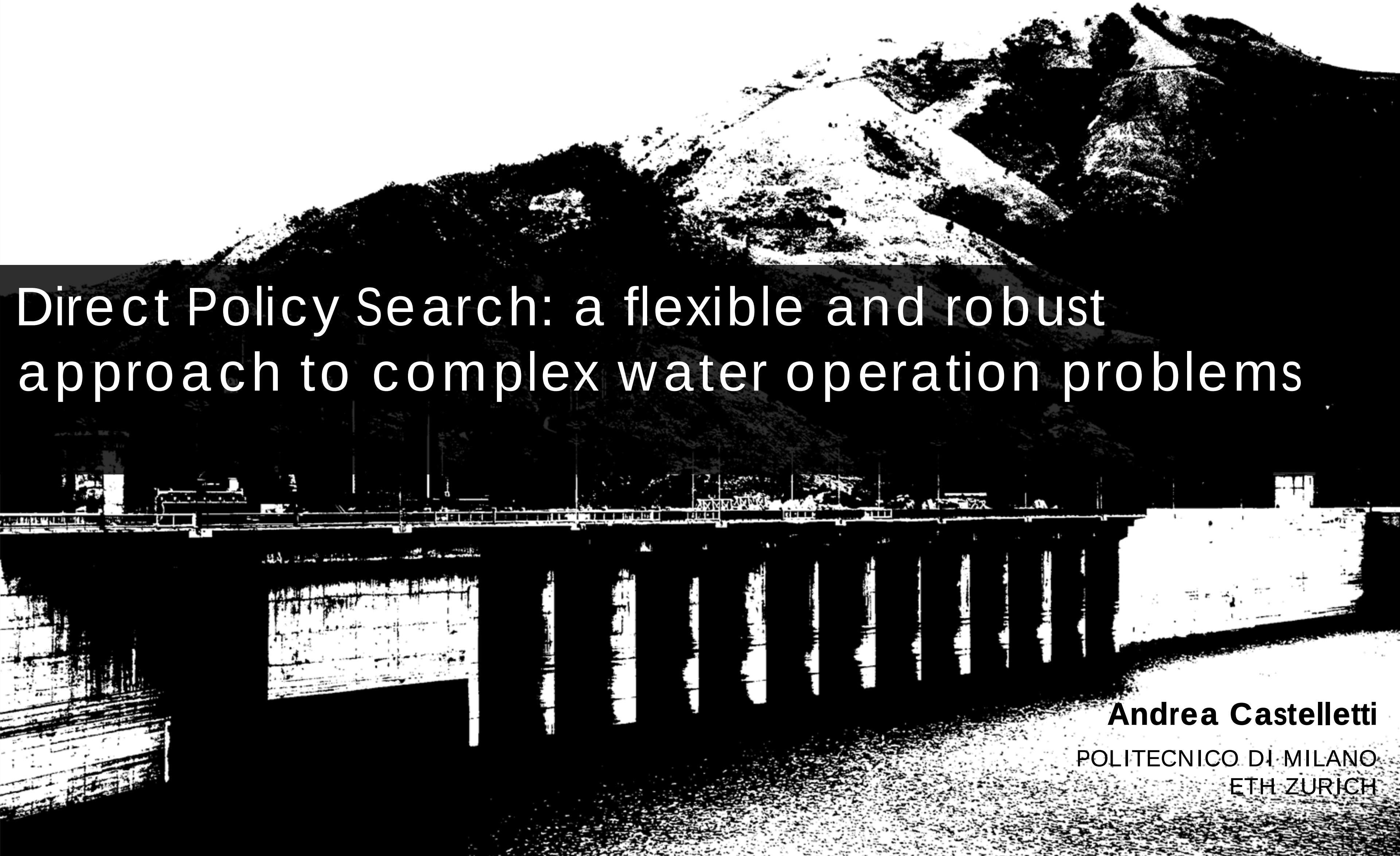
POLITECNICO MILANO 1863

ETH Zürich

FEEM | MILANO 15.06.2017

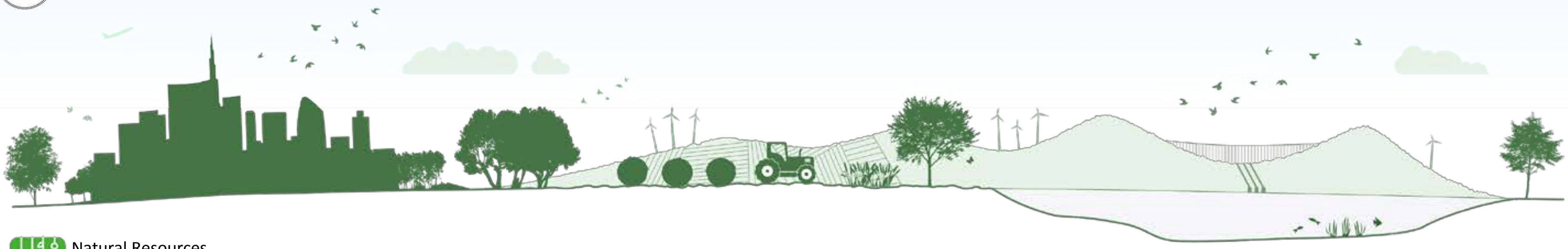


Direct Policy Search: a flexible and robust approach to complex water operation problems

Andrea Castelletti

POLITECNICO DI MILANO
ETH ZURICH

POLITECNICO
MILANO 1863



Natural Resources
Management

Water Resources Policy, Management and Control

Environmental big data analytics

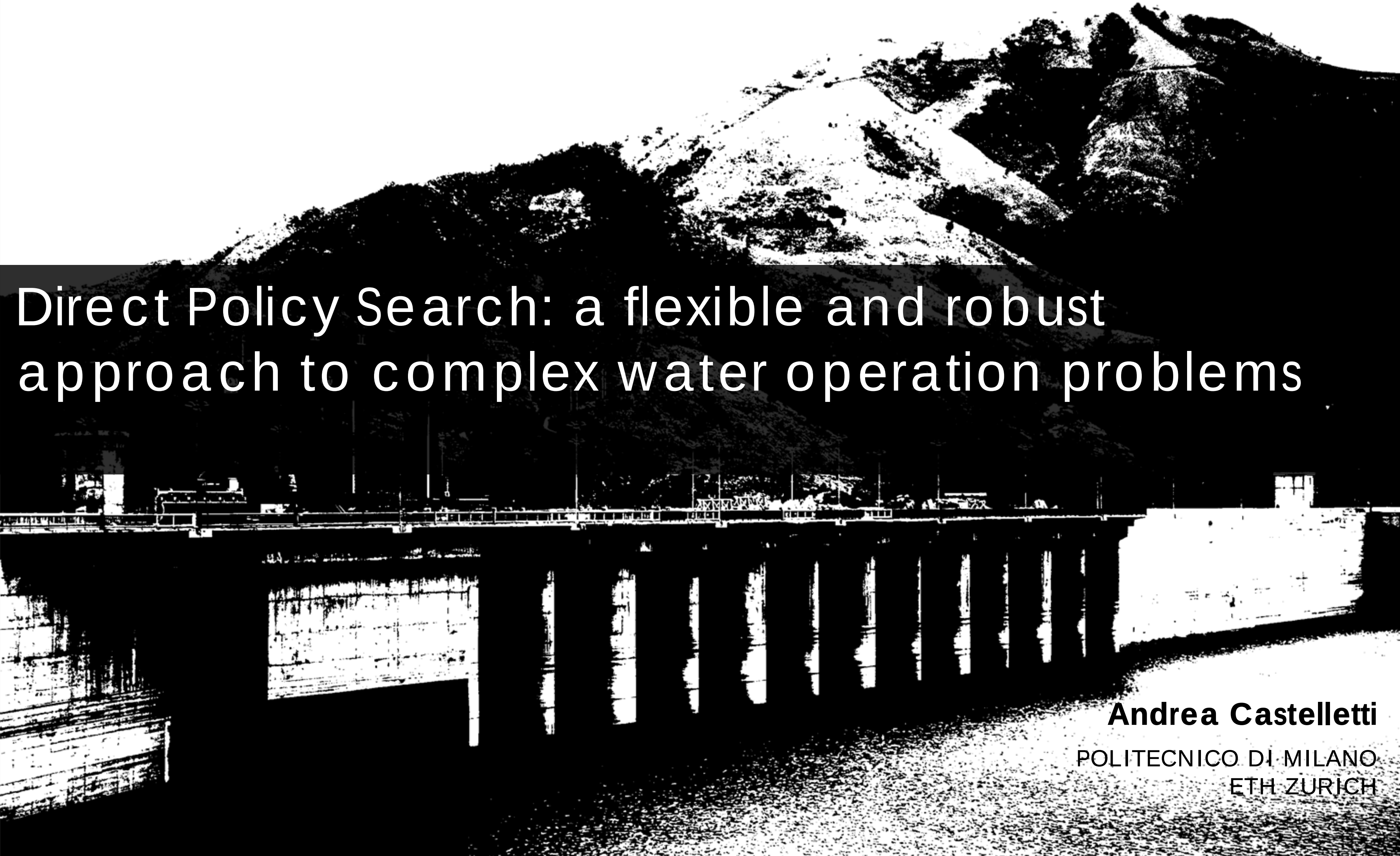
Operational geomorphology

http://www.nrm.deib.polimi.it/ @NRMPolimi

POLITECNICO MILANO 1863

ETH Zürich

FEEM | MILANO 15.06.2017



Direct Policy Search: a flexible and robust approach to complex water operation problems

Andrea Castelletti

POLITECNICO DI MILANO
ETH ZURICH

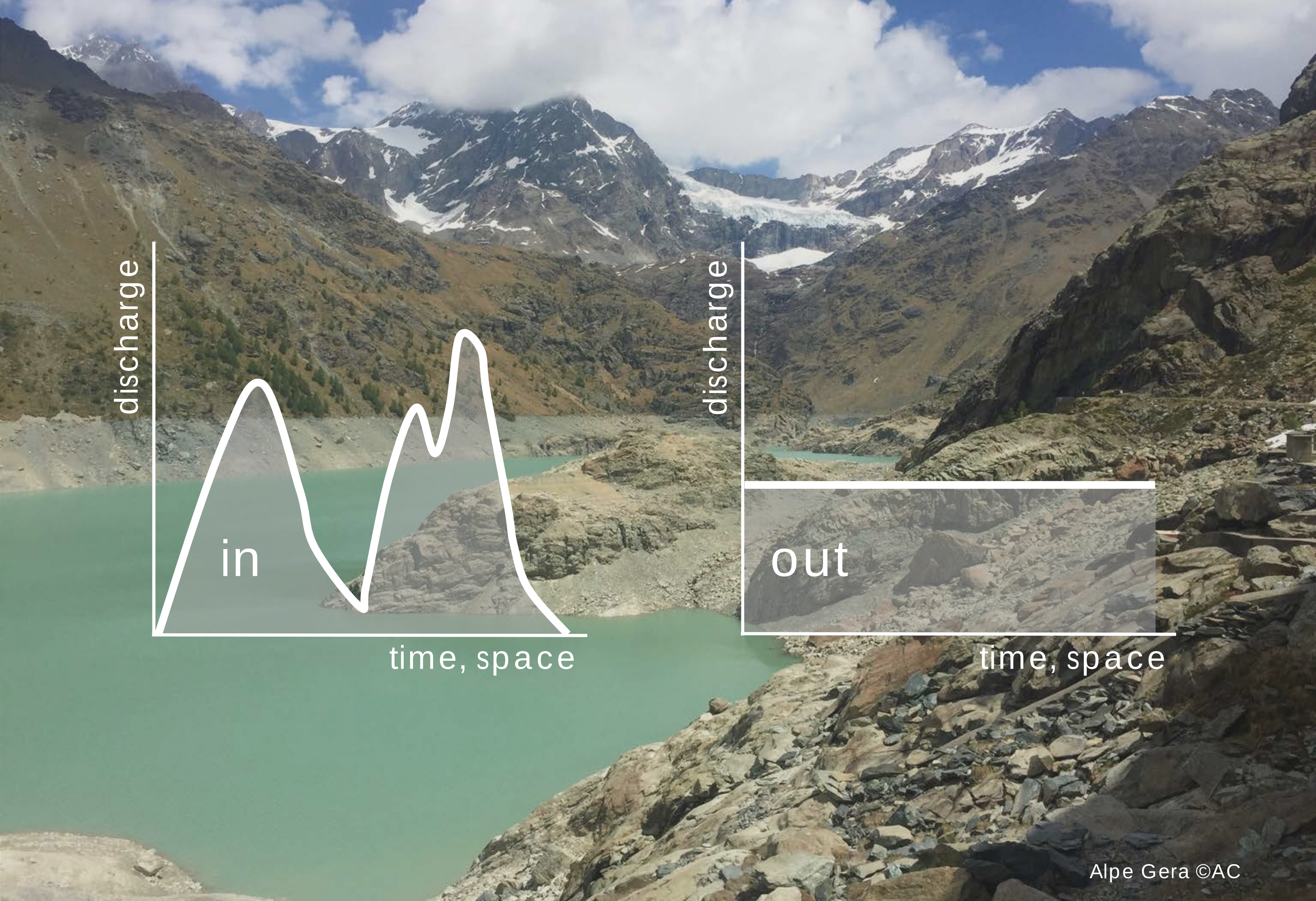
Dams: An ancestral technology ...

Source: http://www.hydriaproject.net

... that recently accelerated

Source: hydrolab.geog.mcgill.ca

Dams: Spatiotemporal water shifters



Still worth research?

(*Paper No. 1864.*)

"The Capacity of Storage-Reservoirs for Water-Supply."

By W. Rippl, Docent at the Royal Technical High School at Gratz (Styria).

1. Introduction.

In the English system for the water-supply of towns, by collecting the drainage of large catchment-basins, one of the most important problems is the determination of the capacity for storage, which should be provided in the reservoirs.

In the earlier works designed on this plan this point did not receive sufficient attention, because at that time the data required were not available. Hence reservoirs were constructed of insufficient size, causing a sensible deficiency in the water-supply in dry seasons. As the dams of the storage-reservoirs could not be raised in height without endangering their stability, new reservoirs and new gathering-grounds had to be added—a proceeding sometimes difficult and always costly.

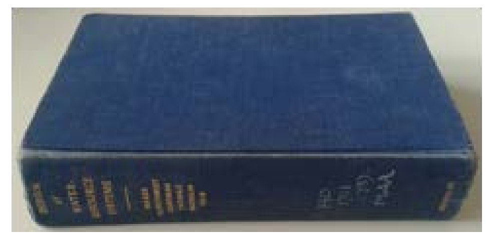
For a long time engineers were obliged to apply the results of experience gained in existing waterworks to the design of new systems, by giving to the reservoirs a fixed capacity for a given area of gathering-ground. If, for example, in an existing system of water-supply, a storage-capacity of 2,500 cubic metres (88,288 cubic feet) was found adequate for 1,000 hectares (2,471 acres) of gathering-ground, the reservoir of a new system was designed to afford a proportionate storage-capacity. But as the amount of storage necessary depends on circumstances which vary in different localities, it is clear that in reservoirs thus designed, it is only by accident that a deficiency of water-supply, in a series of years, is prevented.

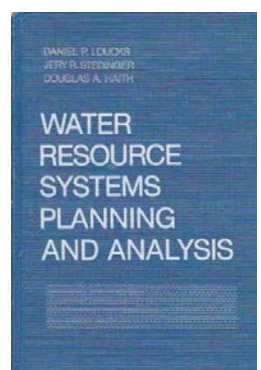
2. The ordinary Formula.

The purpose of the storage-reservoir is to equalise the fluctuations of supply and demand during an indefinitely long period of time. The circumstances of an average year are therefore not sufficient to determine the quantity to be stored. Hence empirical rule has been adduced, based on the conditions which

Ripple, W. (**1883**) The capacity of storage reservoirs for water supply. Minutes of the Proceedings, Institution of Civil Engineers, Vol 71. Thimas Telfors 270-278

Maass et al (**1962**), Design of water resources systems, Harvard University Press, Cambridge, Mass.

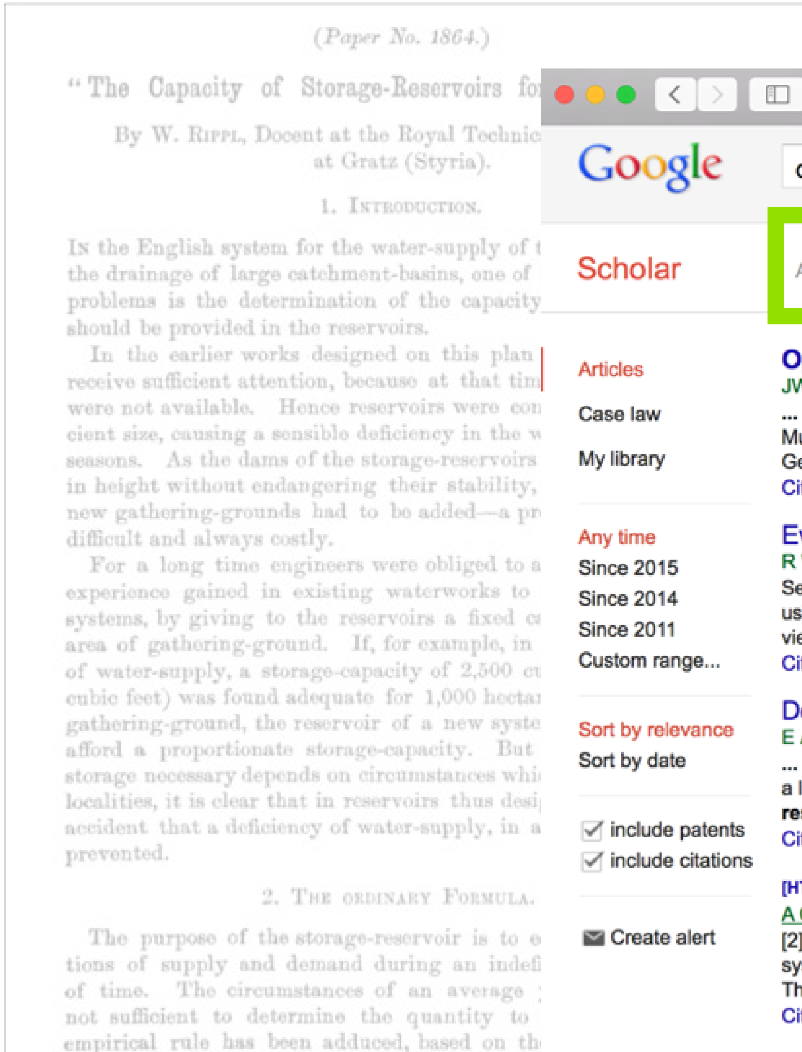




Loucks et al. (**1981**), Water resources systems planning and analysis, Prentice-Hall

Still worth research?

Ripple, W. (**1883**) The capacity of storage reservoirs



(Paper No. 1864.)

"The Capacity of Storage-Reservoirs fo

By W. Rippl, Docent at the Royal Technic
at Gratz (Styria).

