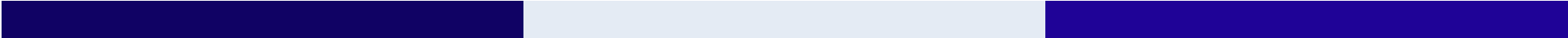


5th EGU Leonardo Conference – Hydrofractals 2013 – STAHY '13
Kos Island, Greece, 17–19 October 2013

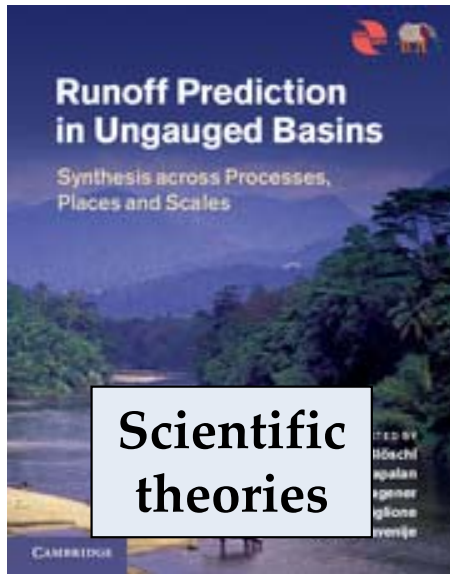


(Towards) a stochastic simulation framework for flood engineering

**Andreas Efstratiadis, Antonis Koukouvinos, Panayiotis Dimitriadis,
Aristoteles Tegos, Nikos Mamassis & Demetris Koutsoyiannis**

Department of Water Resources & Environmental Engineering, National
Technical University of Athens, Greece

Flood science, flood engineering and uncertainty



Scientific theories

Hydrol. Earth Syst. Sci., 13, 2151–2168, 2009
 www.hydrol-earth-syst-sci.net/13/2151/2009/
 © Author(s) 2009. This work is distributed under
 the Creative Commons Attribution 3.0 License.



Modelling runoff at the plot scale taking into account rainfall partitioning by vegetation: application to stemflow of banana (*Musa* spp.) plant

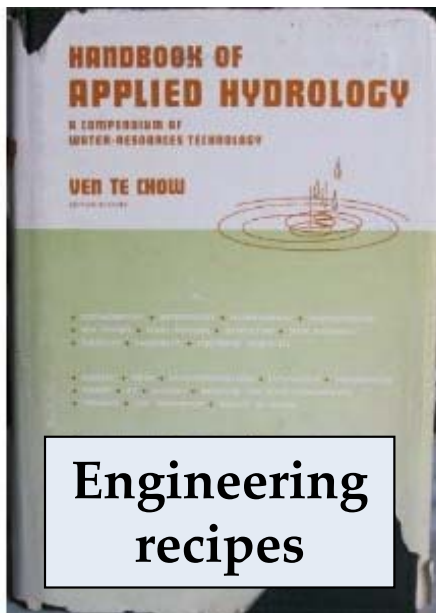
J.-B. Charlier^{1,*}, R. Moussa², P. Cattani¹, Y.-M. Cabidoche³, and M. Voltz²

¹CIRAD, UPR Systèmes bananiers et ananas, Capesterre-Belle-Eau, Guadeloupe, 97130, France
²INRA, Laboratoire d'étude des Interactions Sol-Agrosystème-Hydrosystème (LISAH), UMR SupAgro-INRA-IRD, Bât. 24, 2 place Viala, 34060 Montpellier cedex 1, France
³INRA, UR 135 Agropédologie de la Zone Caraïbes, Domaine Duclos, 97170 Petit-Bourg, Guadeloupe (FWI)
 *now at: Université de Franche-Comté-CNRS/UMR 6249 Chrono-environnement, UFR des Sciences et Techniques, 16 route de Gray,

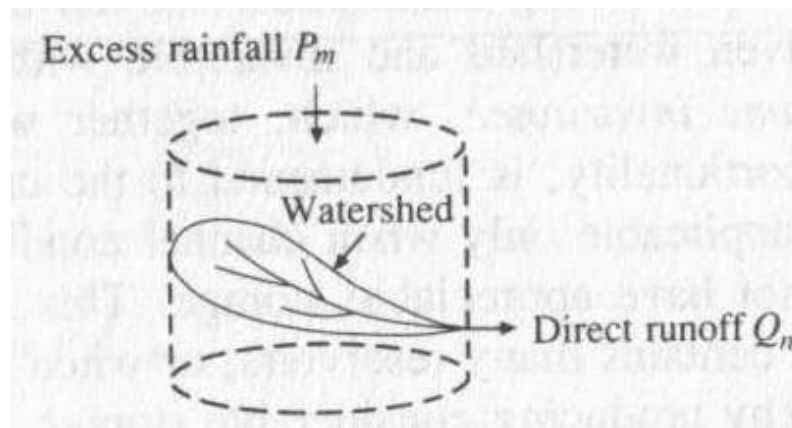
Received: 26 May
 Revised: 6 October

Plot scale, process-oriented, bottom-up

Abstract. Rainfall intensity of rainwater runoff generation. The Nash and Sutcliffe error. This was used during residual canopy and then redistributed into throughfall and stemflow. Rainfall intensities at the soil surface are therefore not spatially uniform, generating local variations of runoff rates. rainfall, for which the stemflow function allowed runoff to be simulated for rainfall intensities lower than the K_s measured at the soil surface. This approach also allowed us to take into

