A closer look at flood risk and future perspectives after changes in climate, hydrology and society

Session GM3.3

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I have seen many storms in my life. Most storms have caught me by surprise, so I had to learn very quickly to look further and understand that I am not capable of controlling the weather, to exercise the art of patience and to respect the fury of nature.
Paulo Coelho

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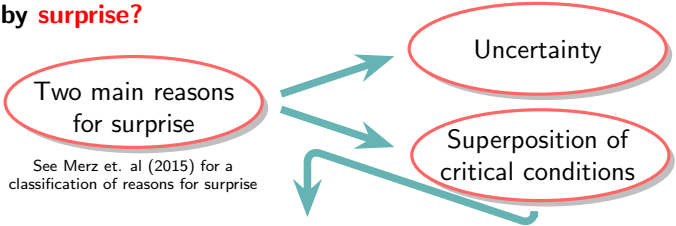
Research question: surprise in environmental extremes

Why environmental extreme events, like floods and droughts, still take communities by surprise?



See Merz et. al (2015) for a classification of reasons for surprise

Assumption: Impactful events are caused by the co-occurrence of critical states of climatic, environmental and societal systems

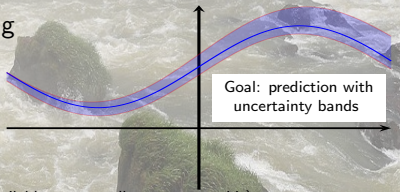
The Sword of Damocles - Félix Auvray, Public domain, via Wikimedia Commons

Key step: deciphering and modelling the interactions between climate, land processes and society by taking uncertainty into account.

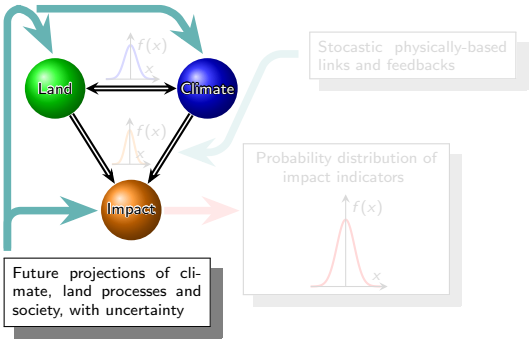
Challenges

"Uncertainty is an uncomfortable position. But certainty is an absurd one"
Voltaire, 1694 - 1778


- **Identify critical co-occurrences**
  Many of them are known - Example: changes of frequency and severity of rainstorms with duration close to the concentration time of the catchment.
- **Make predictions** of future states of the involved systems (e.g., climate) **with uncertainty**.
- **Identify the physical reasons for uncertainty** in the definition of the above links.
- **Identify physical basis of links and feedbacks** between co-occurring critical states.
- **Build a theory** to represent uncertainty in the underlying physical model.
- **Identify a model to represent the physics** of the system and the **physically-based** uncertainty.



Building a theory



Pillars of the theory are:

- Deterministic process based models of links and feedbacks between systems.
- Stochastic operators to transform deterministic models into stochastic physically-based models.
- Uncertainty model to define the stochastic operator through a stochastic kernel.

Required information (data) is:

- Predictions (with uncertainty) of climate, land processes and societal system.
- Probabilistic definition of links and feedbacks.

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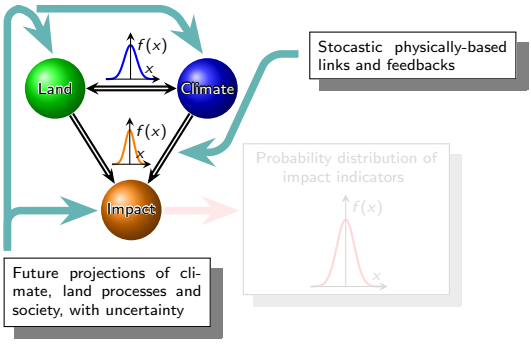

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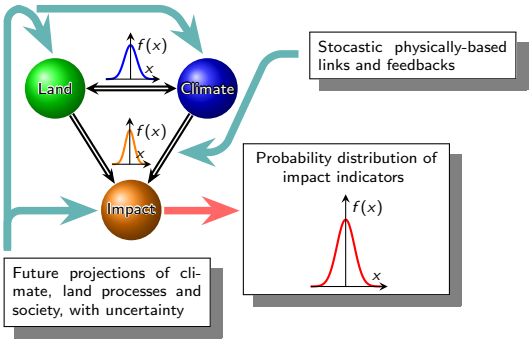