1. Introduction.

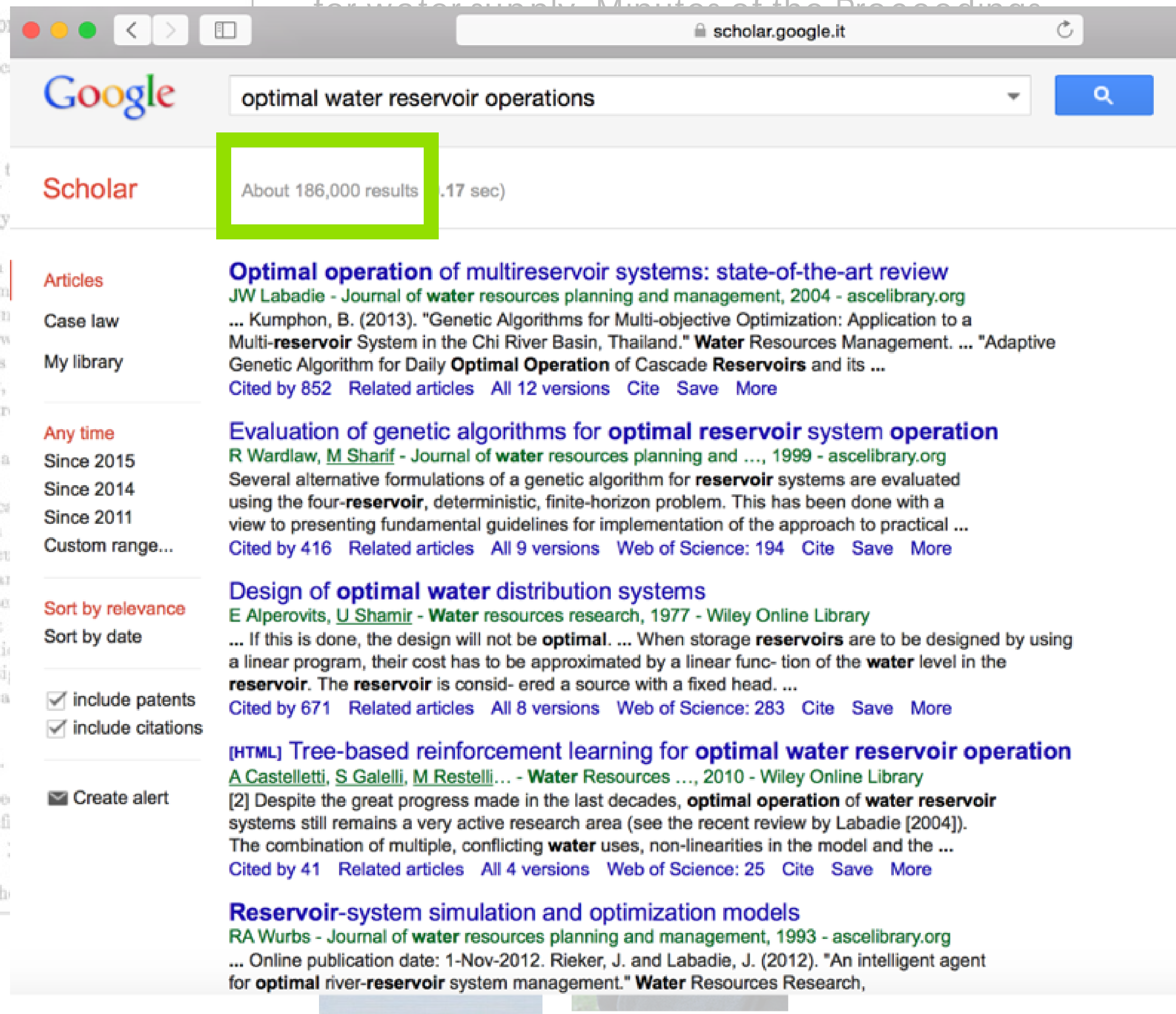
In the English system for the water-supply of t
the drainage of large catchment-basins, one of
problems is the determination of the capacity
should be provided in the reservoirs.

In the earlier works designed on this plan
receive sufficient attention, because at that tim
were not available. Hence reservoirs were con
cient size, causing a sensible deficiency in the w
seasons. As the dams of the storage-reservoirs
in height without endangering their stability,
new gathering-grounds had to be added—a pr
difficult and always costly.

For a long time engineers were obliged to a
experience gained in existing waterworks to
systems, by giving to the reservoirs a fixed ca
area of gathering-ground. If, for example, in
of water-supply, a storage-capacity of 2,500 cu
cubic feet) was found adequate for 1,000 hectar
gathering-ground, the reservoir of a new syste
afford a proportionate storage-capacity. But
storage necessary depends on circumstances whi
localities, it is clear that in reservoirs thus desi
accident that a deficiency of water-supply, in a
prevented.

2. The ordinary Formula.

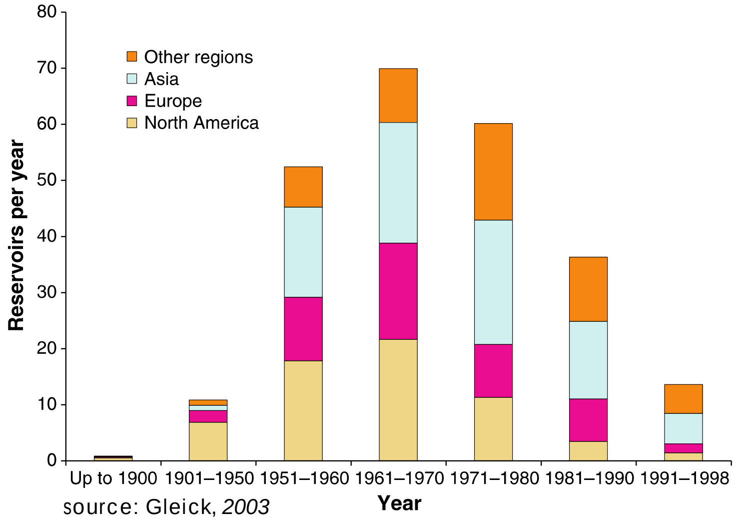
The purpose of the storage-reservoir is to e
tions of supply and demand during an indefi
of time. The circumstances of an average
not sufficient to determine the quantity to
empirical rule has been adduced, based on th



Maybe yes ...

for 3 challenging reasons
and 2 new opportunities

The 1st challenge: peak vs untapped

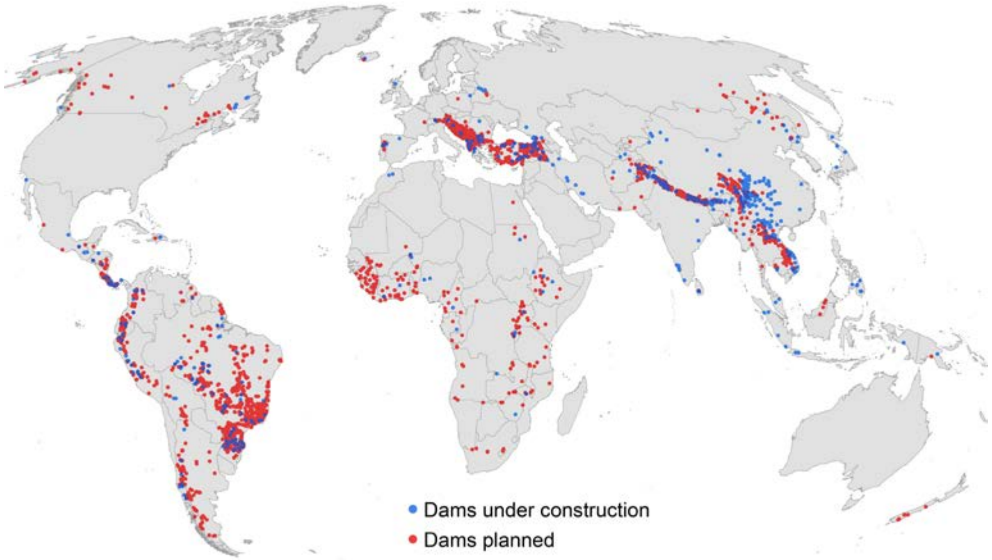


source: Gleick, *2003*

Despite for some analyst water supply **expansion is constrained** (PEAK WATER) ….

P.H. Gleick & M. Palanniappan, *PNAS*, 107(25), 2010.

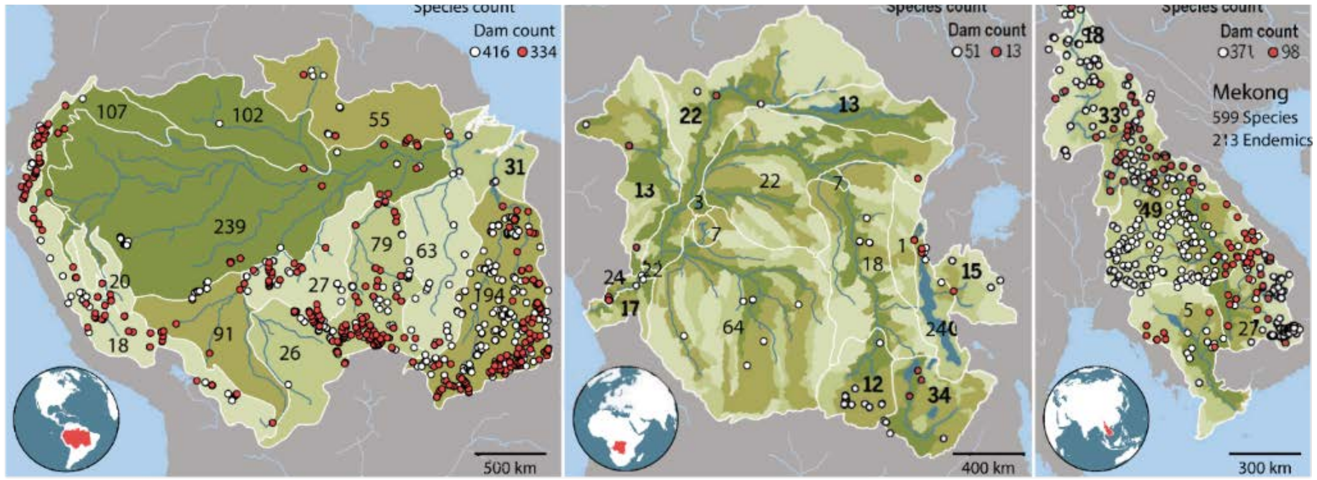
… for others the **untapped** potential is still huge, especially in Africa and China



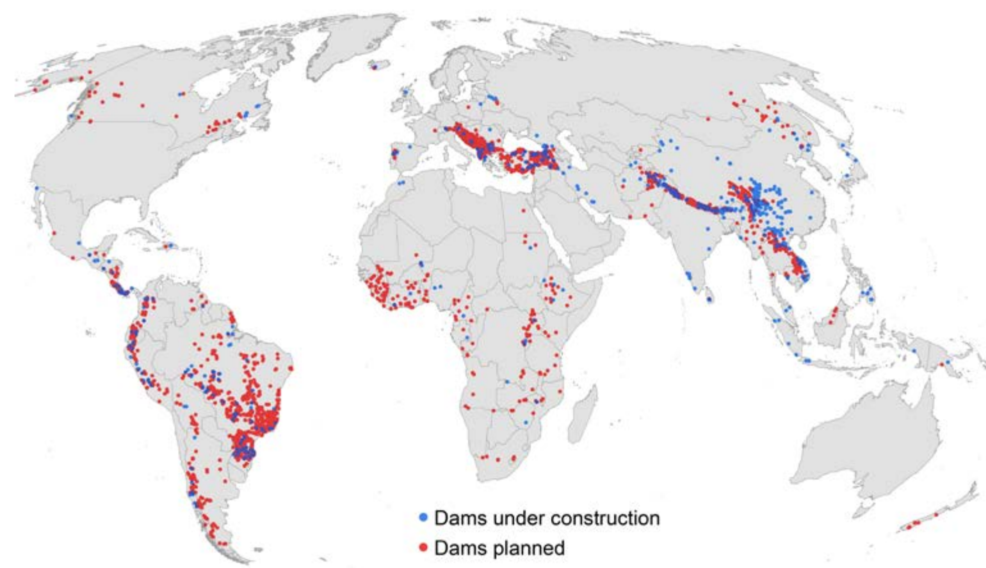
source: Zerfl et al 2014

The 1st challenge: peak vs untapped

Amazon *Kongo* *Mekong*

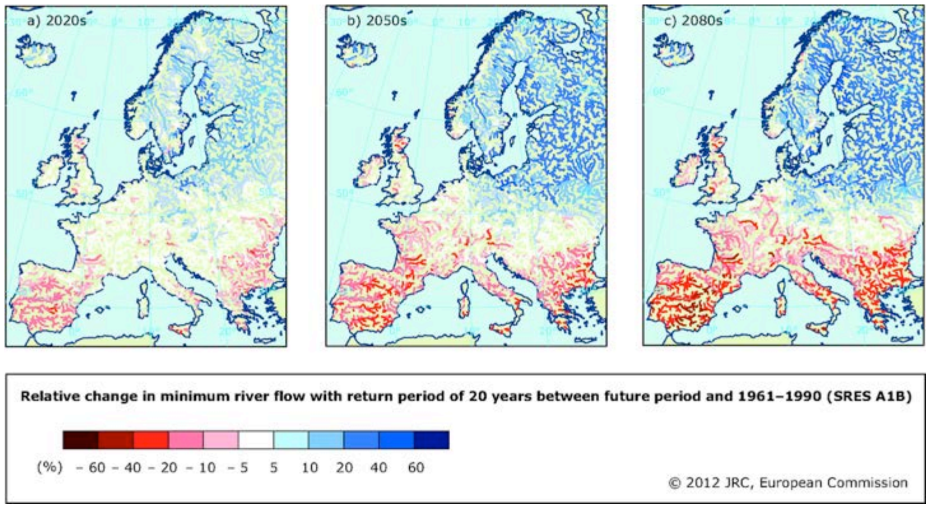


... for others the **untapped** potential is still huge, especially in Africa and China



source: Zerfl et al 2014

The 2nd: increasing uncertainty

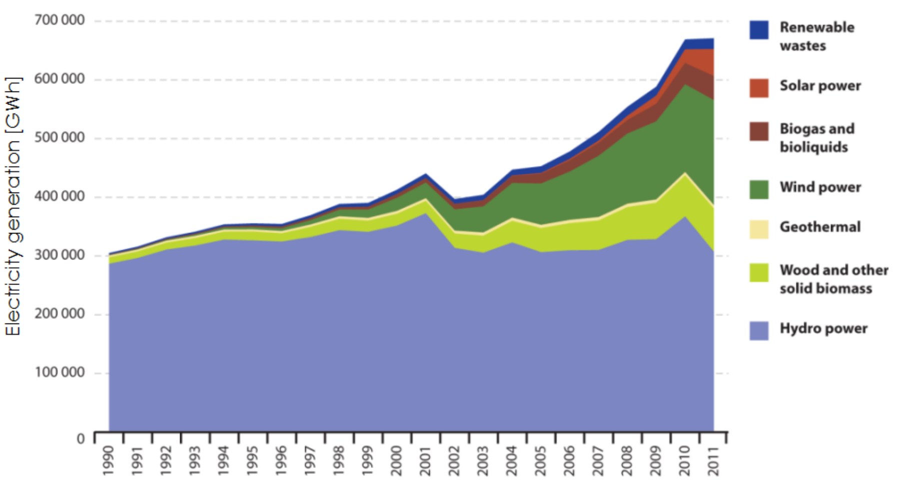


CLIMATE CHANGE

- More intense extremes
- More variable extremes
- Changes in water demand

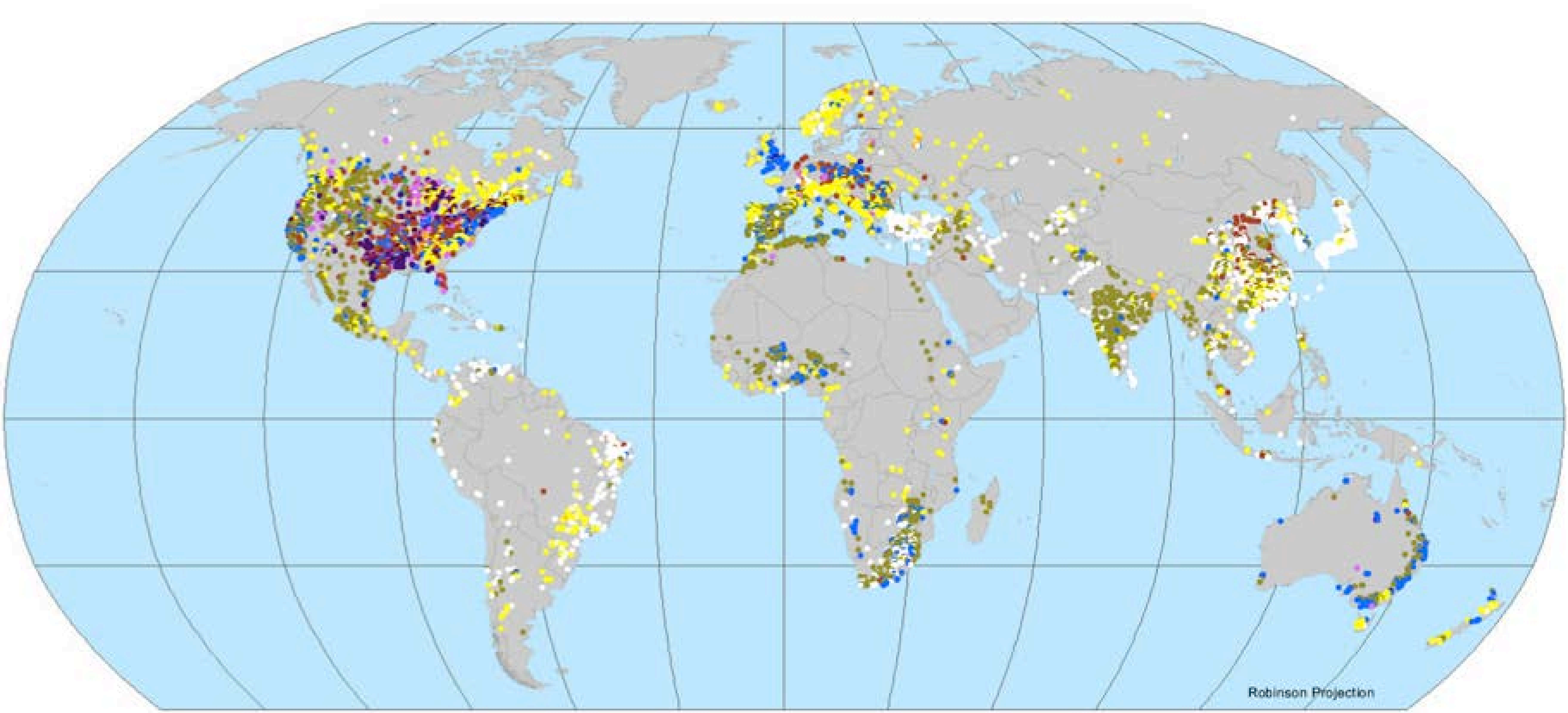
SOCIO-ECONOMIC CHANGE

- Increased price variability
- Change in energy demand
- Change in energy markets



Source: http://ec.europa.eu/eurostat/

The 3rd: expanding the purposes



Source: Lehner, 2011

Dam Main Use

- Fisheries
- Flood control
- Hydroelectricity
- Irrigation
- Navigation
- Not classified
- Other
- Recreation
- Water supply