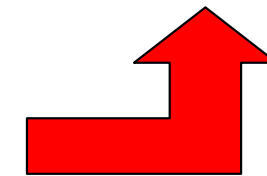
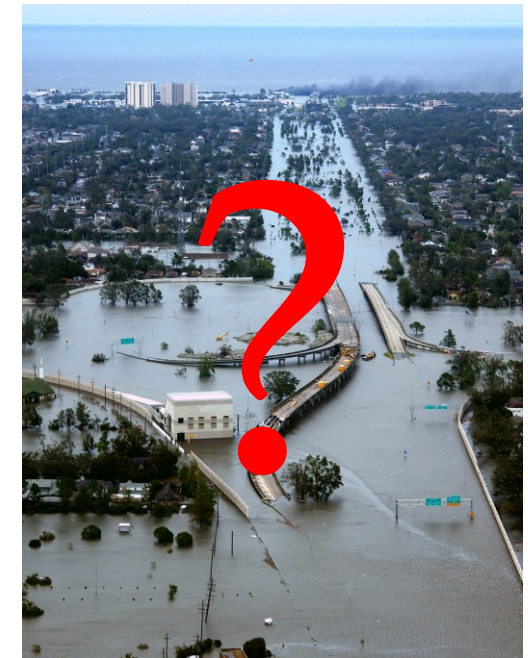
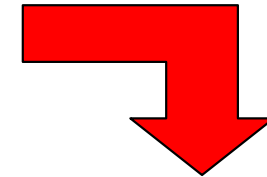


Engineering recipes



Basin-scale, top-down

Predictions are still poor...



Design is still inefficient...

Flood design, risk and uncertainty

- ❑ **Problem statement:** Estimate the *design load* for a flood quantity of interest q (peak flow, flood volume, flow depth, flow velocity, inundated area), which corresponds to a specific *return period*, T .
- ❑ **Remark:** The return period is a *socio-economic constraint* that determines the acceptable *risk*, r , during the life time of the system under study.
- ❑ **Direct solution** (often infeasible, due to data lack or scarcity): Fit a suitable statistical distribution to an observed sample of q values and estimate the design value q_T through probabilistic analysis.
- ❑ **Common indirect solution:** Assign T to the *input* (i.e. rainfall, x), for which it is easier to find records of sufficient length and accuracy, and use an *event-based model* $q = f(x)$ (hydrological, hydraulic) to simulate the response of the flood system.
- ❑ **Assumption:** The entire modelling procedure is *deterministic*, thus for a specific return period of rainfall, a single response value is obtained, i.e. $q_T = f(x_T)$.
- ❑ **Inconsistency:** The *actual statistical behaviour* of the flood quantity is represented only partially, through the return period of rainfall.
- ❑ **Source of inconsistency:** The *model uncertainties* are ignored, thus $q_T \neq f(x_T)$.

The recipe: Monte Carlo simulation

- ❑ To handle uncertainties in flood modelling :
 - all uncertain quantities (either constant or time-varying) should be represented as **random variables**;
 - the **total flood risk** should be estimated by integrating the uncertainties of all individual variables that interrelate in flood generation (since the design flood is obtained from a *joint probability*).
- ❑ This option can be offered by **Monte Carlo (stochastic) simulation**, which is the most effective and powerful technique for analysing systems of high complexity and uncertainty (Koutsoyiannis, 2005; Montanari & Koutsoyiannis, 2012).
- ❑ Monte Carlo (MC) simulation comprises three components:
 - Pre-processing statistical (or stochastic) models to generate synthetic samples of the uncertain quantities;
 - Deterministic models to represent the flood-related processes;
 - Post-processing statistical models to analyze the model responses.
- ❑ The MC approach allows for estimating the **whole probability distribution of the output variables**, instead of a design value with a one-to-one correspondence to a unique input.

Outline of MC computational procedure

Event-based simulation (flood risk assigned to rainfall)

Application of an **ombrian curve** to estimate the total rainfall depth $h(T)$

Generation of **synthetic hyetographs**, where all partial depths sum up to $h(T)$

Generation of multiple sets of **initial conditions** and **parameter** values

Multiple runs of an **event-based hydrological model** with different hyetographs and parameter values

Statistical analysis of model outputs and estimation of **design loads** for a given total flood risk

Continuous simulation (flood risk assigned to q)

Generation of **synthetic rainfall time series**, for long enough time horizon

Generation of multiple sets of **parameter** values

Multiple runs of a **continuous simulation model** with different parameter values

