5 REASONS NOT TO USE NUMERICAL MODELS IN WATER RESOURCES MANAGEMENT

Francesca Pianosi, University of Bristol
3 things I am not going to talk about

1. Water is an essential resource
2. Water resources are under increasing pressure
3. We need novel approaches to water resources management

1 question I would rather discuss
Can numerical models help to improve water resources management?
5 REASONS

NOT TO USE NUMERICAL MODELS
IN WATER RESOURCES MANAGEMENT

Francesca Pianosi, University of Bristol
4 REASONS
NOT TO USE NUMERICAL MODELS IN WATER RESOURCES MANAGEMENT

Francesca Pianosi, University of Bristol
The models we use are so complex that we have no idea what is really happening in there.
As we use increasingly complex models we need formal, structured approaches to support model calibration, verification and diagnostic evaluation.

→ Sensitivity Analysis (SA) is a set of statistical techniques that provide such a structured approach.

X-Ray Vision: Fish Inside out: [www.mnh.si.edu/exhibits/x-ray-vision/](http://www.mnh.si.edu/exhibits/x-ray-vision/)

WHAT

does the model predict?

WHY

does it predict so?
Application example to hydrological model

Sensitivity of model performance to variations in the 13 model parameters
[model: HBV+snow accounting as in Kollat et al 2012 WRR]
Application example to hydrological model

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Sensitivity of model performance to variations in the 13 model parameters [model: HBV+snow accounting as in Kollat et al 2012 WRR]
Application example to flood inundation model

floodplain friction
channel friction
forcing hydrograph
spatial resolution

forcing hydrograph

flow (m³/s)
influential factors
time (hour)
EGU presentation on Sensitivity Analysis

Wed, 15 – 11:45 - Session NH1.6 - Room G6 - EGU2015-13145
The application of Global Sensitivity Analysis to quantify the dominant input factors for hydraulic model simulations by James Savage et al.

Wed, 15 – Session NP1.3/HS2.3.16 - Blue Posters - EGU2015-2218
Global Sensitivity Analysis of Environmental Models: Convergence, Robustness and Validation by Fanny Sarrazin et al.

Fri, 17 – Session NH3.11 – Blue Posters - EGU2015-6555
Robustness for slope stability modelling under deep uncertainty by Susana Almeida et al.

Mon, 13 – 13:30 – Session HS3.3 – PICO Session - EGU2015-1356
SAFE(R): A Matlab/Octave Toolbox (and R Package) for Global Sensitivity Analysis

bristol.ac.uk/cabot/resources/safe-toolbox/
Pianosi et al. EMS in press
We use increasingly complex and ‘non-intuitive’ models

Increasing availability of data types adds up to model complexity

However

We have more and more sophisticated methods to investigate model behaviour and

We have ever growing computing power to put those methods into practice
REASON #2

Water resource management problems involve multiple, conflicting sectors

Therefore there is no possibility to take rational (‘optimal’) decisions
Example from Ticino River, Italy

How to redefine the Minimum Environmental Flow for the river?

Bizzi et al. 2012 *JoH*

Indicators of Hydrological Alteration - Stochastic Dynamic Programming - Multi-Criteria Analysis

![Graph showing aggregate index of hydrological alteration with flow (m³/s)]
Example from Ticino River, Italy

How to redefine the Minimum Environmental Flow for the river?
Bizzi et al. 2012 JoH

Indicators of Hydrological Alteration - Stochastic Dynamic Programming - Multi-Criteria Analysis

Flow (m³/s)

Supply vulnerability

aggregate index of hydrological alteration

13-CON (current)

13-VAR

60-CON

60-VAR

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Example from Lake Como basin

How to mitigate the conflict between upstream and downstream users?

Anghileri et al. 2013 JWRPM

Multi-objective optimization of system operation under different institutional setups

Coordinated

Centralized

Historical

Hydropower revenue (€/day)

Supply vulnerability (m$^3$/s)$^2$

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Multi-Criteria Analysis and Multi-Objective Optimization provide the framework to analyze tradeoffs between conflicting criteria and to design Pareto-optimal solutions.