1st opportunity: new and more data

Towards pervasive sensing of the water cycle

more/better informed operation

HUMAN SENSORS

VIRTUAL SENSORS

CITIZEN SCIENCE

LABS ON CHIP

CROWNSOURCING

REMOTE SENSING

SMART SENSORS

SMART DUST

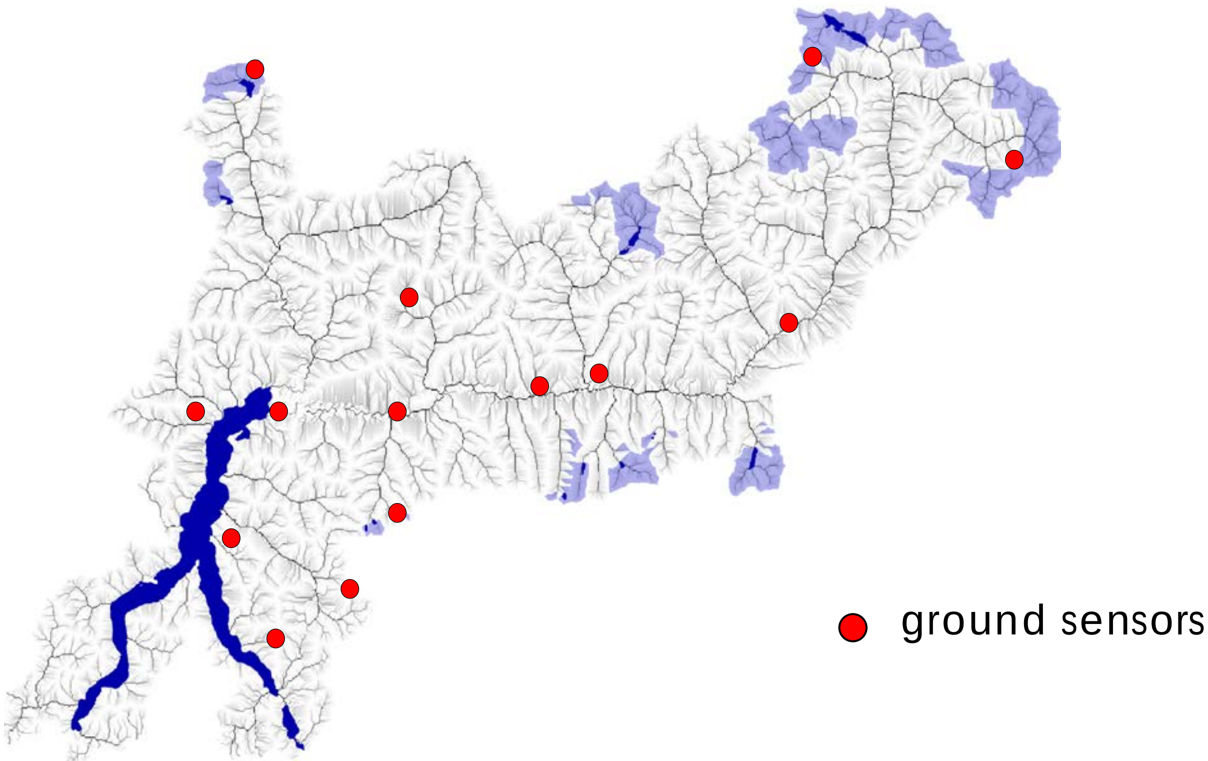
ENVINODES

CYBERINFRASTRUCTURES

1st opportunity: new and more data

Towards pervasive sensing of the water cycle

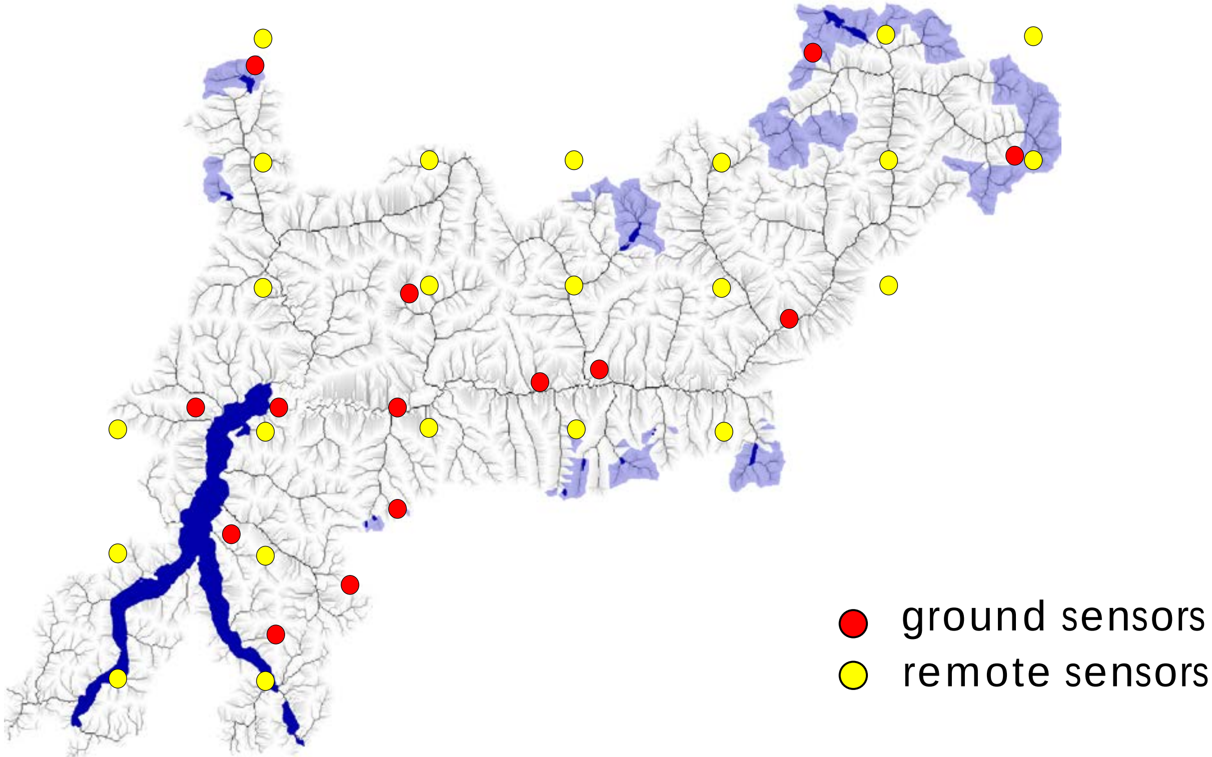
more/better informed operation



1st opportunity: new and more data

Towards pervasive sensing of the water cycle

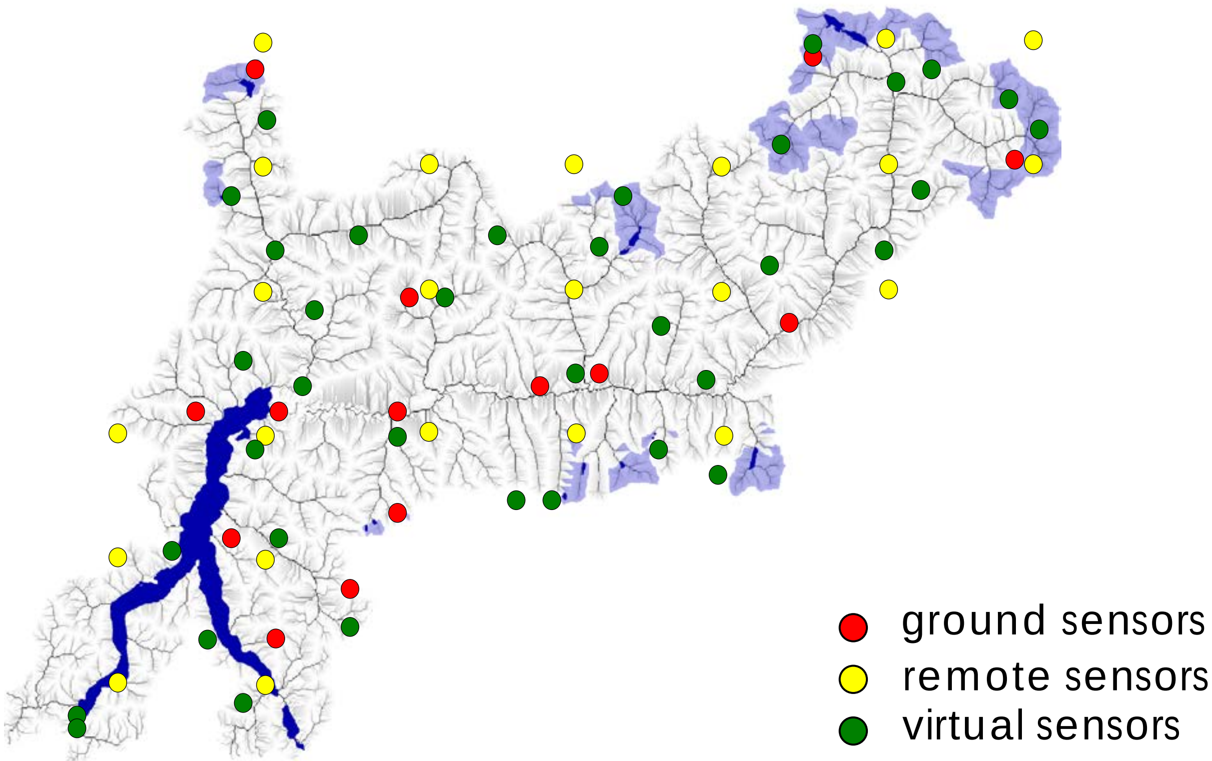
more/better informed operation



1st opportunity: new and more data

Towards pervasive sensing of the water cycle

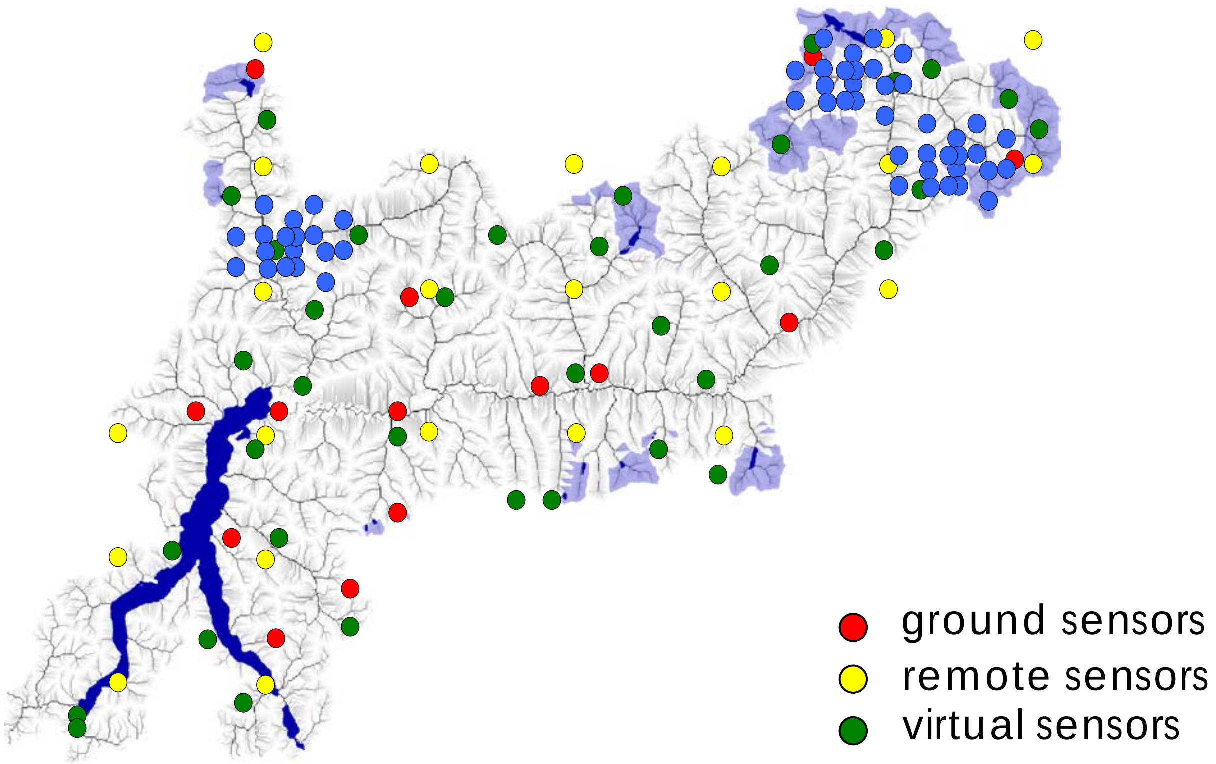
more/better informed operation



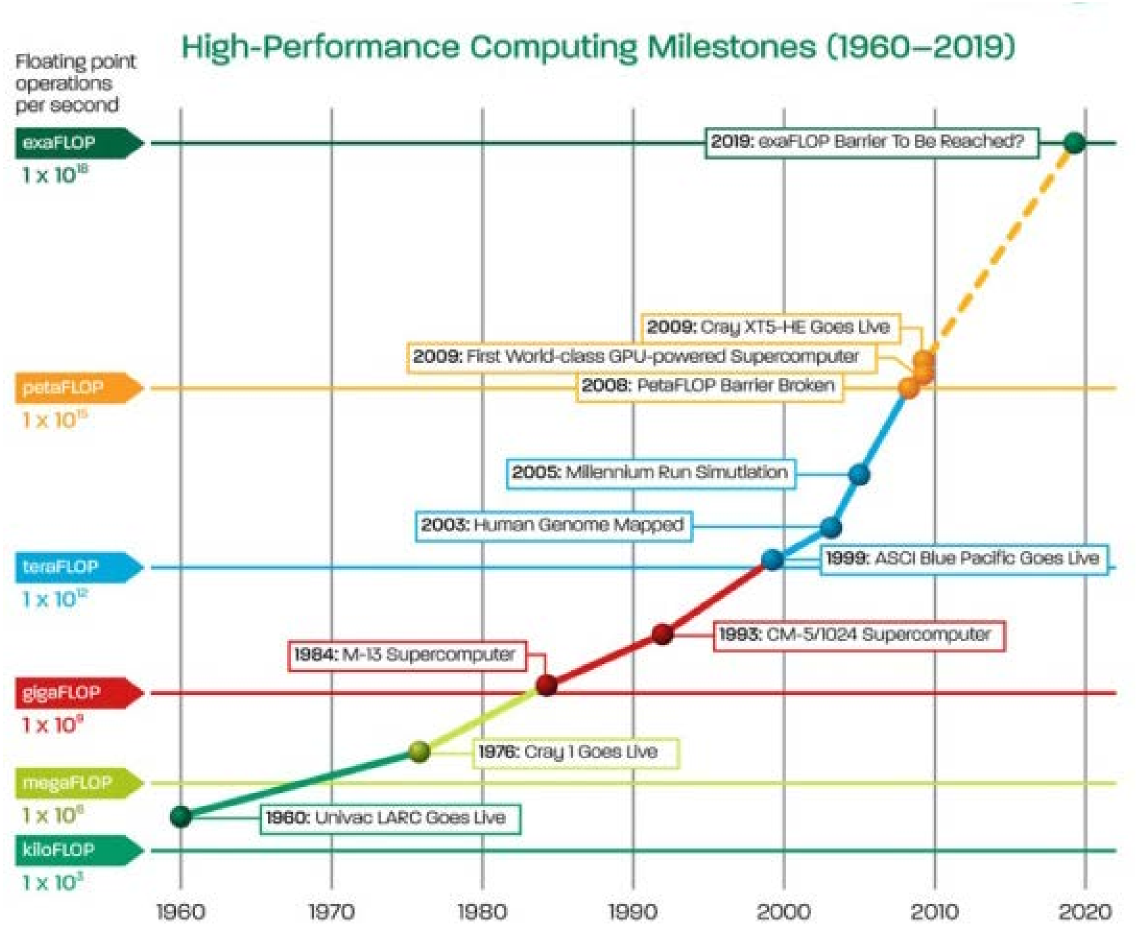
1st opportunity: new and more data

Towards pervasive sensing of the water cycle

more/better informed operation



2nd opportunity: computing power



Dam operation design
is an optimal control problem

The problem: feedback control

The long-term optimal operation of water resource systems can be formulated as a ***q*-objective stochastic optimal control problem**

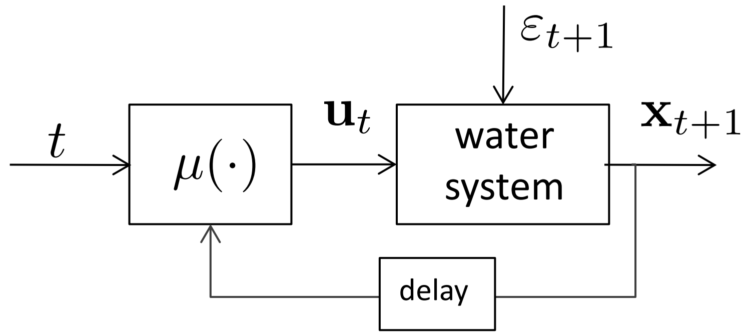
$$\min_{\mu_t(\cdot)} \mathbf{J} = |J^1 \;\; J^2 \ldots J^q|$$

subject to

$$\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \varepsilon_{t+1})$$

$$\mathbf{u}_t = \mu_t(\mathbf{x}_t)$$

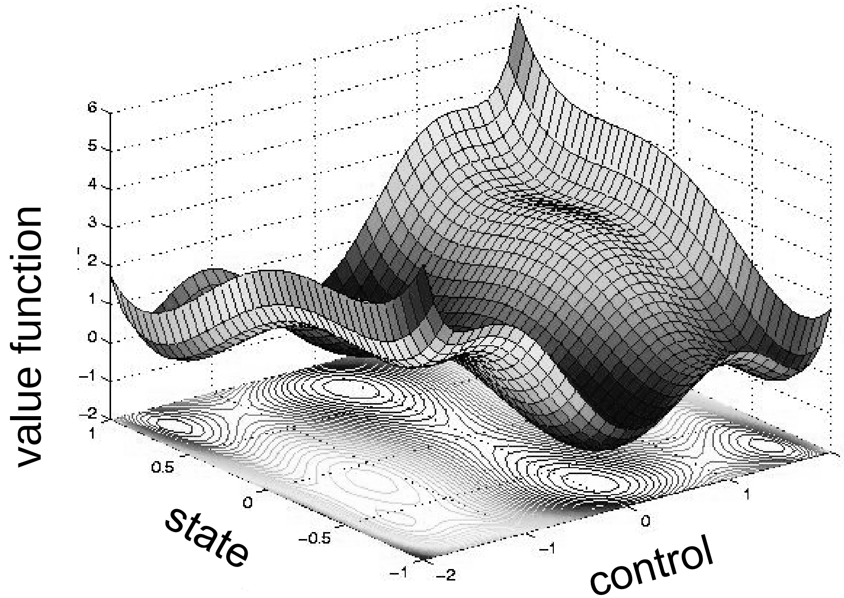
$$\varepsilon_{t+1} \sim \phi(\cdot)$$






The classic solution: Stochastic Dynamic Programming

Richard Bellman



SDP provides an **optimal solution** under the following assumptions:

1) Discrete variable domain

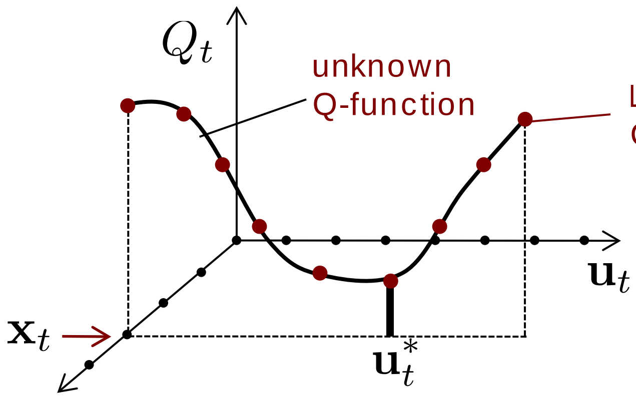
2) Objectives and constraints must be time-separable