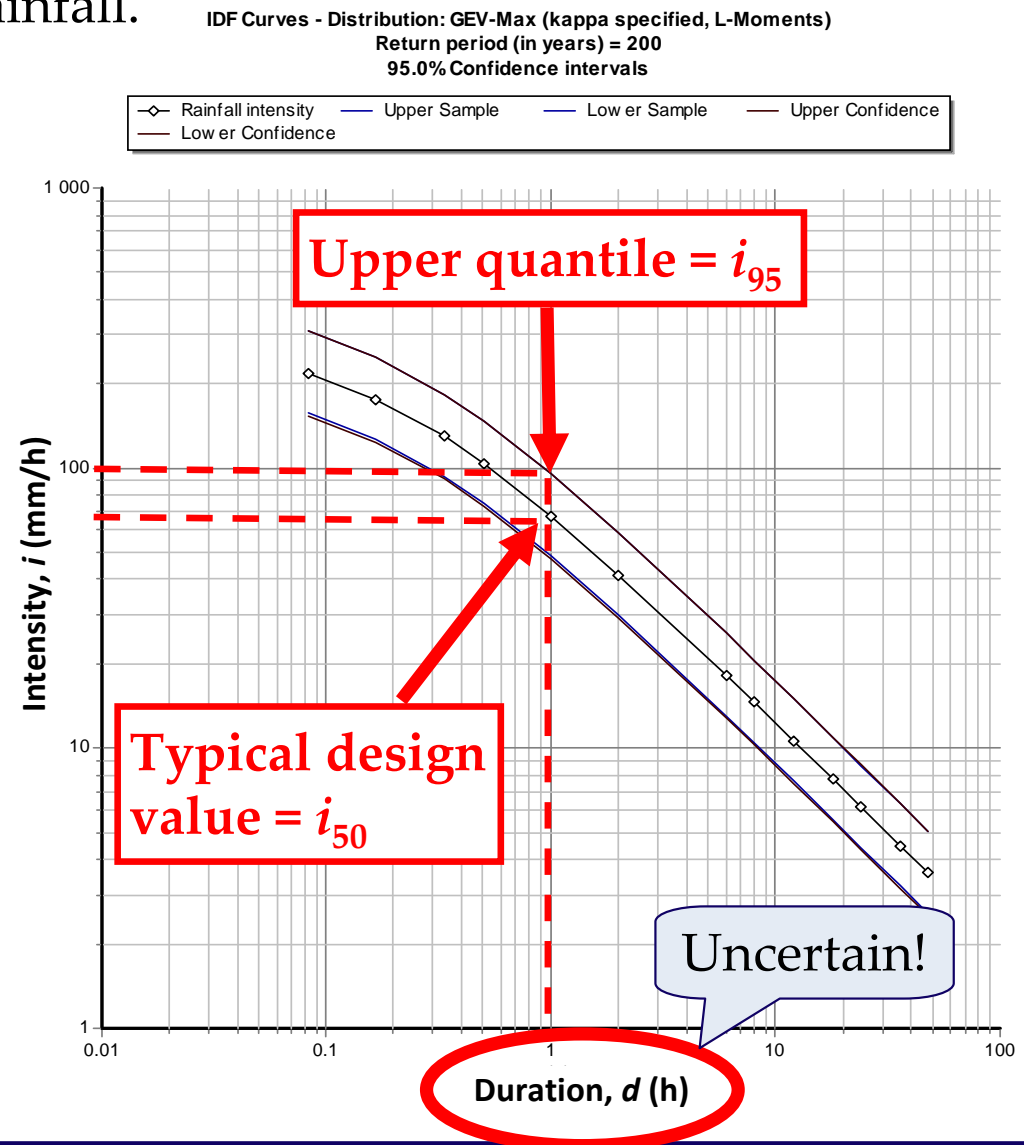
Calculation of **T -year flood quantity** by analyzing the annual maxima from the simulated time series of q

Uncertainty issues in design storm modelling

- ❑ The design storm for a specific return period T is defined in terms of storm duration D , total depth h , time pattern of partial rainfall depths (hyetograph) and spatial distribution – all these quantities/procedures are uncertain.
- ❑ The **storm duration** D depends on the *time of concentration* t_c , which is a highly uncertain quantity, not only because different approaches provide significantly different estimations, but also because t_c is strongly related to the flood quantity itself (Grimaldi *et al.*, 2012).
- ❑ The **rainfall depth** $h(d, T)$ corresponding to a specific return period T and duration (time interval) d is uncertain, since it is estimated through *statistical models*, whose parameters are inferred from (usually small) historical samples.
- ❑ The construction of the design hyetograph, i.e. the estimation of the **temporal distribution** of partial rainfall depths, on the basis of deterministic patterns (e.g. alternative blocks) fails to represent the actual statistical behaviour of rainfall, thus providing unrealistic *autocorrelation structures*.
- ❑ The **spatial distribution** of the rainfall event over the basin's area is uncertain, since it depends on complex factors, such as the *topography* and the *weather type*, which are not considered in typical integration approaches (e.g. the areal reduction factor) than only account for the basin size and the duration.

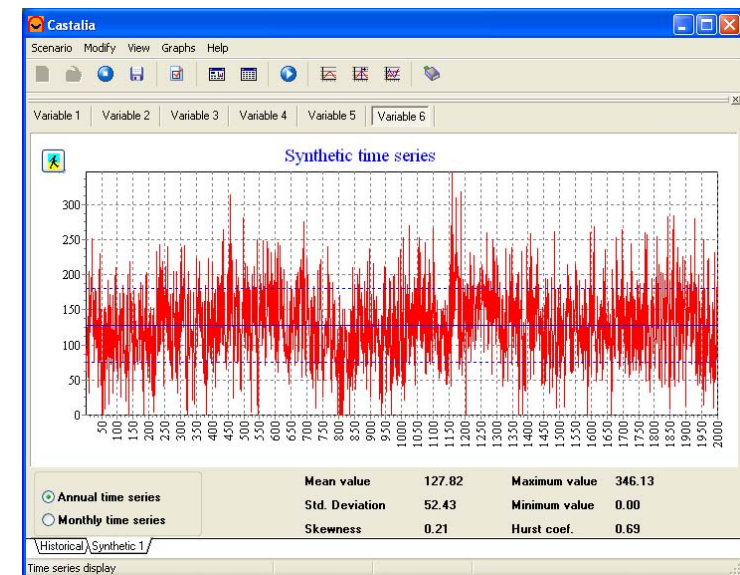
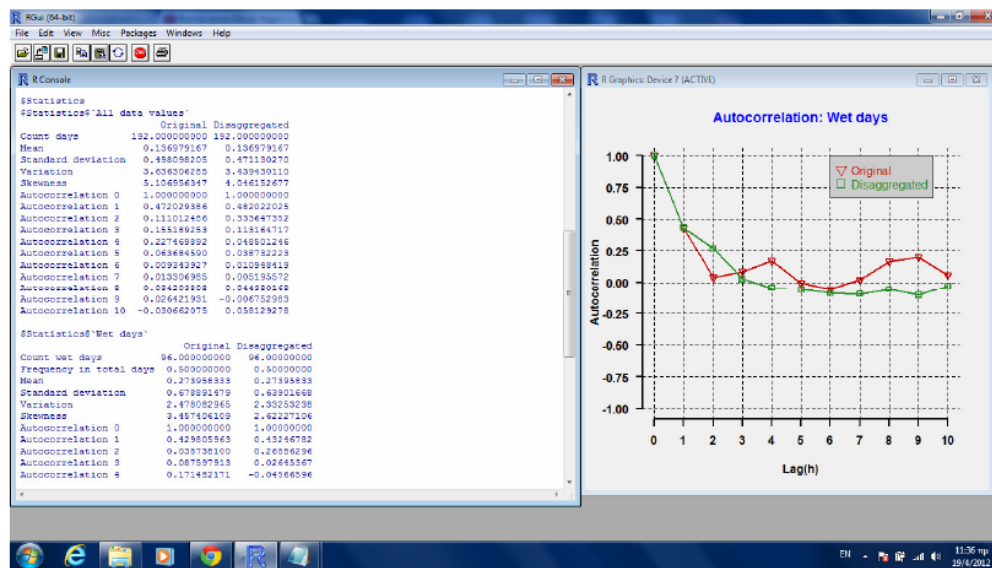
MC simulation for estimating the confidence intervals of ombrian curves