Sometimes win-win solutions can be found.

In all cases, MCA and MOO help supporting the investigation of tradeoffs and therefore increase transparency of decisions.
Model predictions are uncertain and it is not possible to make good decisions based on uncertain predictions.
Example from 4-reservoirs system in the Seine river basin, France

How much can we improve the efficiency of existing infrastructure by making the best use of model forecasts?

Ficchi et al., JWRPM, under review

Rule Curves approach

Forecasts-based approach

Sequence of flow volumes at reservoirs inlet/outlet

Hydrologic-hydraulic simulation over prediction horizon

10-days ahead weather forecasts

Real-Time Optimization

Anticipated costs (objective function)
Step 1: Assessing the potential of Real-Time Optimisation

Simulation over 15-year period (01/08/1973-01/11/1988)

- Mean duration of event (days)
  - High: 5, Low: 3

- Max duration of event (days)
  - High: 15, Low: 10

- Max excess flow (m3/s)
  - High: 150, Low: 125

- No of days with event
  - High: 9, Low: 6

- No of stations with >1 event
  - High: 3, Low: 2
Step 2: Assessing the value of available forecasts for Real-Time Optimisation

RTO with PF

10-days ahead 'Perfect' Forecasts

RTO with DF

10-days ahead Deterministic Forecasts

RTO with EF

10-days ahead Ensemble Forecasts

from European Centre for Medium-Range Weather Forecasts (ECMWF)
Step 2: Assessing the value of available forecasts for Real-Time Optimisation

Simulation over flood event in February, 2007

- **RTO with PF**: 10-days ahead 'Perfect' Forecasts
- **RTO with DF**: 10-days ahead Deterministic Forecasts
- **RTO with EF**: 10-days ahead Ensemble Forecasts

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<thead>
<tr>
<th>Forecast Type</th>
<th>Mean Duration (days)</th>
<th>Max Duration (days)</th>
<th>Max Excess Flow (m3/s)</th>
<th>No of Days with Excess Flow</th>
<th>No of Stations with &gt;0 Events</th>
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Step 2: Assessing the value of available forecasts for Real-Time Optimisation

Simulation over flood event in February, 2007

- Explicit consideration of forecast uncertainty can almost fill the performance loss due to forecasts inaccuracy

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Average cost normalized wrt cost with PF (%)

0 10 20 30 40
DF EF
Although uncertain, model predictions can still have value for decision-making.

**Explicit consideration of uncertainty in decision (optimisation) methods help making better decisions.**

Combining prediction models and decision theory provides a new way to look at models: from focusing on accuracy in predictions to focusing on value for decision-making.
Models are a simplification of the real world, and their predictions are just the reflection of their underlying assumptions.

Therefore we cannot trust and implement the decision that a model suggests is ‘best’.
Model results are certainly wrong…

But does this really matter?

Christopher Columbus (1451-1506)
Example from Lake Como basin

How to mitigate the conflict between upstream and downstream users?

Anghileri et al. 2013 JWRPM

Multi-objective optimization of system operation under different institutional setups
Modeling exercises are an opportunity for us to

- think about our understanding of a problem,
- bring expertise and knowledge together,
- organize knowledge in a structured way,
- discover unexpected behaviours or connections,
- reduce uncertainty about the problem,
- identify knowledge gaps,
- raise new questions,
- ...

The main outcome of the modeling exercise is the learning process induced by the model construction (?)
CONCLUSIONS
things I would do differently of my research so far

Spend more time on:
1. understanding problem context, formulation, previous works, etc.
2. interpreting numerical results and their broader implications
3. discussing limitations of the proposed solution approach

WHERE I AM NOW

WHERE I’M AIMING AT
THANK YOU

SEE THE GLASS HALF FULL AND CARRY ON SAILING

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