3) Disturbance process is time-independent

SDP and the 3 curses

In practice, SDP suffers from 3 major limitations

1) **Curse of dimensionality**: computational cost grows exponentially with state, control and disturbance dimension [*Bellman*, 1967];



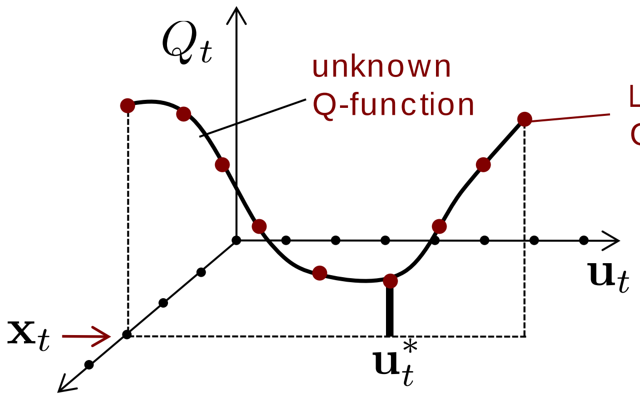
$$\propto N_x^{n_x} \times N_u^{n_u} \times N_\varepsilon^{n_\varepsilon} \times T$$

computations are numerically performed on a discretized variable domain

SDP and the 3 curses

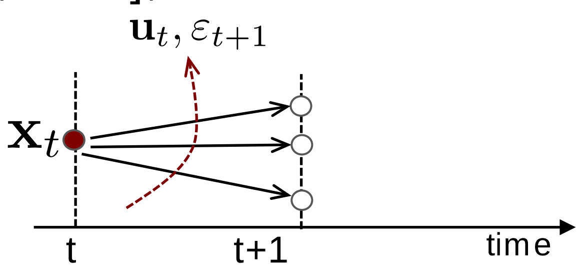
In practice, SDP suffers from 3 major limitations

1) **Curse of dimensionality**: computational cost grows exponentially with state, control and disturbance dimension [*Bellman*, 1967];



computations are numerically performed on a discretized variable domain

2) **Curse of modelling**: any variable considered among the operating rule's arguments has to be described by a dynamic model [*Bertsekas and Tsitsiklis*, 1996];

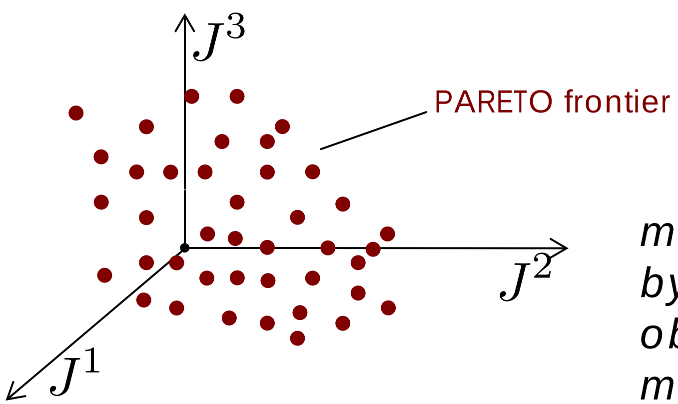


models are used in a multiple one-step-ahead-simulation mode

SDP and the 3 curses

In practice, SDP suffers from 3 major limitations

3) Curse of multiple objectives: computational cost grows factorially with the number of objectives considered [*Powell*, 2011].

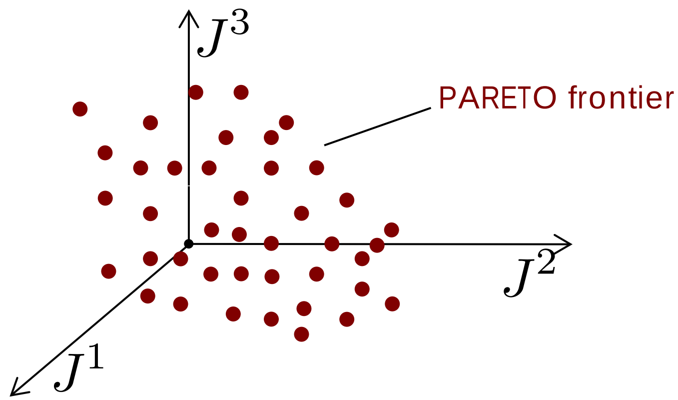


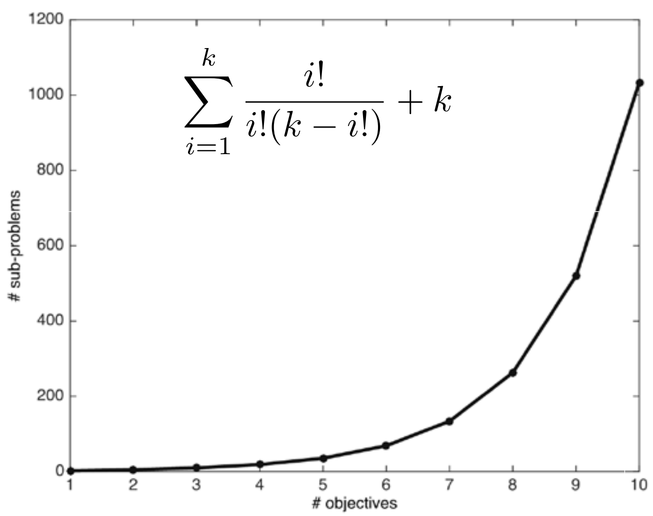
multi-objective problems are solved by reiteratively solving single objective problems (weighting method)

SDP and the 3 curses

In practice, SDP suffers from 3 major limitations

3) Curse of multiple objectives: computational cost grows factorially with the number of objectives considered [*Powell*, 2011].





Beyond SDP: ADP and RL

Approximate Dynamic Programming and **Reinforcement Learning** provide a framework to overcome some or all the SDP's curses.

[Powell, 2007; Busoniu et al. 2011]

VALUE FUNCTION-BASED APPROCHES:

- Approximate value iteration [Johnson et, 1993]
- Approximate policy iteration

Model-free or model-based // parametric or non-parametric

POLICY SEARCH-BASED APPROACHES:

- Direct policy search

Simulation-based optimization // parametric

ROLLING POLICIES

Beyond SDP: ADP and RL

Approximate Dynamic Programming and **Reinforcement Learning** provide a framework to overcome some or all the SDP’s curses.

[Powell, 2007; Busoniu et al. 2011]

VALUE FUNCTION-BASED APPROCHES:

- Approximate value iteration [Johnson et, 1993]
- Approximate policy iteration

Model-free or model-based // parametric or non-parametric

POLICY SEARCH-BASED APPROACHES:

- Direct policy search

Simulation-based optimization // parametric

ROLLING POLICIES

Multi-objective Direct Policy Search (MODPS)

Assume the operating rule belongs to a **given family of functions** and search the optimal solution in the **policy's parameter space**

$$\mathbf{u}_t = \mu_t(\mathbf{x}_t, \theta_t)$$

[Oliveira and Loucks, 1999; Koutsoyiannis and Economou, 2003]

Multi-objective Direct Policy Search (MODPS)

Assume the operating rule belongs to a **given family of functions** and search the optimal solution in the **policy's parameter space**

$$\mathbf{u}_t = \mu_t(\mathbf{x}_t, \theta_t)$$

ORIGINAL PROBLEM

$$\min_{\mu_t(\cdot)} \mathbf{J} = |J^1 \ J^2 ... J^q|$$

subject to

$$\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \varepsilon_{t+1})$$

$$\mathbf{u}_t = \mu_t(\mathbf{x}_t)$$

$$\varepsilon_{t+1} \sim \phi(\cdot)$$

$$\mathbf{x}_t \in \mathbb{R}^{n_x}$$

$$\mathbf{u}_t \in \mathbb{R}^{n_u}$$

$$\varepsilon_t \in \mathbb{R}^{n_\varepsilon}$$

POLICY SEARCH PROBLEM

$$\min_{\theta_t} \mathbf{J} = |J^1 \ J^2 ... J^q|$$

subject to

$$\mathbf{x}_{t+1} = f_t(\mathbf{x}_t, \mathbf{u}_t, \varepsilon_{t+1})$$

$$\mathbf{u}_t = \mu_t(\mathbf{x}_t, \theta_t)$$

$$\varepsilon_{t+1} \sim \phi(\cdot)$$

$$\mathbf{x}_t \in \mathbb{R}^{n_x}$$

$$\mathbf{u}_t \in \mathbb{R}^{n_u}$$

$$\varepsilon_t \in \mathbb{R}^{n_\varepsilon}$$

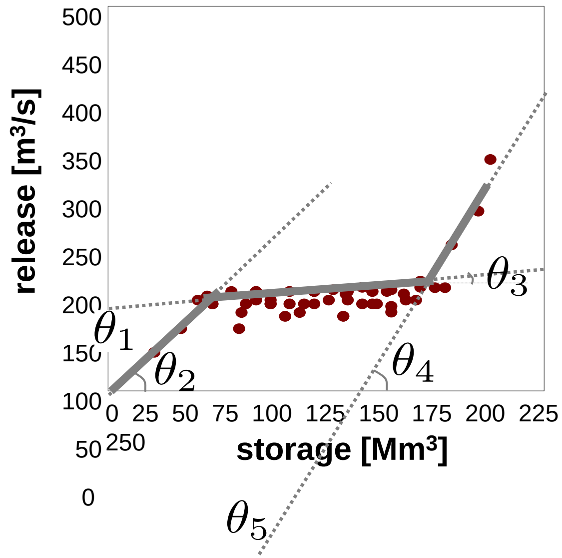
$$\theta_t \in \Theta_t \in \mathbb{R}^{n_\theta}$$

[Oliveira and Loucks, 1999; Koutsoyiannis and Economou, 2003]

Selecting the policy approximation: Ad hoc/Empirism

WHEN

1. The system is already in operation

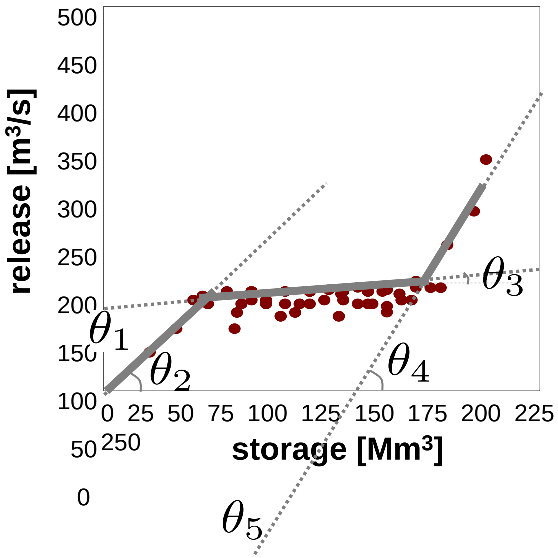


Identify existing regularities in a sample of the operator behaviour
[*Guariso et al*, 1986]

Selecting the policy approximation: Ad hoc/Empirism

WHEN

1. The system is already in operation



Identify existing regularities in a sample of the operator behaviour [*Guariso et al*, 1986]

2. the system is simple (i.e. one reservoir) AND/OR the systems has one single objective (e.g. water supply) [*Oliveira and Loucks*, 1999]

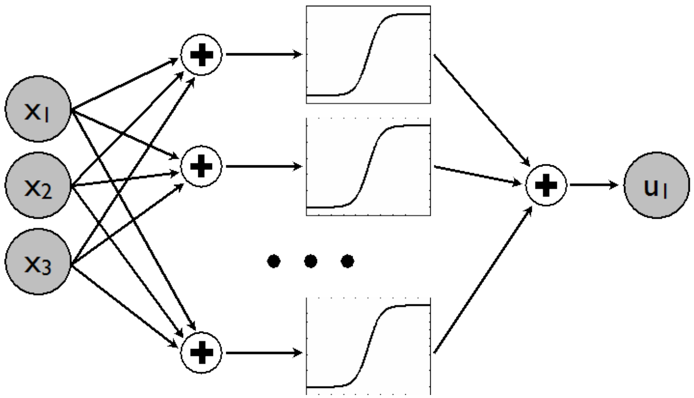
- NEW York City rule [*Clark*, 1950]
- Space rule [*Clark*, 1956]
- Standard Operating Policy [*Draper*, 2004]
- …..

Rules of thumb identified empirically

Selecting the policy approximation: Universal Approx.

Provided that some conditions are met, an Universal Approximator is approximate arbitrarily closely every continuous function.

ARTIFICIAL NEURAL NETWORKS [*Cybenko* 1989, *Funahashi* 1989, *Hornik et al.* 1989]



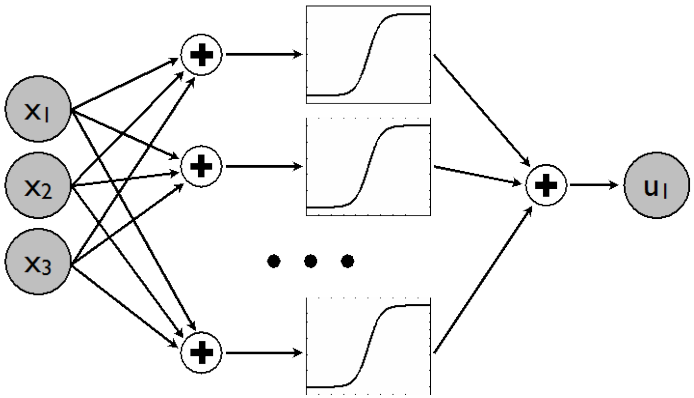
Parameter dimension

$$\underbrace{n_\theta = n_u(N}_{\text{Number of NEURONS}}(n_x + 2) + 1)$$

Selecting the policy approximation: Universal Approx.

Provided that some conditions are met, an Universal Approximator is approximate arbitrarily closely every continuous function.

ARTIFICIAL NEURAL NETWORKS [*Cybenko* 1989, *Funahashi* 1989, *Hornik et al.* 1989]

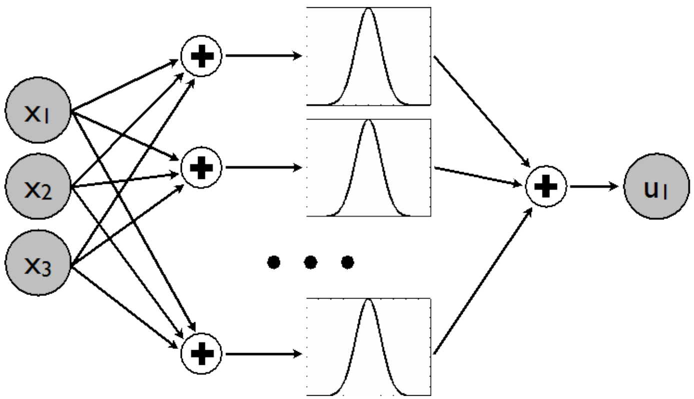


Parameter dimension

$$\underbrace{n_\theta = n_u(N(n_x + 2) + 1)}$$

Number of NEURONS

GAUSSIAN RADIAL BASIS FUNCTIONS [*Busoniu et al.* 2011]



Parameter dimension

$$n_\theta = N(2n_x + n_u)$$

Number of BASES

Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)

Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)
- Sensitivity to parameter initialization (no-preconditioning)

Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)
- Sensitivity to parameter initialization (no-preconditioning)
- Non differentiable objective functions
- Multiple objectives

Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)
- Sensitivity to parameter initialization (no-preconditioning)
- Non differentiable objective functions
- Multiple objectives
- Sensitivity to noise

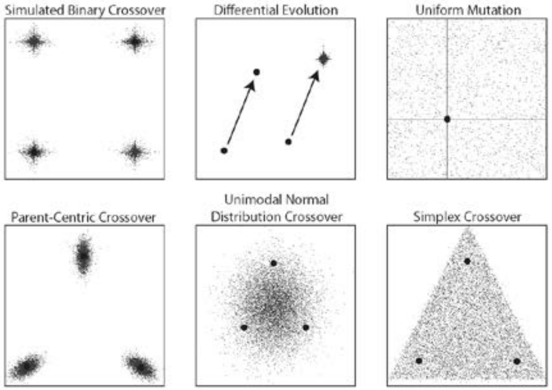
Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)
- Sensitivity to parameter initialization (no-preconditioning)
- Non differentiable objective functions
- Multiple objectives
- Sensitivity to noise

BORG [Hadka and Reed 2012; Reed et al. 2013]

a MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM



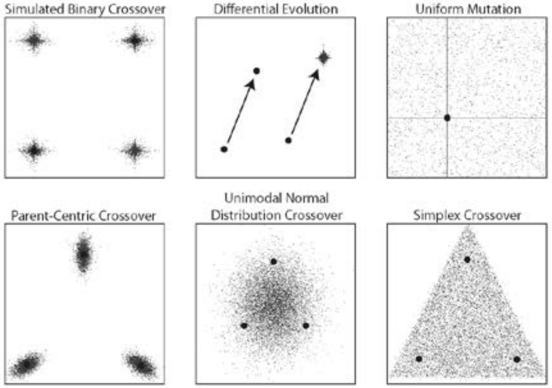
BORG is self-adaptive and employs

- ***multiple search operators*** adaptively selected during the optimization
- ***e-dominance archiving*** with internal operators to detect search stagnation
- ***randomized restarts*** to escape local optima

Selecting the optimization algorithm

Key problem features

- High dimensional search spaces (rich parameterizations)
- Complex search spaces (many local minima)
- Sensitivity to parameter initialization (no-preconditioning)
- Non differentiable objective functions
- Multiple objectives
- Sensitivity to noise



BORG [Hadka and Reed 2012; Reed et al. 2013]

a MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM

BORG is self-adaptive and employs

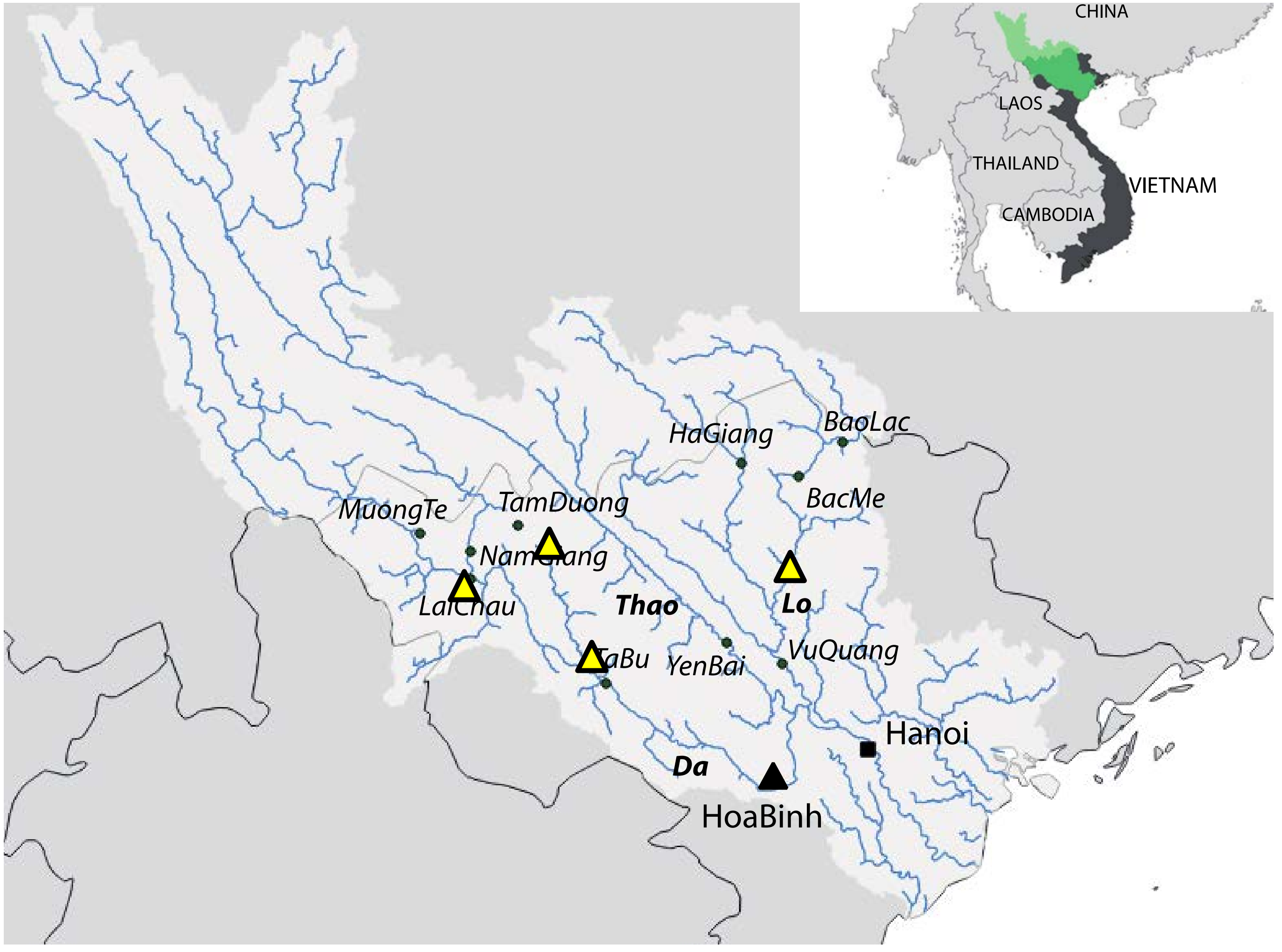
- ***multiple search operators*** adaptively selected during the optimization
- ***e-dominance archiving*** with internal operators to detect search stagnation
- ***randomized restarts*** to escape local optima