- ❑ The construction of ombrian curves is the most common task related to the probabilistic description of extreme rainfall.
- ❑ The quantification of uncertainty of ombrian curves is difficult, because analytical expressions for its confidence limits do not exist, except for few distributions (normal, exponential) that are yet unsuitable for describing rainfall maxima (Koutsoyiannis, 2004).
- ❑ Tyrallis *et al.* (2013) developed a generalized Monte Carlo approach for calculating approximate confidence intervals for *any distribution*, which is also implemented in Hydrognomon software (poster P-40).



Stochastic simulation of input rainfall

- ❑ Different generation schemes are applied for providing synthetic rainfall data, by means of individual **storm events** and full **time series**, for event-based and continuous simulation, respectively.
- ❑ **Multivariate stochastic simulation** models ensure a consistent representation of the **spatiotemporal distribution** of rainfall over the basin area (thus, simplistic integration approaches, such as the areal reduction factor, are avoided).

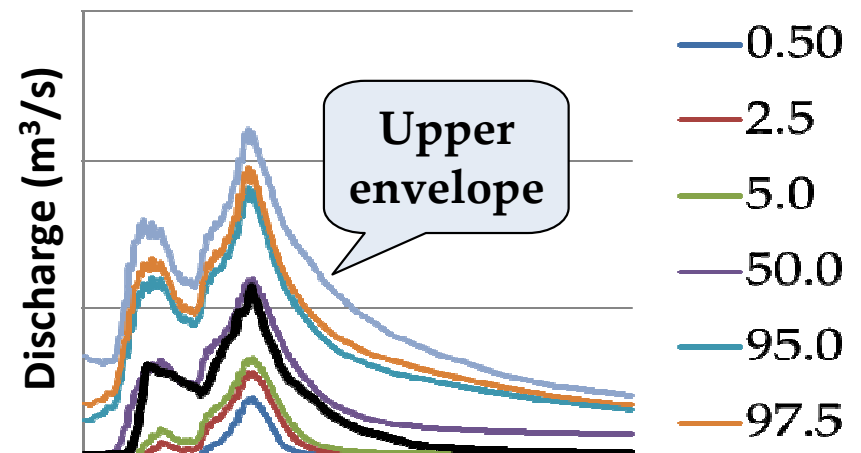


Hyetos-R: Generation of hourly rainfall through a Bartlett-Lewis rectangular pulses rainfall model and a disaggregation scheme (Koutsoyiannis & Onof, 2001; Kossieris *et al.*, 2012 – poster P-39)

Castalia: Multivariate stochastic model for generating synthetic time series at multiple time scales, from over-annual to daily (Efstratiadis *et al.*, 2013b)

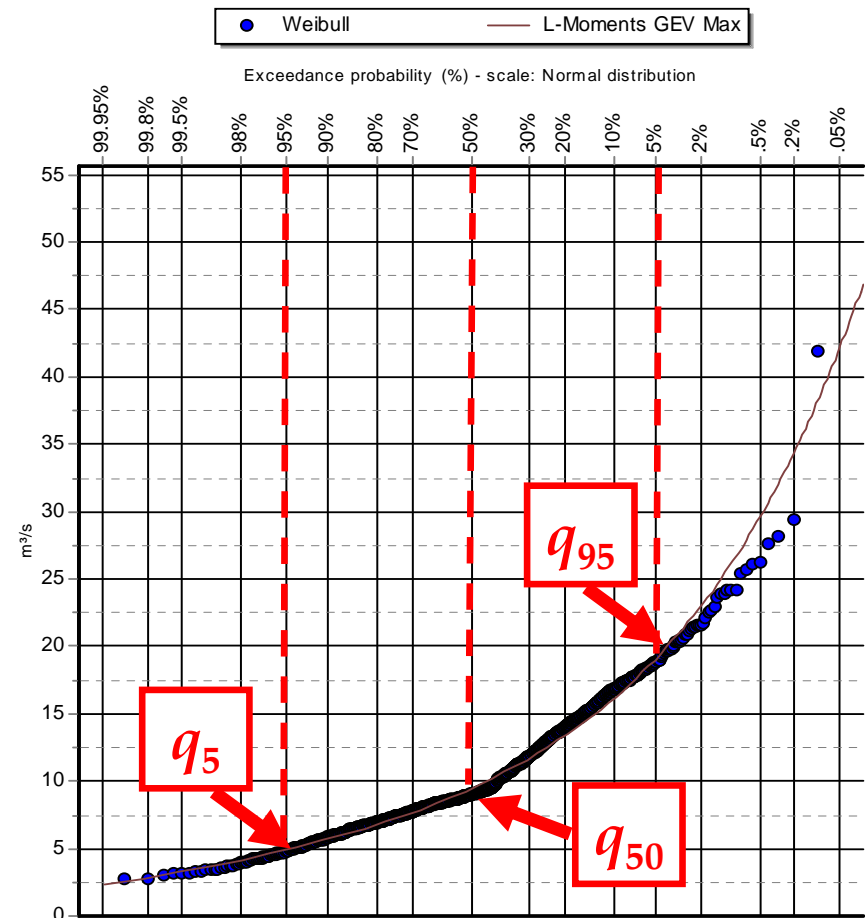
MC handling of uncertainty in hydrological models