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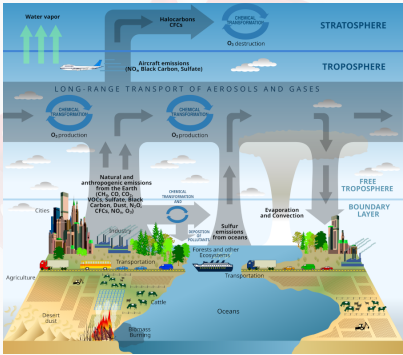
Take home message

- **"The World of Nature is unpredictable".**
  Lack of predictabiity means uncertainty, which implies randomness, that in turn can be modelled through stochastics.
- Deterministic, physically-based models for the interactions between systems can be easily transformed into stochastic models providing a best estimate with uncertainty.
- Operationally, the transformation is obtained by turning from one to many (statistically selected) predictions to account for uncertainty.
- The statistical selection of predictions is essential to ensure a rigorous estimation of uncertainty.



By Phillipe Rekacewicz - Strategic Plan for the U.S. Climate Change Science Program, Public Domain

Stochastic physically-based modelling: a generalised theory of pattern modelling with uncertainty

Montanari and Koutsoyiannis (M&K, 2012), proposed a blueprint to reframe in a stochastic setting a deterministic process-based model. From the deterministic model

Model prediction — Deterministic model

$$Q = S(\Theta, \mathrm{X})$$

Parameters — Input data

We move to its stochastic counterpart

Probability distribution of model prediction — Transfer operator from deterministic to stochastic

$$f_Q(Q) = K_S f_{\Theta,\mathrm{X}}(\Theta, \mathrm{X})$$

Parameters — Input data

After some math development we end up to:

Probability distribution of model prediction — Probability distribution of model error

$$f_Q(Q) = \int_\Theta \int_\mathrm{X} f_e(Q - S(\Theta, \mathrm{X}) | \Theta, \mathrm{X}) f_\Theta(\Theta) f_\mathrm{X}(\mathrm{X}) d\Theta d\mathrm{X}$$

Input data — Parameters

Definition of the probability distribution of model error is the key step

Stochastic physically-based modelling: a generalised theory of pattern modelling with uncertainty

Probability distribution of model prediction

Probability distribution of model error

$$f_Q(Q) = \int_\Theta \int_X f_e(Q - S(\Theta, X)\,|\,\Theta, X)\, f_\Theta(\Theta)\, f_X(X)\, d\Theta dX$$

Input data **Parameters**

This is a general theory. Includes, as a specific case, the traditional stochastic black box models

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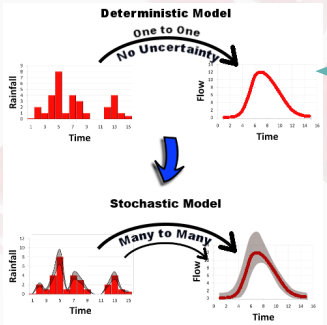
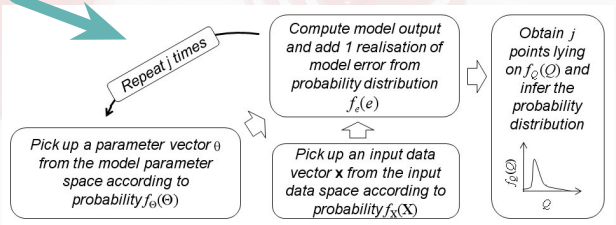
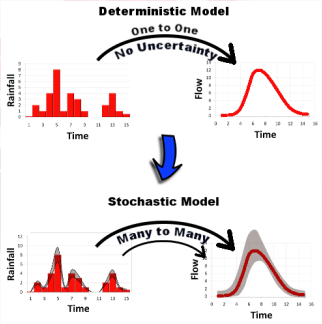




Interpreting uncertainty

- Uncertainty cannot be eliminated.
- Uncertainty is defined through probability distributions.
- The most reliable way of estimating predictive uncertainty is comparison with the observed reality. The prediction error results from the aggregation of each uncertainty source (example of uncertainty sources: parametric uncertainty, input data uncertainty, model structural uncertainty etc).
- Comparison with observed reality is not always possible. Alternatively, uncertainty can be estimated by quantifying each uncertainty source and aggregating them via simulation.
- Uncertainty quantification is supported by the understanding of its physical basis.