EMODPS : Evolutionary Multiobjective Direct Policy Search

Giuliani et al. [2015]. Journal of Water Resources Planning and Management

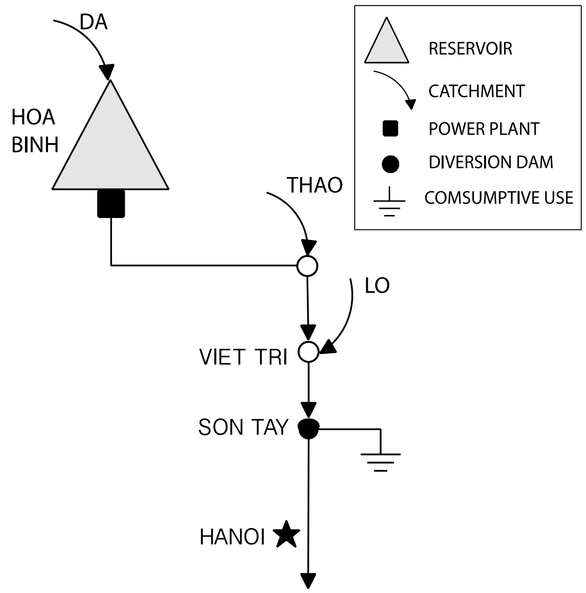
From a more practical angle

Red-Thai Binh River System - Vietnam



Integrated Management of Red-Thai Binh Rivers System (IMRR) funded by the Italian Ministry of Foreign Affairs http://www.imrr.info/

Hoa Binh reservoir - Vietnam



Main characteristics

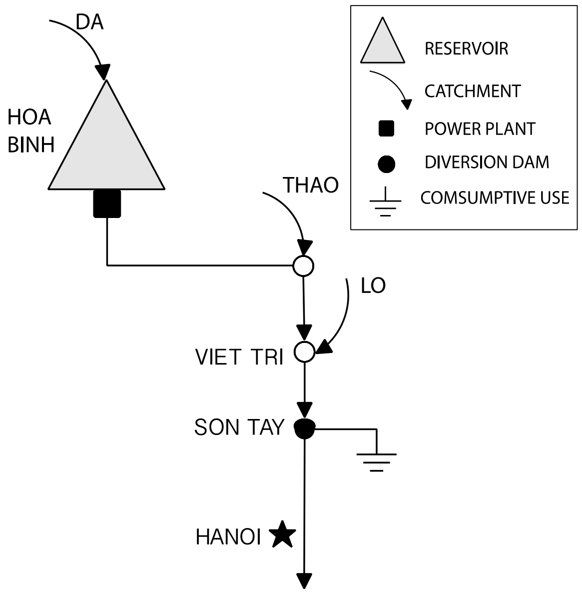
- Catchment area 52,000 km^2
- Active capacity 6 x 10^9 m^3
- 8 penstocks 2,360 m^3/s (240 MW)
- 12 bottom gates 22,000 m^3/s
- 6 spillways 14,000 m^3/s
- 15% national energy (7,800 GWh)

Operating objectives

- Hydropower production
- Flood control (Hanoi)

source: IWRP2008

Experimental Setting: ANN vs RBF



STATE VECTOR (n_x=5)

- 2 time indexes (sin, cosin)
- Storage
- Previous day inflow to reservoir
- Previous day lateral inflow

CONTROL VECTOR (n_u=1)

- release from the reservoir

ALGORITHM SETTING and **RUNNING**

- Default Borg MOEA parameterization [Hadka and Reed 2013]
- NFE = **500,000** per replication
- **20** replications to avoid dependence on randomness (seeds)
- Historical horizon 1962-1969, which comprises normal, wet and dry years

Giuliani et al. [2015]. Journal of Water Resources Planning and Management

Policy performance – operating objectives

ANN
RBF

Hydropower - kWh/d

Floods – cm^2/d

Giuliani et al. [2015]. Journal of Water Resources Planning and Management

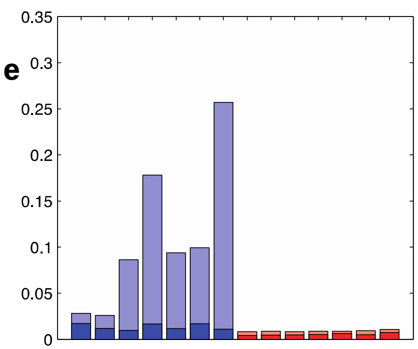
Policy performance – front approximation quality

ANN
RBF

Hydropower - kWh/d

Floods – cm^2/d

Solid = best
Transparent = average

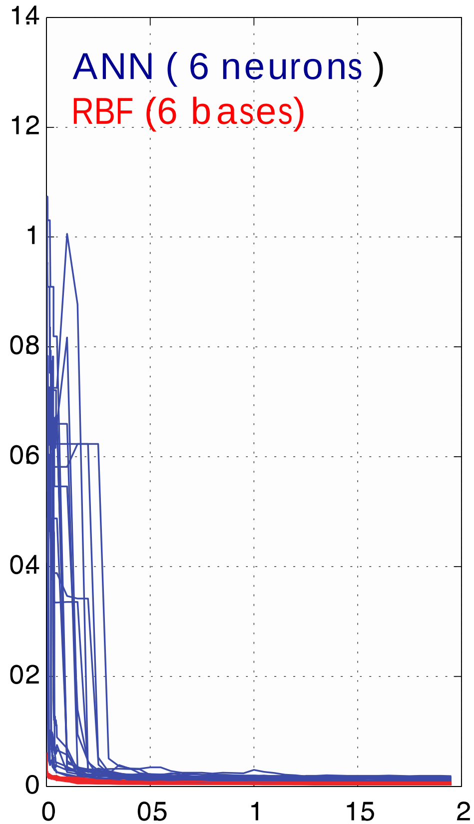


CONVERGENCE

CONSISTENCY

DIVERSITY

Run time search dynamics (NFA = 2M)



NFA (x10⁶)

NFA ($x10^6$)

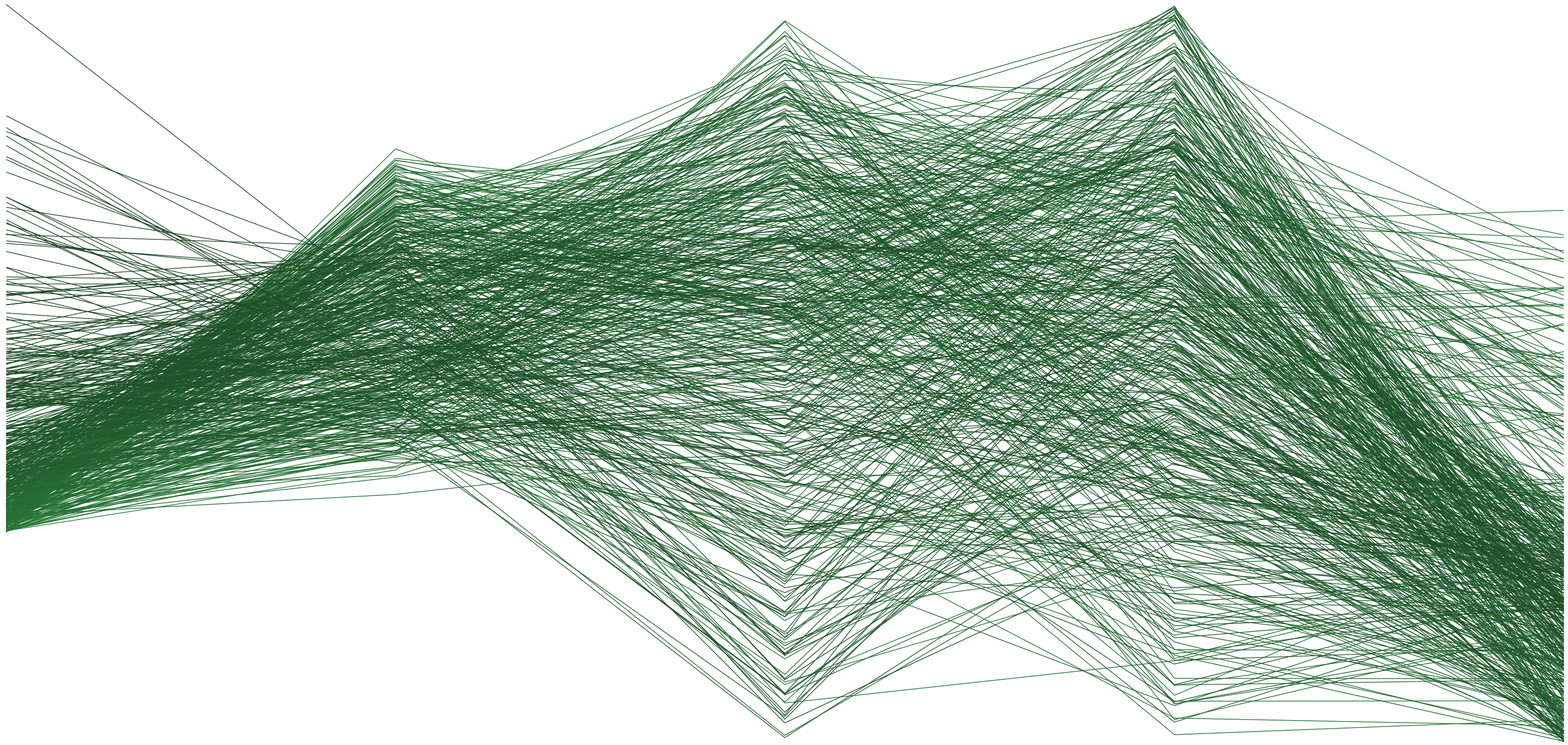
NFA ($x10^6$)