- ❑ Hydrological models are governed by intrinsic (structural) uncertainties, due to the **complexity** of flood processes, their **nonlinear interactions** and their dependence to the **antecedent soil moisture conditions**.
- ❑ Model parameters are uncertain, because:
 - they are empirically estimated through **calibration** or **regionalization**;
 - many of them are **variables** and not constants;
 - some of them are mutually **correlated**.
- ❑ The multiple sources of uncertainty can be summarized in terms of **statistical distributions** (pdfs) of parameters; given that all pdfs are known, it is possible to generate random parameter sets and employ an event-based model in a MC setting to obtain a set of simulated hydrographs.
- ❑ In gauged basins, pdfs can be determined by analyzing samples of optimized values from multiple flood events (**poster P-05**).
- ❑ Instead of a unique hydrograph, the MC approach provides a sample of simulated hydrographs, from which **design envelopes** can be extracted.

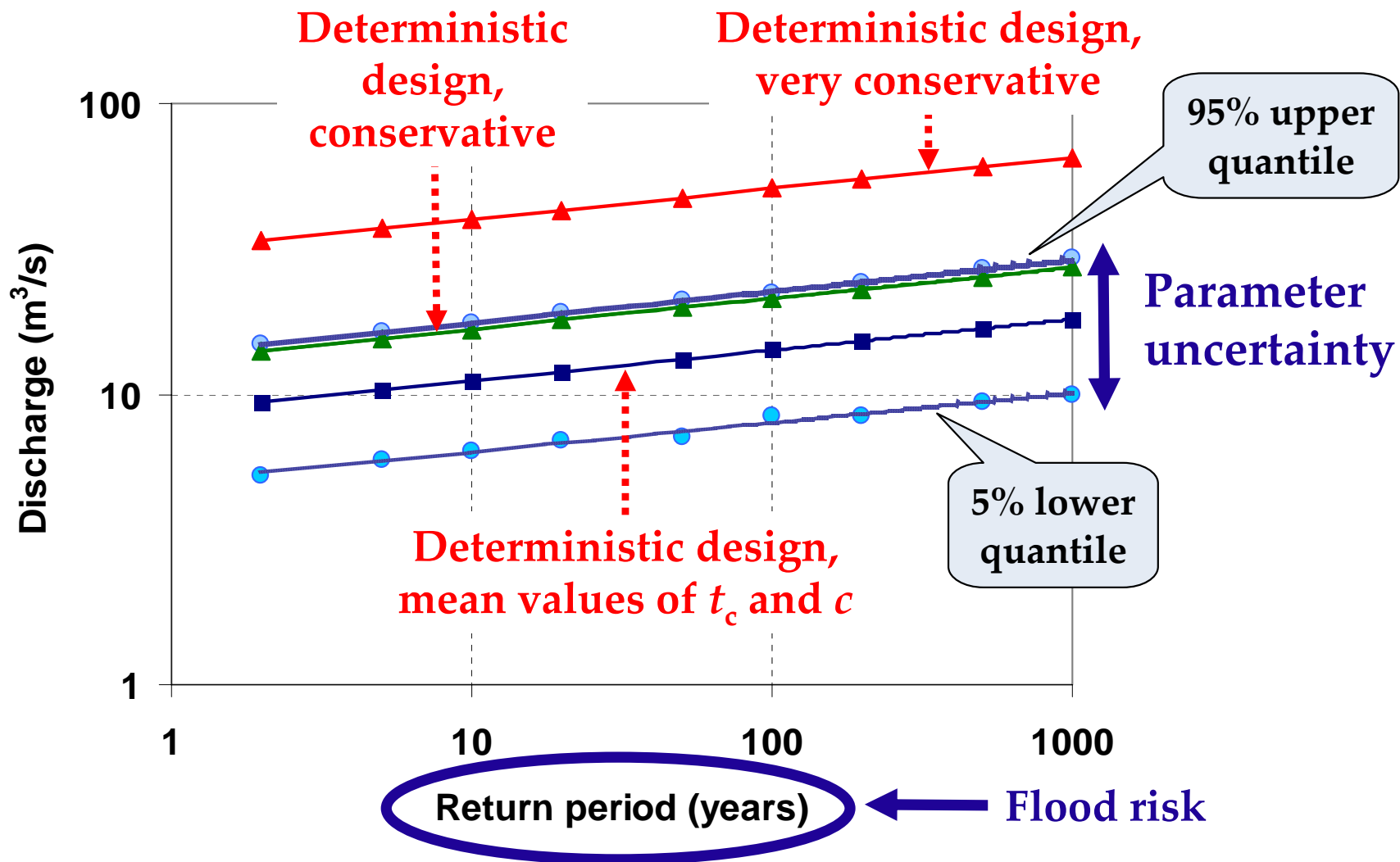


Simple MC experiment with the rational method

