherent variability of physical systems, from **model uncertainty**;
  - Embed **Hurst-Kolmogorov dynamics** within process representation;
  - Prefer **simple models** over complex ones;
  - Take advantage of **all sources of information**.

Short list of benchmark articles

- Andréassian, V., *et al.*, What is really undermining hydrologic science today?, *Hydrol. Process.*, 21, 2819–2822, 2007.
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