CONVERGENCE

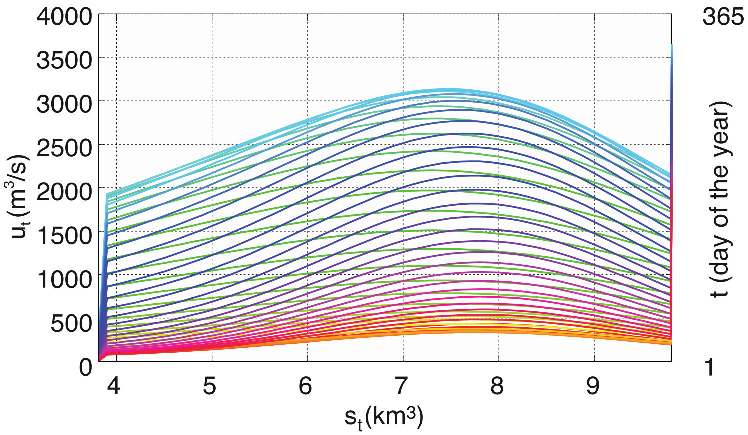
CONSISTENCY

DIVERSITY

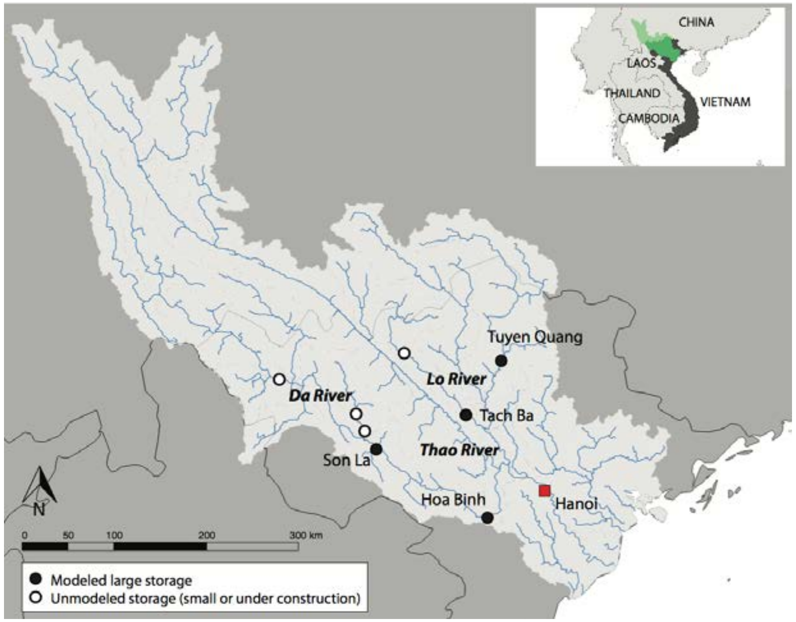
Policy visual analytics

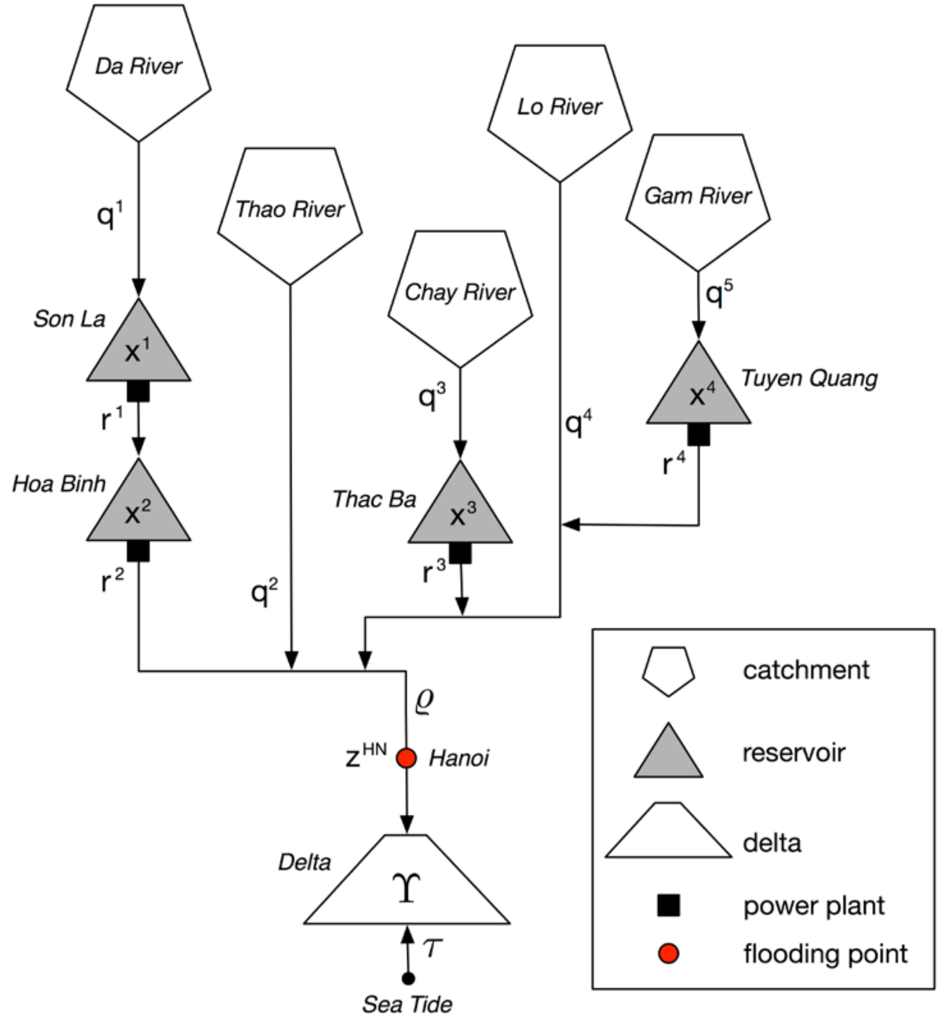


Policy visual analytics



EMODPS scalability: system dimensionality



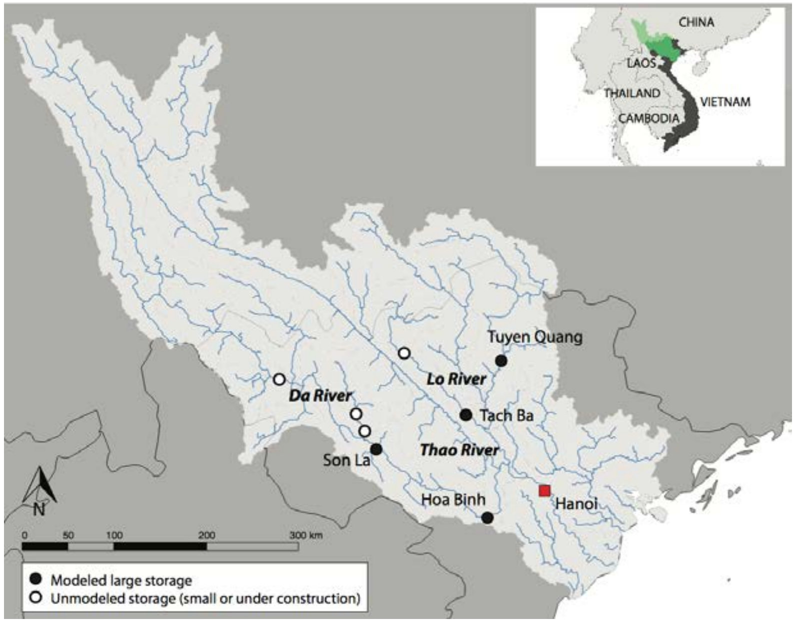


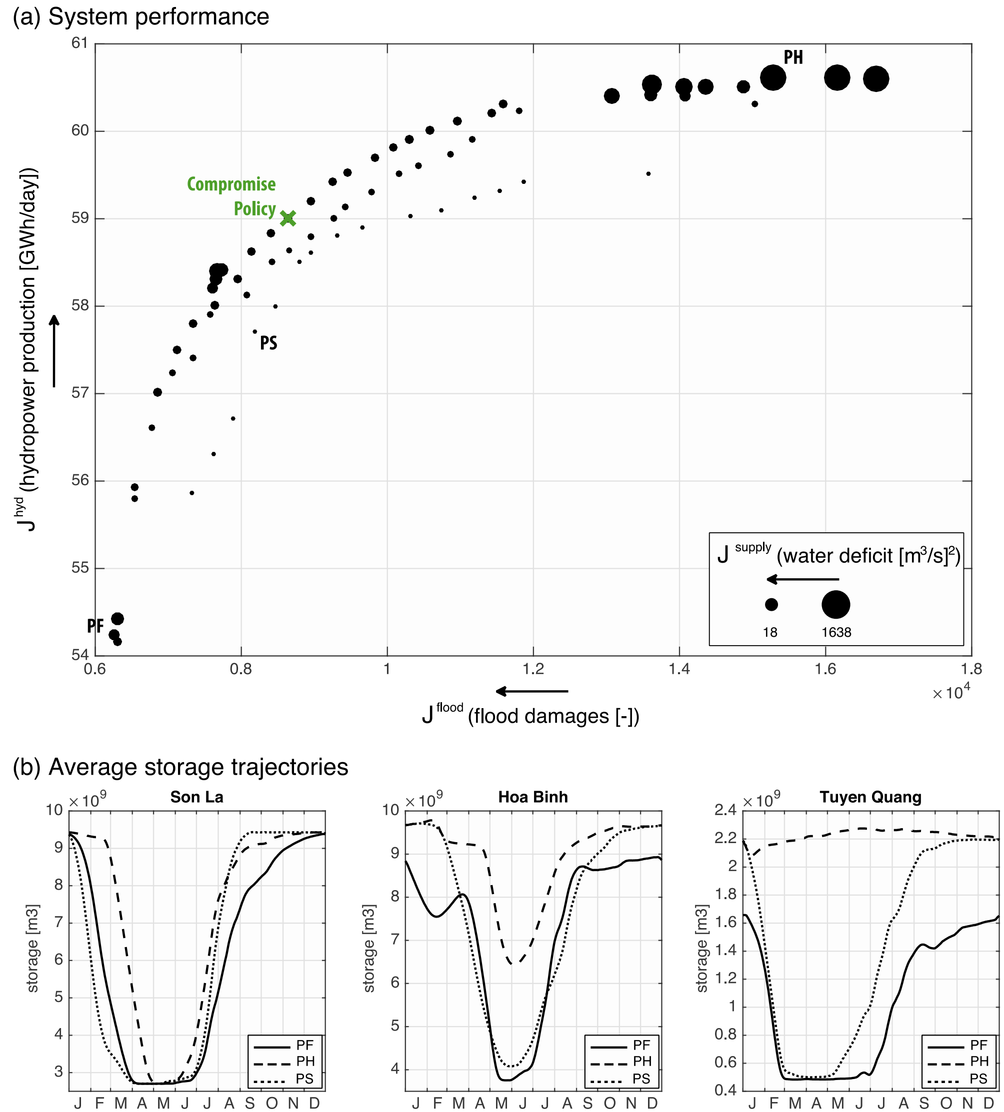
Problem complexity:

- 4 reservoirs
- 5 sub-catchments
- 176 decision variables (policy parameters)
- 3 competing objectives

Giuliani et al. [2017]. IEEE Transactions on Control System Technology

EMODPS scalability: system dimensionality



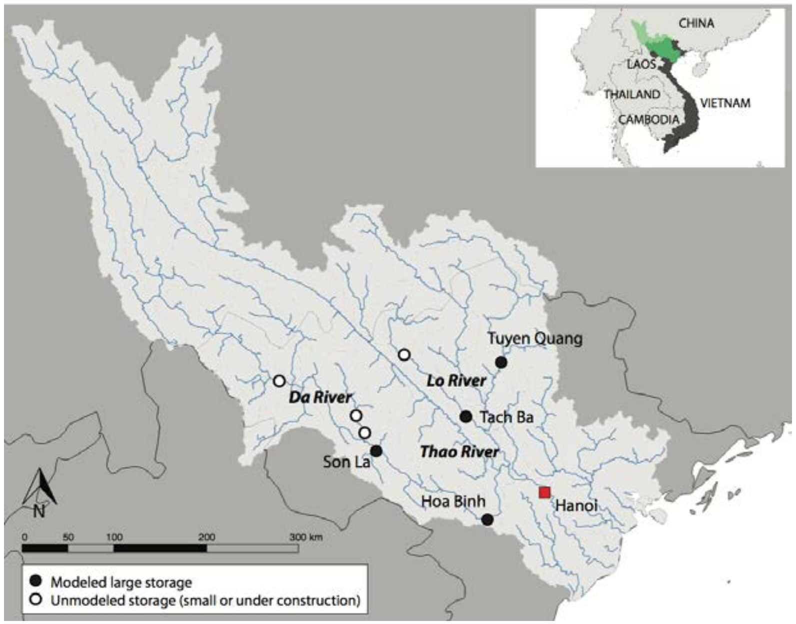


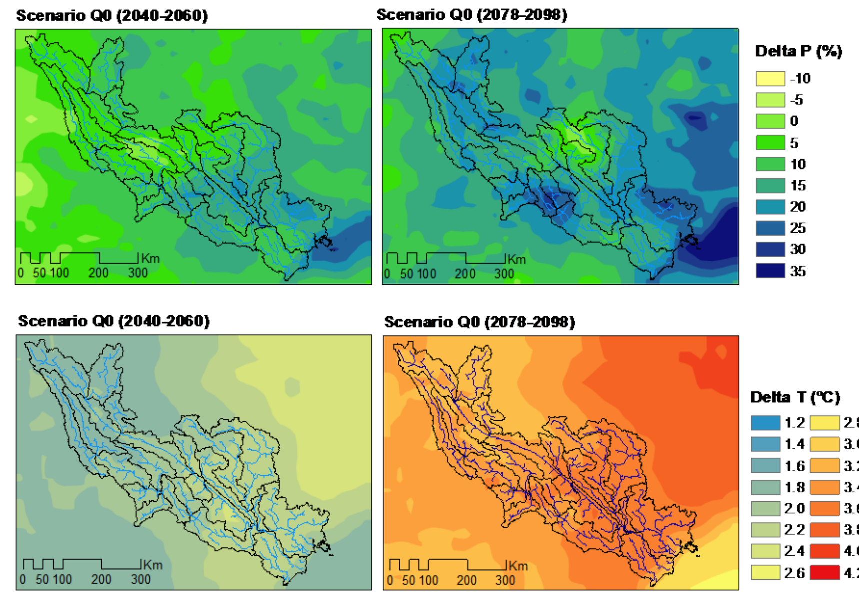
Problem complexity:

- 4 reservoirs
- 5 sub-catchments
- 176 decision variables (policy parameters)
- 3 competing objectives

Giuliani et al. [2016]. IEEE Transactions on Control System Technology

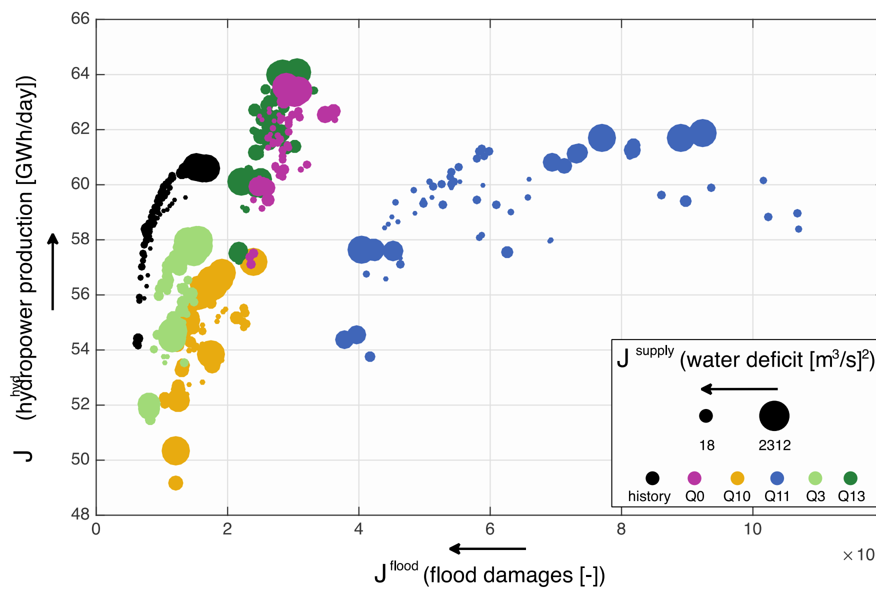
EMODPS scalability: multiple scenarios





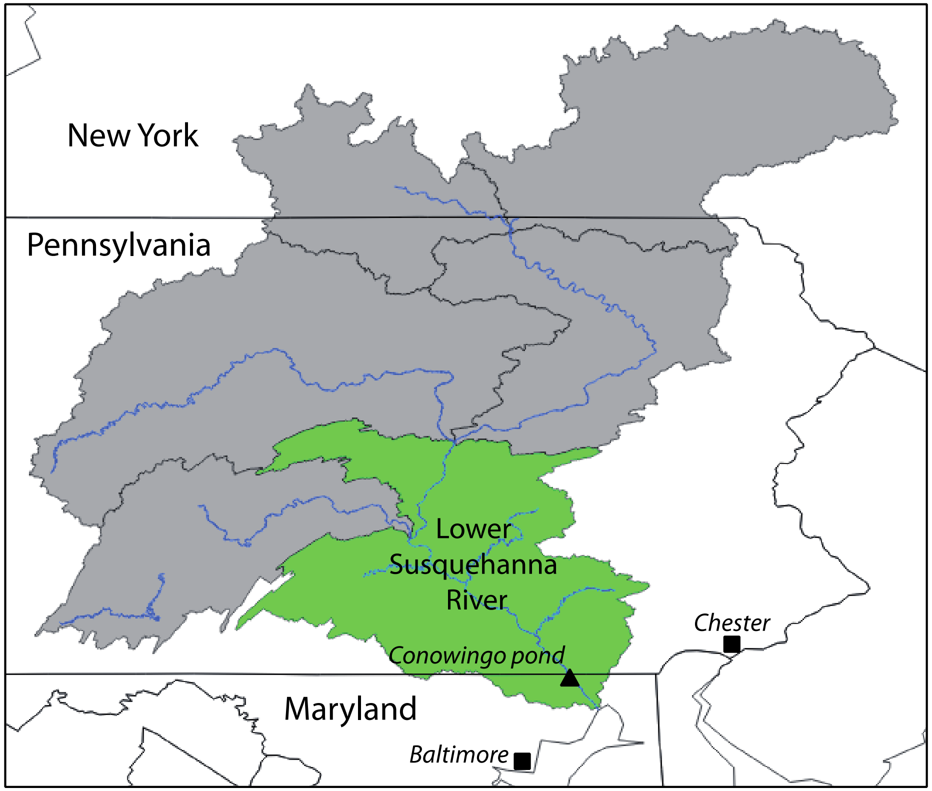
Problem complexity:

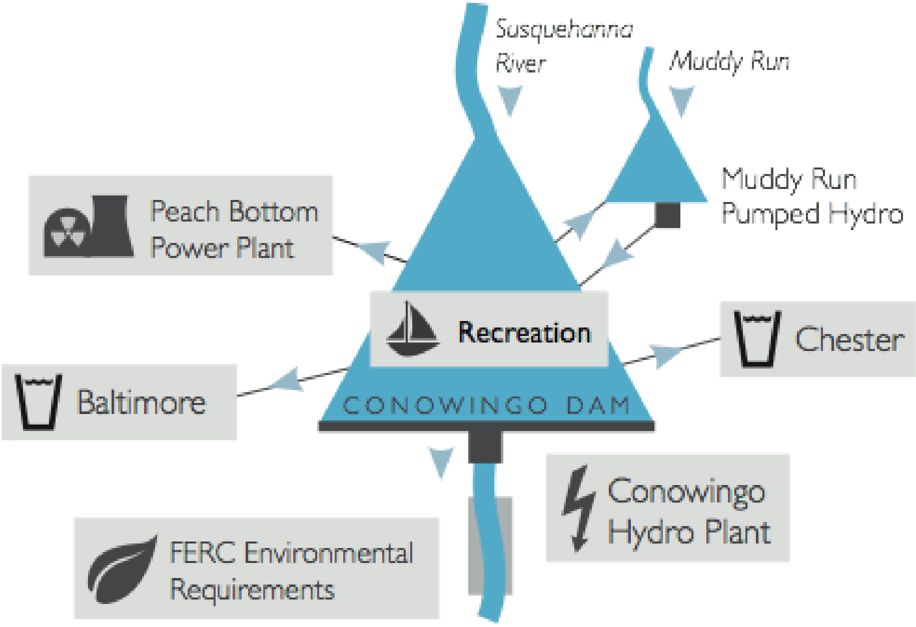
- 4 reservoirs
- 5 sub-catchments
- 176 decision variables (policy parameters)
- 3 competing objectives



Giuliani et al. [2016]. Environmental Research Letter

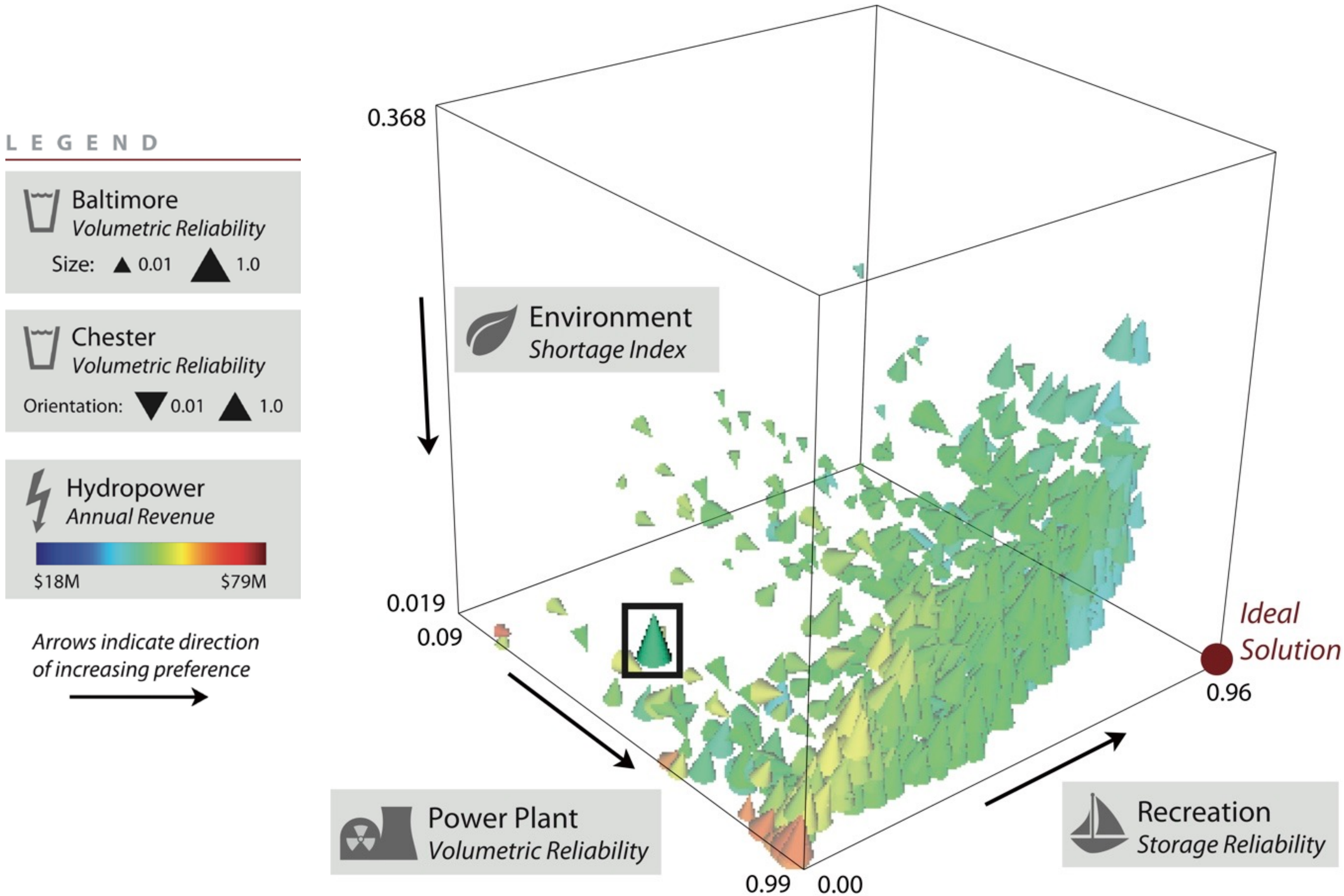
EMODPS scalability: number of objectives





Giuliani et al. [2015]. Water Resources Research

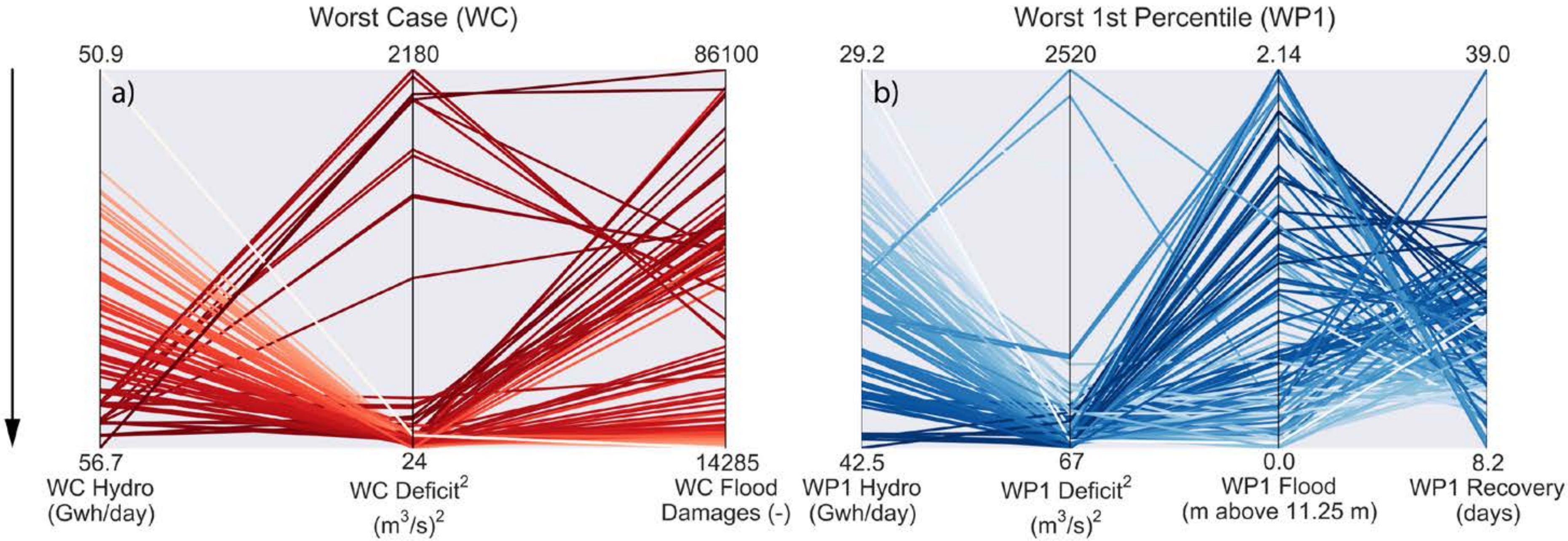
EMODPS scalability: number of objectives