- Input data for deterministic analysis ($q = c i A$):
 - Basin area $A = 10 \text{ km}^2$, ARF = 0.25
 - idf relationship (ombrian curve) $i = 36.1 T^{0.106} (d + 0.196)^{-0.794}$
 - Average time of concentration $t_c = 1.0 \text{ h} (= d)$
 - Average runoff coefficient $c = 0.40$
- Deterministic applications:
 - average values of t_c and c
 - conservative and very conservative values ($t_c = 0.75 / 0.50 \text{ h}$, $c = 0.50 / 0.60$)
- MC simulation (Efstratiadis *et al.*, 2013a):
 - Parameters are normally distributed, $t_c \sim N(1.0, 0.25)$ and $c \sim N(0.40, 0.10)$
 - For a given return period T , a set of 1000 random values of t_c and c are generated to provide 1000 values of q .
 - For each T , a statistical distribution is fitted to simulated peak flow values.



“Safe” design vs. design under uncertainty

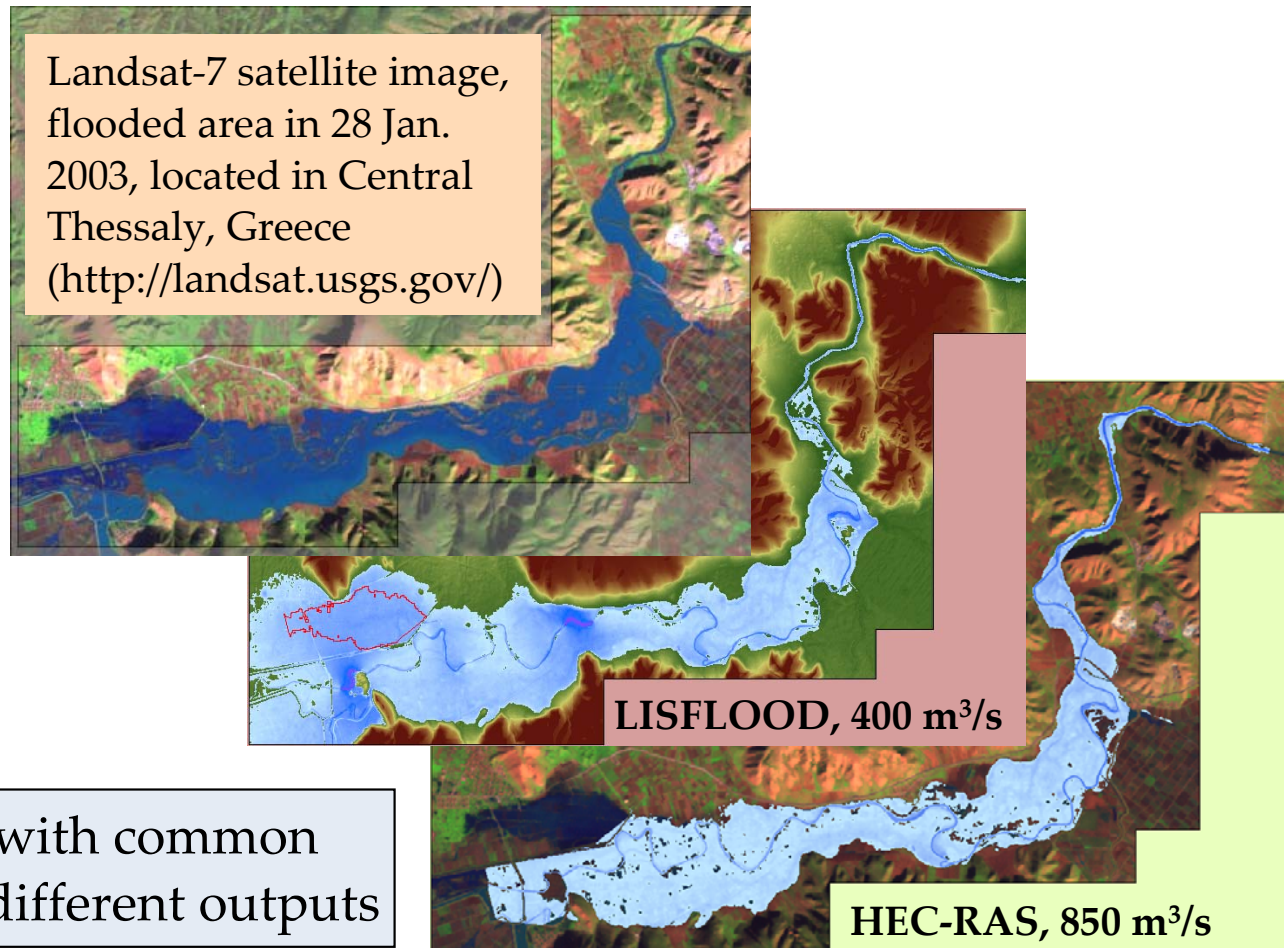


MC simulation allows for quantifying the confidence limits of peak flows, due to the *uncertainty of model parameters*, while simplistic engineering approaches may result to extremely high design values, in an attempt to ensure *safety*.