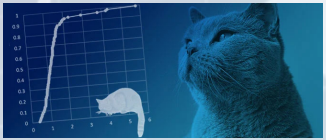


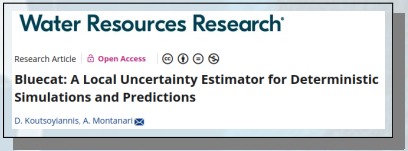
BLUECAT: looking for simplicity and operational efficiency

www.albertomontanari.it/bluecat

BLUECAT transforms a deterministic prediction model into a stochastic prediction model (Koutsoyiannis and Montanari (2022) & Montanari and Koutsoyiannis (2024)).
See my oral presentation Thursday, May 1st, Session HS4.3, room 2.15, 15:35–15:45, EGU25-5861

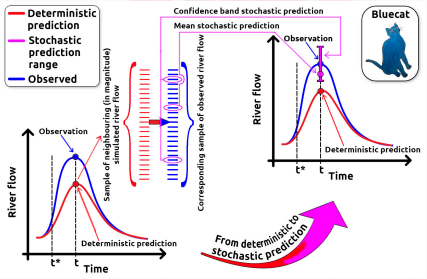
- From a point prediction we obtain the probability distribution of the predictand. From the above probability distribution we estimate the average (or median) prediction along with its confidence band for an assigned confidence level.
- BLUECAT is more than an uncertainty assessment method: it is rather a new prediction model with a stochastic structure. BLUECAT can be applied in conjunction with any deterministic prediction model.





BLUECAT: workflow

- A point prediction is obtained with a deterministic model.
- A sample of neighbouring (in magnitude to the point prediction) simulated river flows is collected from the calibration period.
- A corresponding sample of observed river flows is collected. This is used to estimate (from data) the probability distribution of the predictand.
- Mean (or median) value is extracted along with the confidence bands.
- The stochastic prediction is obtained along with uncertainty assessment.



BLUECAT: assumptions

Note: in what follows, deterministic and stochastic model are D-model and S-model, respectively. BLUECAT assumptions:

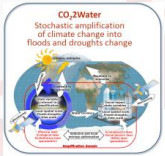
- The stochastic processes describing the modelled variables are stationary during the calibration and application period. Non-stationarity can be accounted for by using non-stationary D-models.
- The calibration data set is extended enough to ensure that sufficient information is available to upgrade the D-model into the S-model.
- Uncertainty is not subdivided in different components as BLUECAT is assumed to automatically incorporate all types, including the uncertainty in input data and parameters, for which no particular provision is necessary.

Why BLUECAT?
"Brisk Local Uncertainty Estimator for generiC simulations And predic-Tions"

BLUECAT refers to the pop-art by Andy Warhol (1928–1987), a success creation stimulated by a simple idea that gives a feeling of positive thinking and optimism.

Climate impact amplification: searching for events

$CO_2$2Water is activating a search for events where climate impact got suddenly amplified and communities were taken by surprise.



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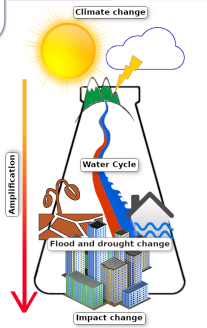
- Flash and large scale floods.
- Droughts with unexpected impact.
- Debris flow events.

The purpose is to elaborate a large data set of surprise events at global scale to propose a checklist for identifying the climatic, hydrological and socio-economic conditions leading to amplification and surprise.
Such checklist may support the identification of areas exposed to risk.
We need data! **Interested in participating** and contribute to papers?
Stay tuned at www.albertomontanari.it/co22water!



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My web site: open education, teaching, research, software, data

- This presentation is available in my website at www.albertomontanari.it.
- Everything is open, can be copied and reproduced (citation is appreciated).
- Everything I do is there. Lecture notes (in English), videos of lectures, scientific papers, presentations, software.
- Highlights: A travel through time to explore past and future megadroughts (interactive ebook); Floods, ten concepts to get protected; Climate change and water: lecture to students.
- Openness stands for dissemination and inclusivity.