Giuliani et al. [2015]. Water Resources Research

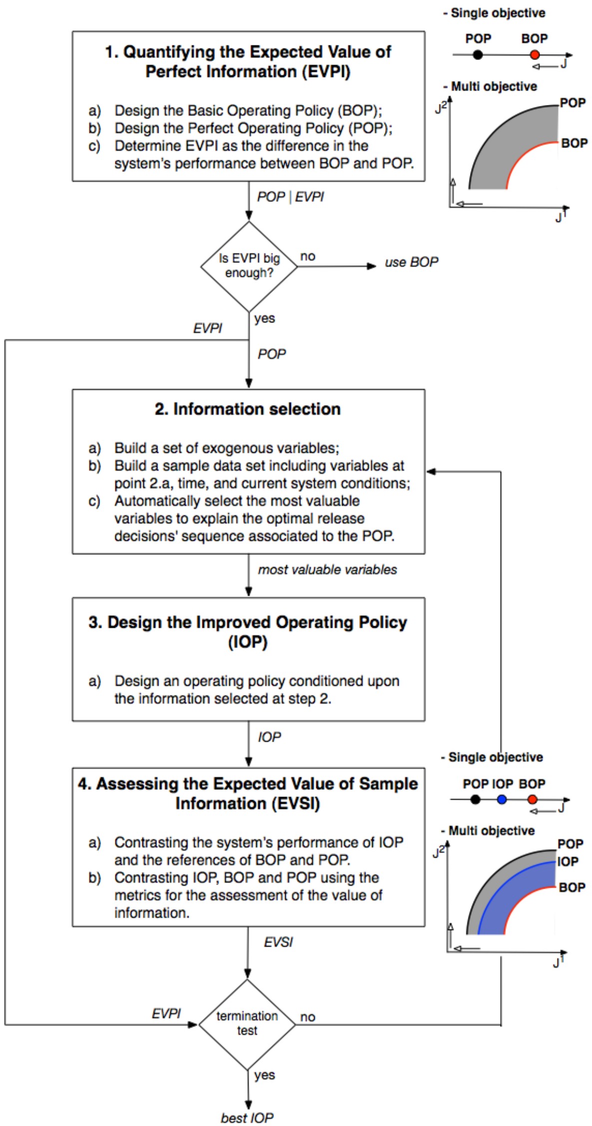
EMODPS scalability: rival problem framings

No constraints on the objective shape = comparing many alternative problem formulations is possible

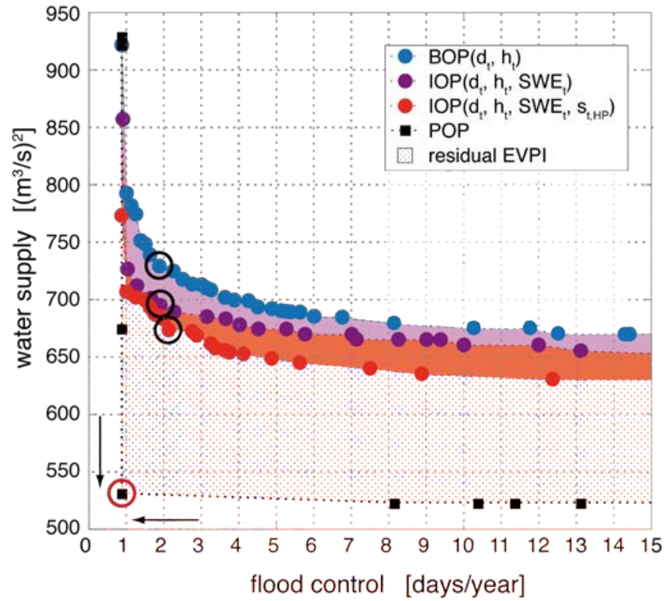


Quinn et al. [2017]. Water Resources Research (under review)

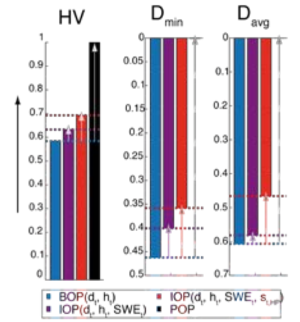
EMODPS scalability: direct use of information



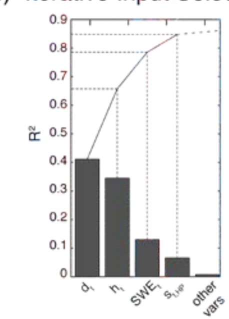
(a) Comparison of Perfect, Basic and Improved Operating Policies performance



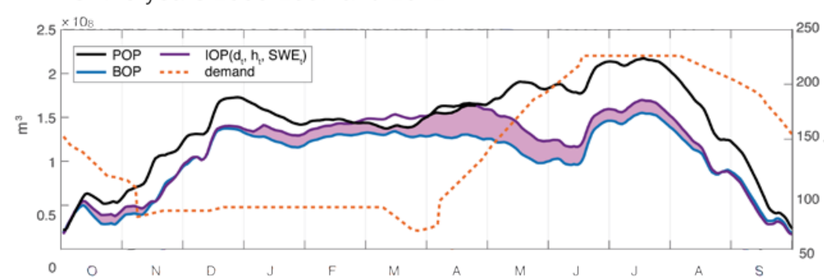
(b) Metrics for the assesment of the Value of Information



(c) Iterative Input Selection

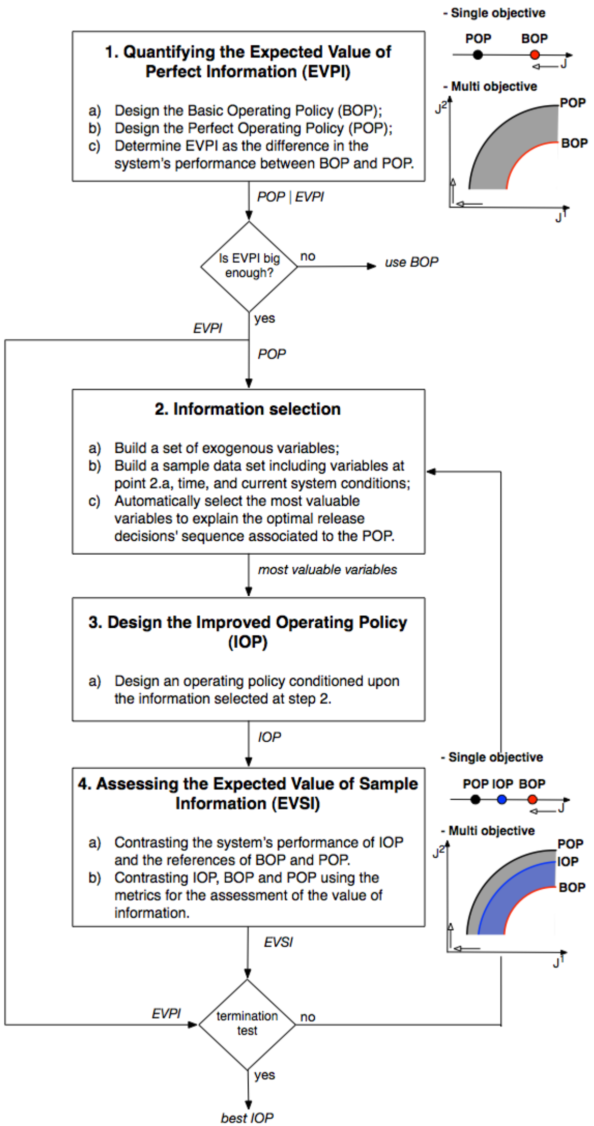


(b) Storage trajectory cyclostationary mean for the years 2006-2007 and 2012

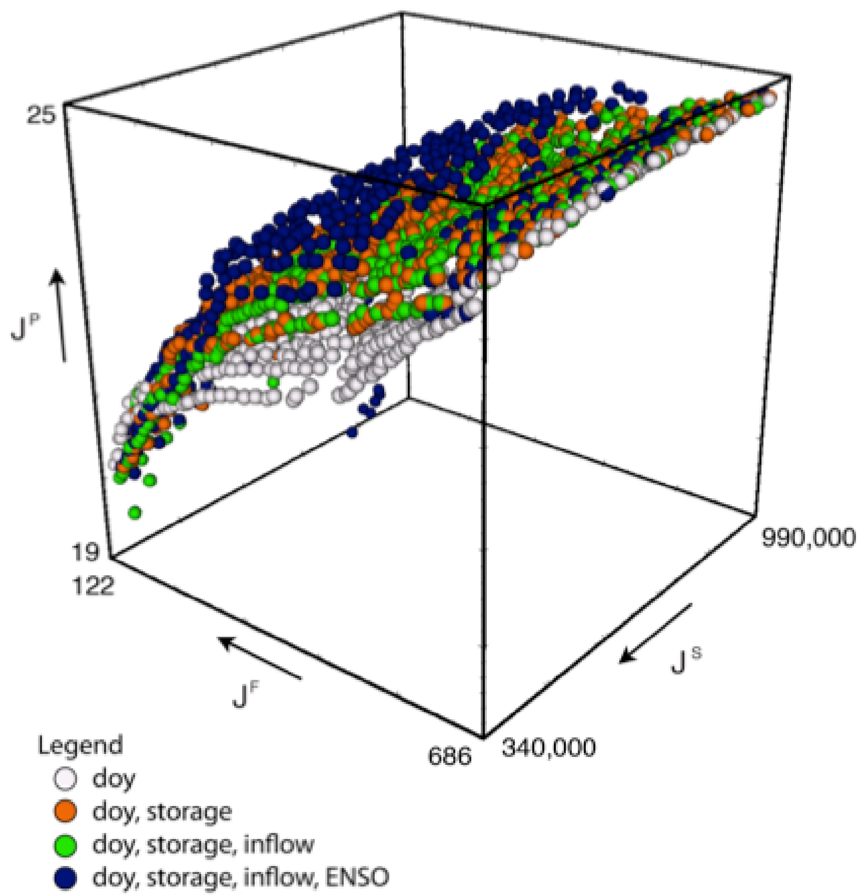


Giuliani et al. [2015]. Water Resources Research Denaro et al. [2017]. Advances in Water Resources

EMODPS scalability: direct use of information

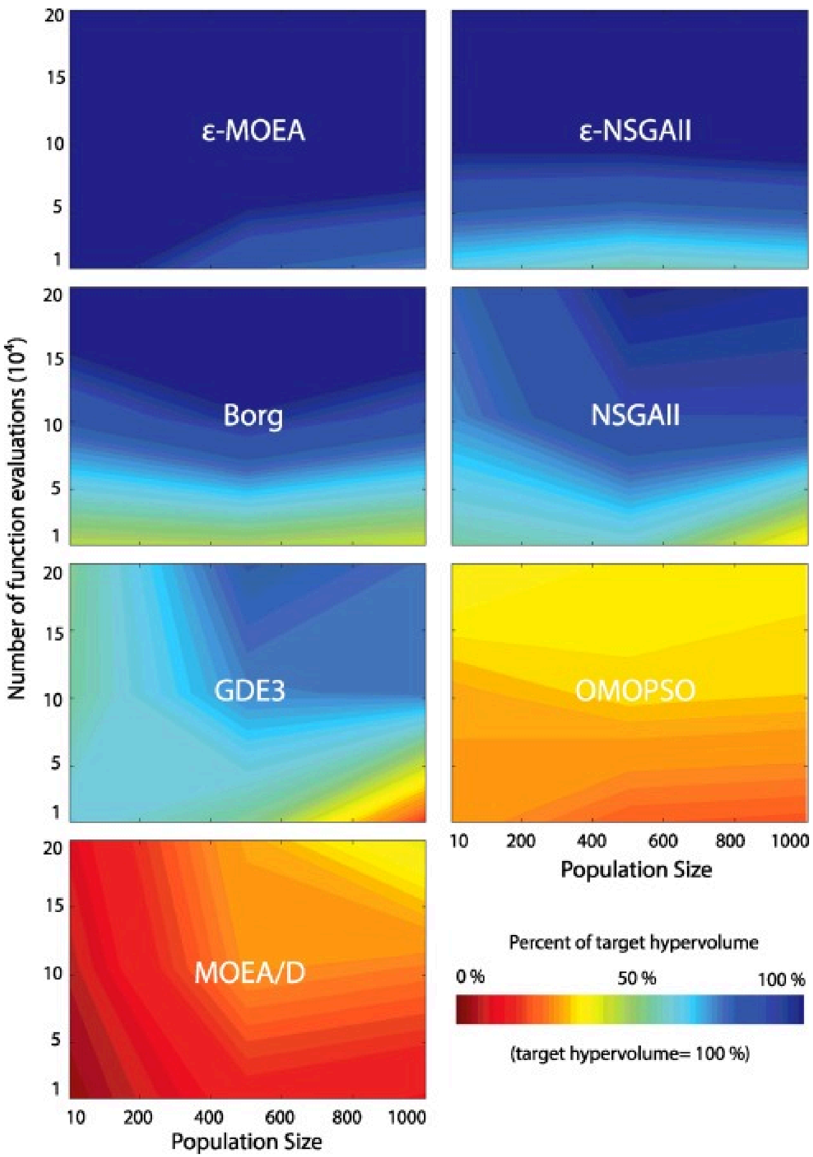


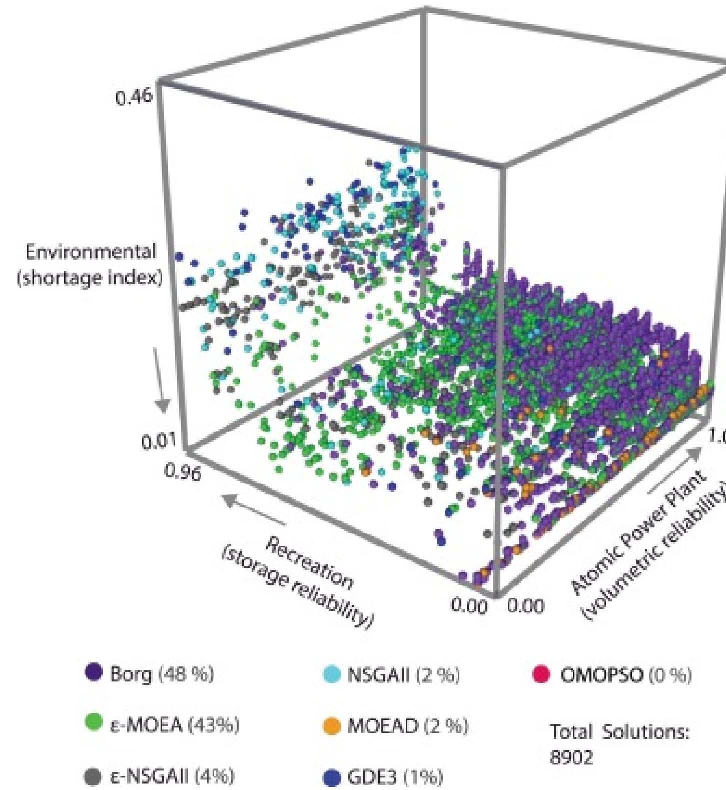
Policy conditioned on ENSO indices

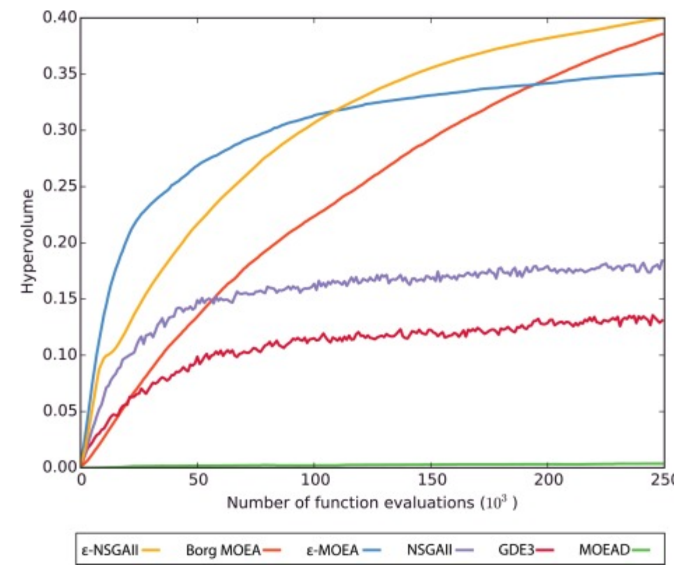


Giuliani et al. [2016]. in preparation

EMODPS diagnostics







Salazar et al. [2016]. Advances in Water Resources

Conclusions

- MODPS framework is an interesting alternative to SDP familiy methods for a number of good reasons

1. No discretization required: **NO curse of dimensionality**;

2. Does not require separability in time of constraints and objective functions (e.g. duration curves): **NO curse of dimensionality**;

3. Can easily include any model-free information as long as this is control-indipendent: **NO curse of modelling**;

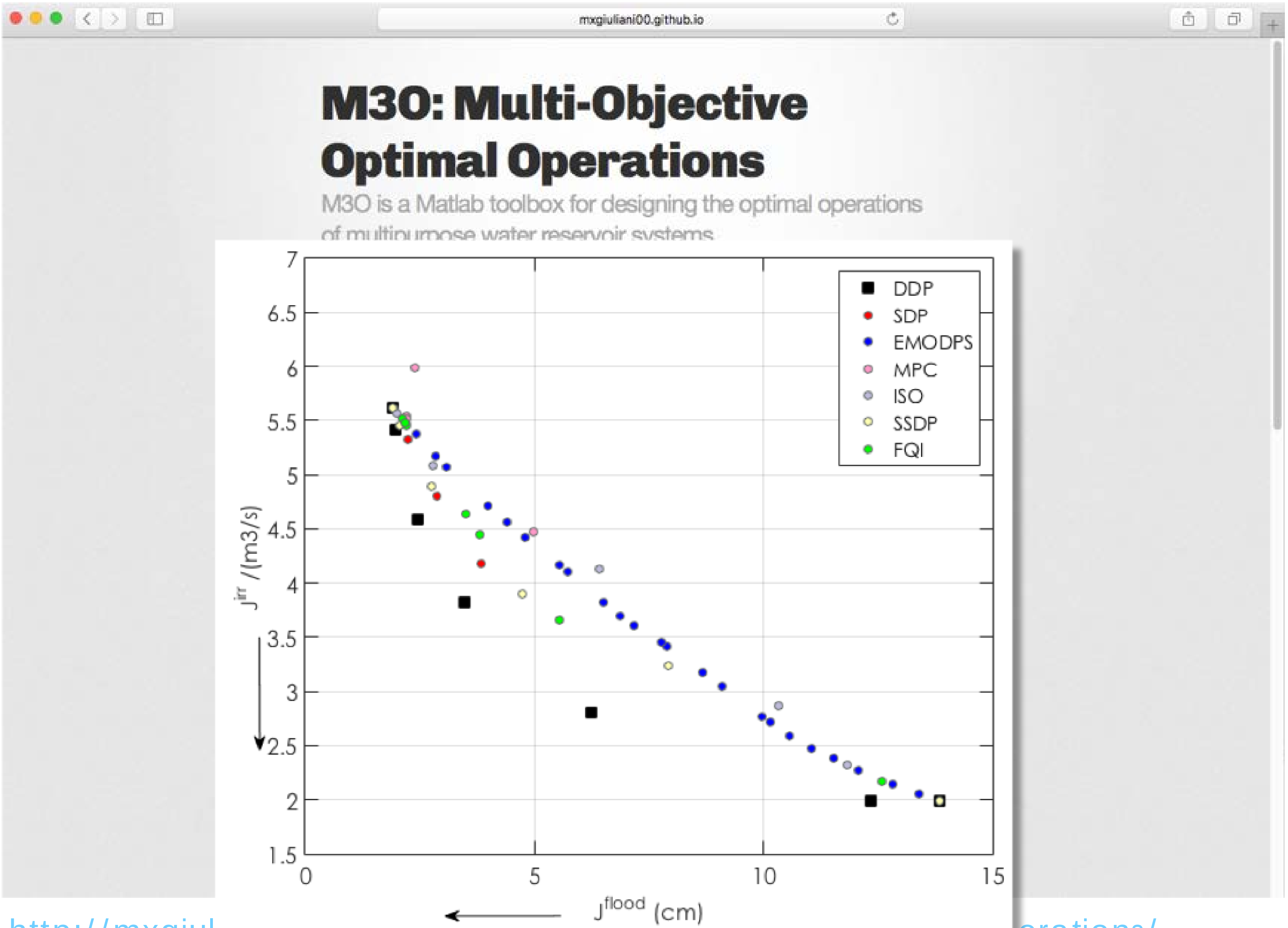
4. Can be combined with any simulation model (also high fidelity ones): **NO curse of modelling**;

5. Can be easily combined with truly multi-objective optimization algorithms: **NO curse of the multiple objectives**.

M3O: a toolbox for reservoir operation design

http://mxgiuliani00.github.io/M3O-Multi-Objective-Optimal-Operations/

M3O: a toolbox for reservoir operation design



http://mxgiuliani00.github.io/M3O-Multi-Objective-Optimal-Operations/

Ongoing projects using EMODPS

Other projects

POLITECNICO MILANO 1863

NRM

Improve the quality of state-of-the-art hydro-climatic forecast capability by targeting the end-users' needs (including **hydropower**) of decision support **EU H2020**

www.imprex.eu

Survey on Weather and Climate Services for Hydropower

The IMPREX project (IMproving PRedictions and management of hydrological EXtremes) is a research project supported by the European Commission under the Horizon 2020 programme (http://www.imprex.eu).