Uncertainty issues in hydraulic modelling

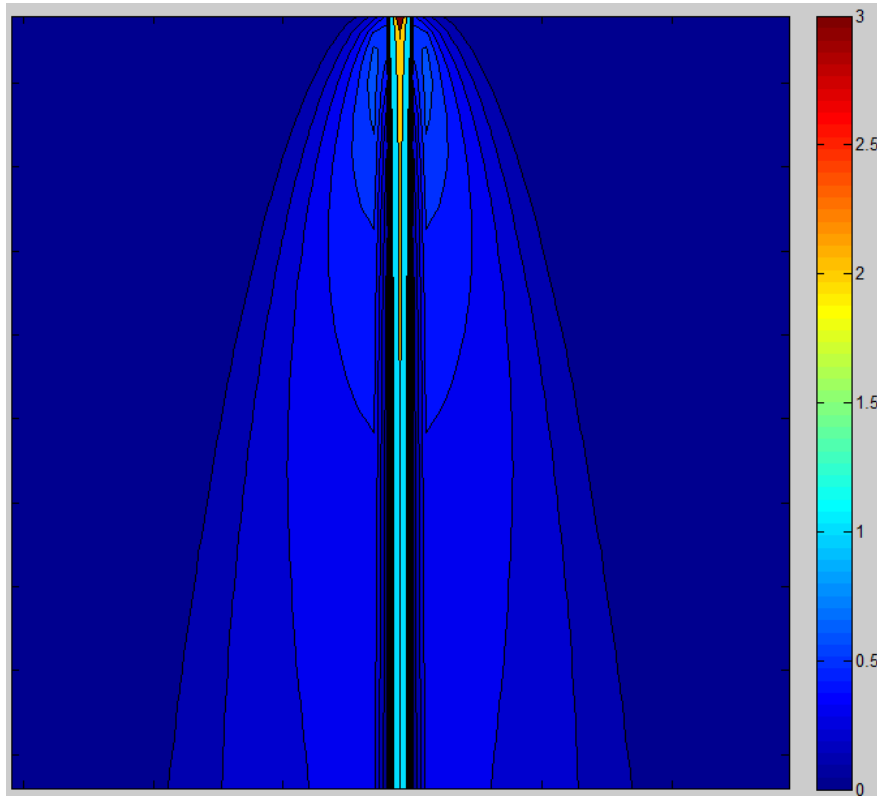
- In hydraulic simulation, uncertainty is even more difficult to handle, since it is present in the **hydrological inputs** (design flood), the **geometrical inputs** (channel geometry, floodplain topography), the **hydraulic parameters** (Manning's coefficient, n), and the configuration of the **numerical scheme** (cell size, boundary conditions, etc.).

Fitting of HEC-RAS (1D) and LISFLOOD-FP (quasi 2D) to the inundated area. The two models are applied using a DEM of 5×5 m; n is estimated from land use maps; open boundary conditions are assumed (Oikonomou *et al.*, 2013). The optimized discharge is $850 \text{ m}^3/\text{s}$ for HEC-RAS (max. water depth 8.59 m) and only $400 \text{ m}^3/\text{s}$ for LISFLOOD-FP (max. water depth 5.96 m).

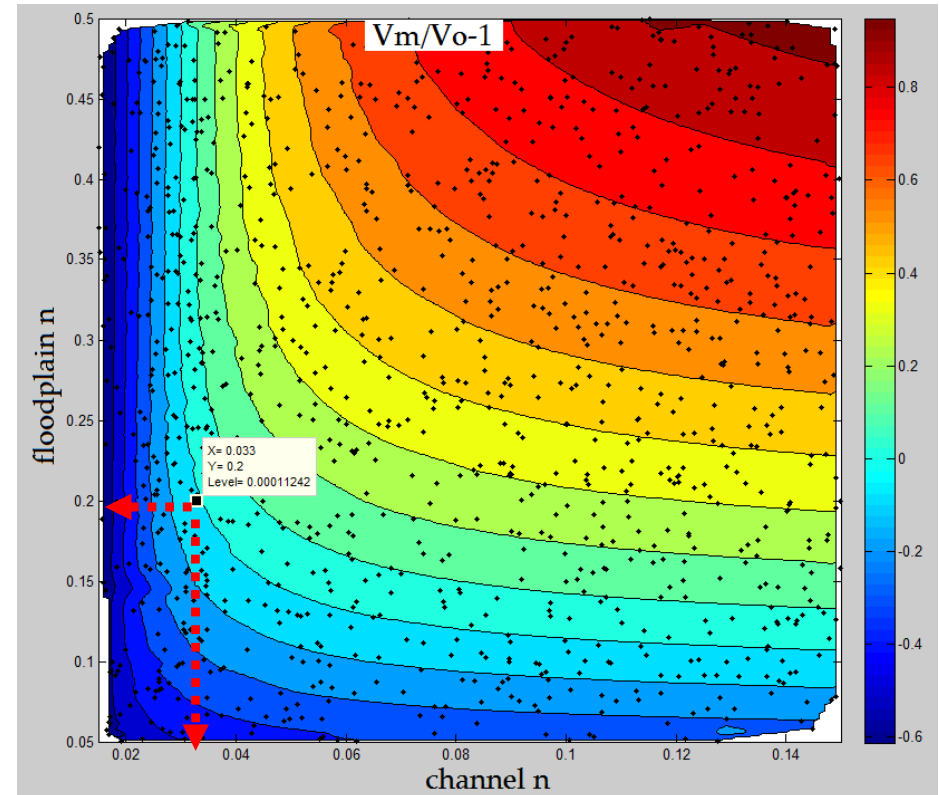


Different numerical schemes, with common inputs, provide substantially different outputs

Does always high accuracy of measurements lead to high accuracy in predictions? An example with n



“Actual” depths obtained through the LISFLOOD-FP model, for the following assumptions: rectangular channel, $b = 5.0$ m, $y = 2.0$ m, $J = 1\%$, $Q \approx 300$ m³/s, channel’s $n = 0.033$, floodplain’s $n = 0.20$, 61×61 cells, cell size 100 m, open boundary conditions.



1000 MC simulations with varying n in channel (0.015 to 0.150) and floodplain (0.050 to 0.500), uniformly distributed. V_m is the modelled and V_o the “deterministic” flood volume, estimated through the LISFLOOD-FP (Dimitriadis *et al.*, 2013)

Conclusions

- ❑ Uncertainty is present in all aspects of flood modelling; however, in common flood engineering, uncertainty is poorly represented (through the return period of rainfall), while most of available tools are applied as **deterministic recipes**.
- ❑ Although such practices are well behind advances in hydrological science, little attention is actually paid to mitigating this gap (cf. Koutsoyiannis, 2013).
- ❑ Monte Carlo approaches, which are applicable in several steps of flood simulation procedure (rainfall, hydrology, hydraulics), provide a powerful means to **quantify uncertainty**, thus avoiding naïve interpretations of **safety**.
- ❑ Many open scientific issues exist, with respect to the proper representation of the **statistical behavior** of the model parameters (particularly in ungauged basins), which is a key premise for employing MC simulations.
- ❑ An important task is to recognize which of the model parameters and other quantities are **time-varying** and which of them are **correlated**.
- ❑ Although **continuous simulation** models, when employed in a MC framework, provide the unique means for a realistic estimation of the **total flood risk**, they are too difficult to be implemented in the everyday practice.
- ❑ Emphasis should be given to build **stochastic event-based models** of improved **physical & statistical** consistency that remain **parsimonious** and **simple to use**.

References

- Blöschl, G., M. Sivapalan, T. Wagener, A. Viglione, & H. H. G Savenije, *Runoff Prediction in Ungauged Basins: Synthesis across Processes, Places and Scales*, Cambridge Univ. Press, 2013.
- Chow, V. T., *Handbook of Applied Hydrology*, McGraw-Hill Book Company, 1964.
- Dimitriadis P., A. Tegos, A. Oikonomou, A. Koukouvinos, A. Efstratiadis, D. Koutsoyiannis, & N. Mamassis, Investigation of 1D and quasi-2D hydraulic flood routing models (in preparation).
- Efstratiadis, A., A. D. Koussis, D. Koutsoyiannis, & N. Mamassis, Flood design recipes vs. reality: Can predictions for ungauged basins be trusted? *Natural Hazards & Earth System Sciences*, 2013a (submitted).
- Efstratiadis, A., Y. Dialynas, S. Kozanis, & D. Koutsoyiannis, Castalia: A multivariate stochastic model for the generation of synthetic time series at multiple time scales, *Environmental Modelling & Software*, 2013b (submitted)
- Grimaldi, S., A. Petroseli, F. Tauro, & M. Porfiri, Time of concentration: A paradox in modern hydrology, *Hydrological Sciences Journal*, 57(2), 217-228, 2012.
- Kossieris, P., D. Koutsoyiannis, C. Onof, H. Tyrallis, & A. Efstratiadis, HyetosR: An R package for temporal stochastic simulation of rainfall at fine time scales, *EGU General Assembly 2012, Geophysical Research Abstracts, V. 14*, Vienna, 2012 (itia.ntua.gr/1200).
- Koutsoyiannis, D., & C. Onof, Rainfall disaggregation using adjusting procedures on a Poisson cluster model, *Journal of Hydrology*, 246, 109–122, 2001.
- Koutsoyiannis, D., Statistics of extremes and estimation of extreme rainfall, 1, Theoretical investigation, *Hydrological Sciences Journal*, 49(4), 575–590, 2004.
- Koutsoyiannis, D., Stochastic simulation of hydrosystems, *Water Encyclopedia*, Vol. 4, Surface and Agricultural Water, edited by J. H. Lehr & J. Keeley, 421–430, Wiley, New York, 2005.
- Koutsoyiannis, D., Reconciling hydrology with engineering, *Hydrology Research*, 2013 (in press).
- Montanari, A., & D. Koutsoyiannis, A blueprint for process-based modeling of uncertain hydrological systems, *Water Resources Research*, 48, W09555, doi:10.1029/2011WR011412, 2012.
- Oikonomou, A., P. Dimitriadis, A. Koukouvinos, A. Tegos, V. Pagana, P. Panagopoulos, N. Mamassis, & D. Koutsoyiannis, Floodplain mapping via 1D and quasi-2D numerical models in the valley of Thessaly, Greece, *EGU General Assembly 2013, Geophysical Research Abstracts, V. 15*, Vienna, 2013 (itia.ntua.gr/1337/).
- Tyrallis, H., D. Koutsoyiannis, & S. Kozanis, An algorithm to construct Monte Carlo confidence intervals for an arbitrary function of probability distribution parameters, *Computational Statistics*, 28(4), 1501–1527, 2013.

Photo source (p. 2): <http://www.cces.ethz.ch/projects/hazri/EXTREMES/img/KatrinaNewOrleansFlooded.jpg>

This presentation is available on-line at:

<http://www.itia.ntua.gr/1384/>

Contact info: andreas@itia.ntua.gr

You are kindly invited to visit the following related posters:

[P-05] Michailidi, E.-M., T. Mastrotheodoros, A. Efstratiadis, A. Koukouvinos, and D. Koutsoyiannis, *Flood modelling in river basins with highly variable runoff*

[P-39] Kossieris, P., A. Efstratiadis, and D. Koutsoyiannis, *Coupling the strengths of optimization and simulation for calibrating Poisson cluster models*

[P-40] Kozanis, S., D. Koutsoyiannis, T. Tsitseli, A. Koukouvinos, and N. Mamassis, *Construction of ombrian curves using Hydrognomon software system*