IMPREX investigates the value of improving predictions of hydrometeorological extremes at short-, medium- and long-range in a number of water sectors, including hydropower.

The project's rationale is based on the fact that we can, and we should, learn from today's experience and practice to better anticipate the needs (and trigger the opportunities) of tomorrow.

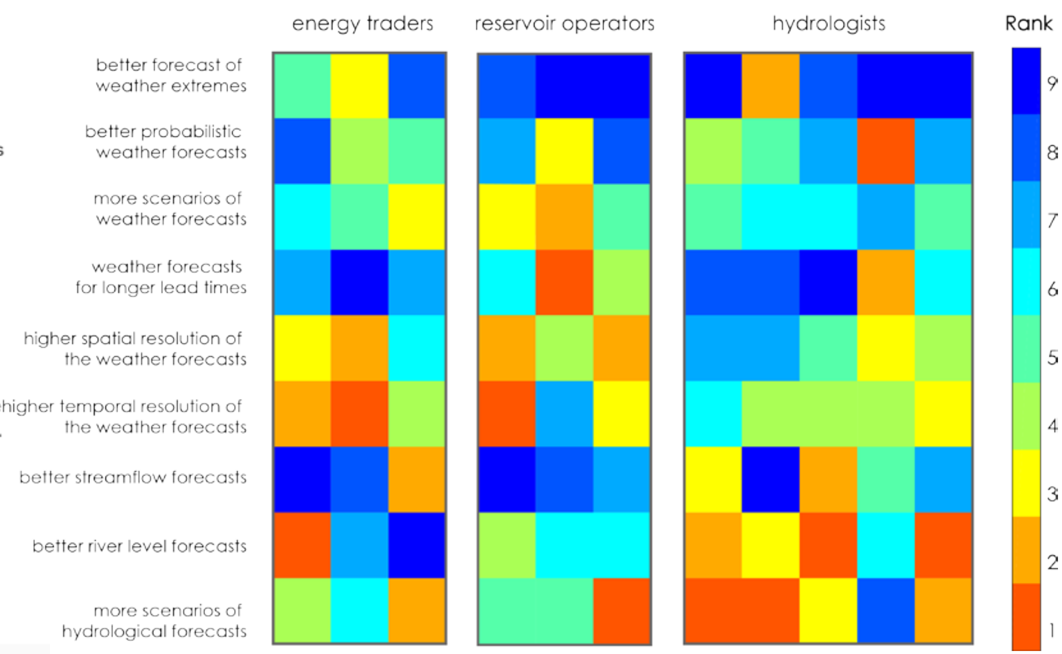
With this particular survey, we aim to collect your viewpoint on the need for and the value of weather and climate services for the hydropower sector in Europe and internationally. The purpose is to help us to improve current forecast products and enhance their usefulness.

Filling in the questionnaire will only take about 10 minutes of your time but will be extremely valuable for the IMPREX project.

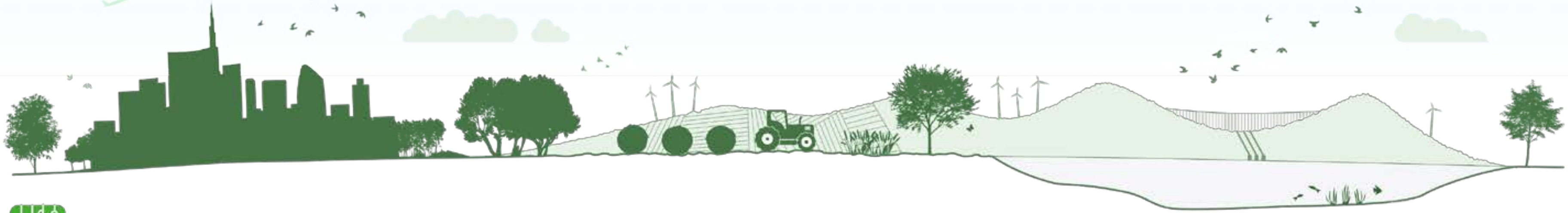
All answers will be treated confidentially and anonymously.

Thank you in advance,

The IMPREX WP8 group



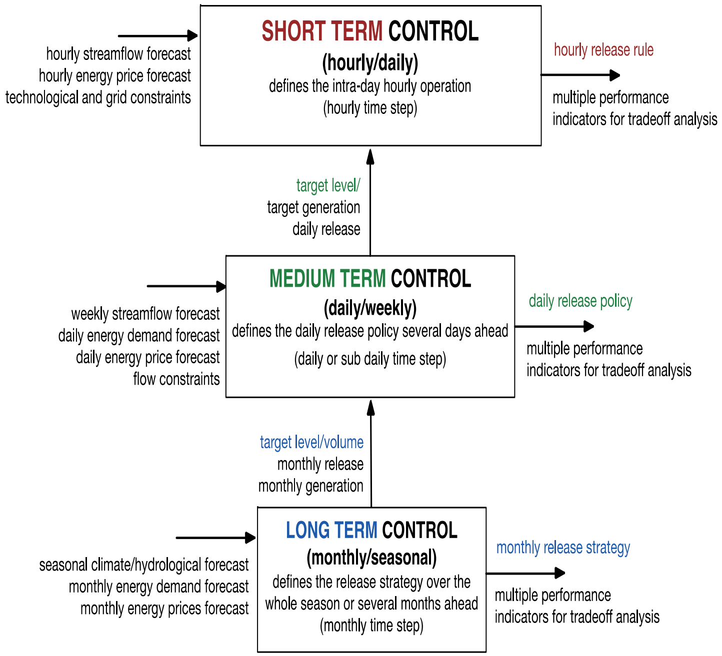
Other projects



NRM

www.imprex.eu

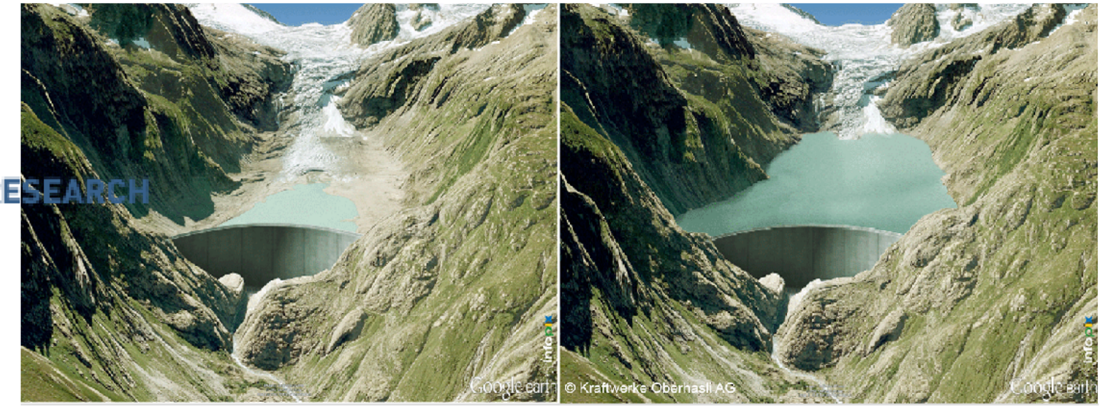
Improve the quality of state-of-the-art hydro-climatic forecast capability by targeting the end-users' needs (including **hydropower**) of decision support **EU H2020**



Anghileri et al [2016]. Water Resources Research

SCCER SoE

SWISS COMPETENCE CENTER for ENERGY RESEARCH
SUPPLY of ELECTRICITY



SCCER SoE

SWISS COMPETENCE CENTER for ENERGY RESEARCH
SUPPLY of ELECTRICITY

In Brief

The aim of the Swiss Competence Center for Energy Research

Mission

The SCCER-SoE is compiling answers to the following

- Is CO_2

Research Partners

ETH zürich, HOCHSCHULE LUZERN, unine, WSL, PAUL SCHERRER INSTITUT PSI, Unil, eawag, EPFL, UNIVERSITÉ DE GENÈVE, HSR, Hes·so VALAIS WALLIS

Industry Partners

axpo, BKW, SIG, nagra., ALSTOM, GEO ENERGIE SUISSE, SULZER, ALPIQ, sarmap, KWO

SCCER SoE

Background

Timescale

In cooperation with the CTI

Energy funding programme
Swiss Competence Centers for Energy Research

www.sccer-soe.ch

Other projects

NRM

DAFNE

A Decision-Analytic Framework to explore the **water-energy-food nexus** in complex and transboundary water resources systems of fast growing developing countries

EU H2020

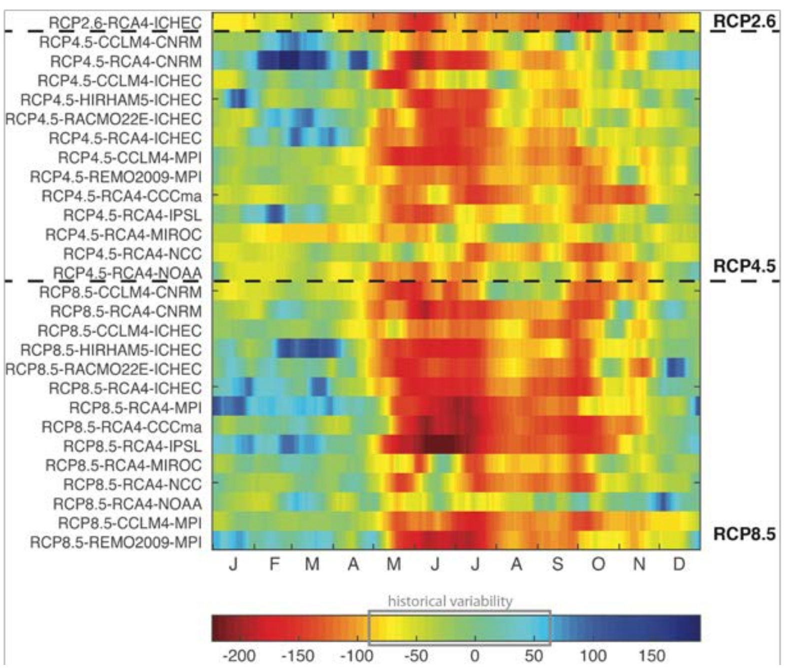
Culley et al [2016]. Water Resources Research

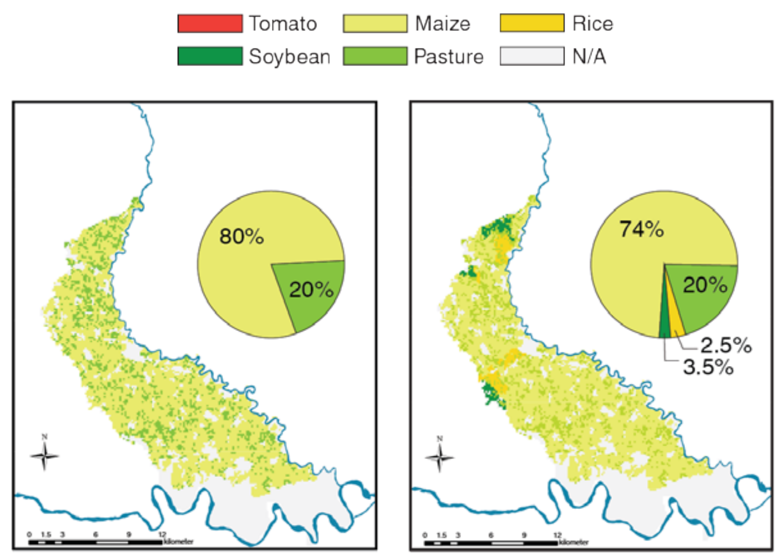
Giuliani & Castelletti [2016]. Climatic Changes

Other projects

NRM

SOft path WATer management adaptation to CHanging climate **Fondazionecariplo**





Giuliani & Castelletti [2016]. Climatic Changes

Giuliani et al [2016]b. Water Resources Research

Other projects

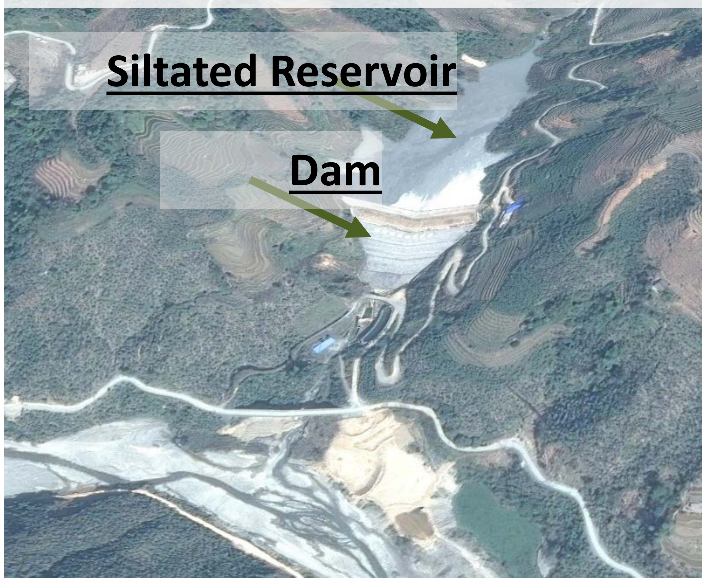
NRM

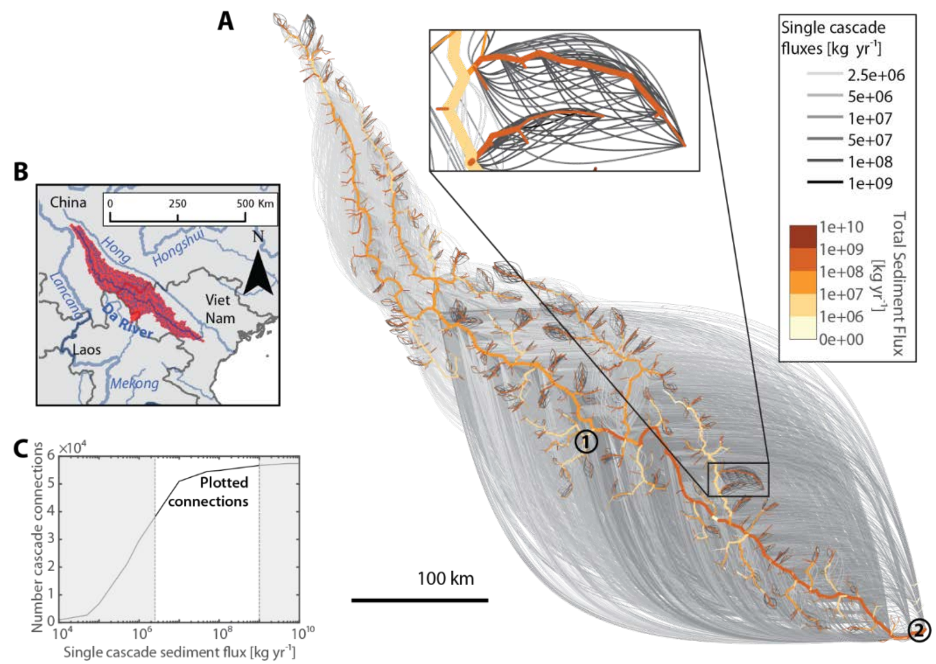
Adaptive Management of Barriers in European Rivers **EU H2020**

AMBER

www.amber.international

Siltated Reservoir, Da River Basin, PRC





Schmitt et al [2015]. Water Resources Research

POLITECNICO
MILANO 1863

www.nrm.deib.polimi.it

References

- J. Zatarain Salazar, P.M. Reed, J.D. Quinn, M. Giuliani, A. Castelletti, Balancing Exploration, Uncertainty and Computational Demands in Many Objective Reservoir Optimization, *Advances in Water Resources,* u.r.
- J.D. Quinn, P.M. Reed, M. Giuliani, A. Castelletti, Rival Framings: A Framework for Understanding how Problem Formulation Uncertainties and Conflicting Preferences Shape Risk Management Tradeoffs in Water Resources Systems, *Water Resources Research*, u.r.
- M. Giuliani, J. D. Quinn, J. D. Herman, A. Castelletti, P.M. Reed, Scalable multi-objective control for large scale water resources systems under uncertainty, *IEEE Transactions on Control Systems Technology*, online, 2017.
- Denaro, D. Anghileri, M. Giuliani, A. Castelletti, Informing the operations of water reservoirs over multiple temporal scales by direct use of hydrometeorological data, *Advances in Water Resources*, 103, 51–63, 2017.
- J. Zatarain Salazar, P.M. Reed, J.D. Herman, M. Giuliani, A. Castelletti, A diagnostic assessment of evolutionary algorithms for multi-objective reservoir control, *Advances in Water Resources* 92, 172–185, 2016.
- M. Giuliani, D. Anghileri, A. Castelletti, P.N. Vu, R. Soncini-Sessa, Large storage operations under climate change: expanding uncertainties and evolving tradeoffs, *Environmental Research Letters*, 11(3), 2016.
- M. Giuliani, A. Castelletti, Is robustness really robust? How different definitions of robustness impact decision-making under climate change, *Climatic Change*, 135(3), 409-424, 2016.
- M. Giuliani, F. Pianosi, A. Castelletti, Making the most of data: an information selection and assessment framework to improve water systems operation. *Water Resources Research* 51(11), 9073–9093, 2015.
- M. Giuliani, A. Castelletti, F. Pianosi, E. Mason, P.M. Reed, Curses, tradeoffs, and scalable management: advancing evolutionary multi-objective direct policy search to improve water reservoir operations. *Journal of Water Resources Planning and Management*, 10.1061/(ASCE) WR.1943-5452.0000570.
- M. Giuliani, J.D. Herman, A. Castelletti, and P.M. Reed, Many-objective reservoir policy identification and refinement to reduce policy inertia and myopia in water management, *Water Resources Research*, 50(4), 3355–3377, 2014.