

PAUL SCHERRER INSTITUT



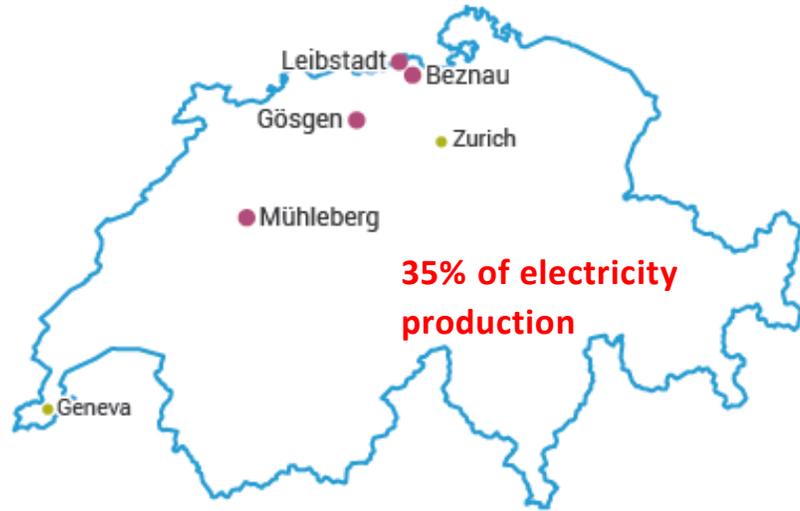
**N. Prasianakis: Head of transport mechanisms group: Laboratory for Waste management**  
In collaboration with R. Haller, L.H. Damiani, M. Mahrous, S. Churakov

# ML workshop meeting 15.06.2021

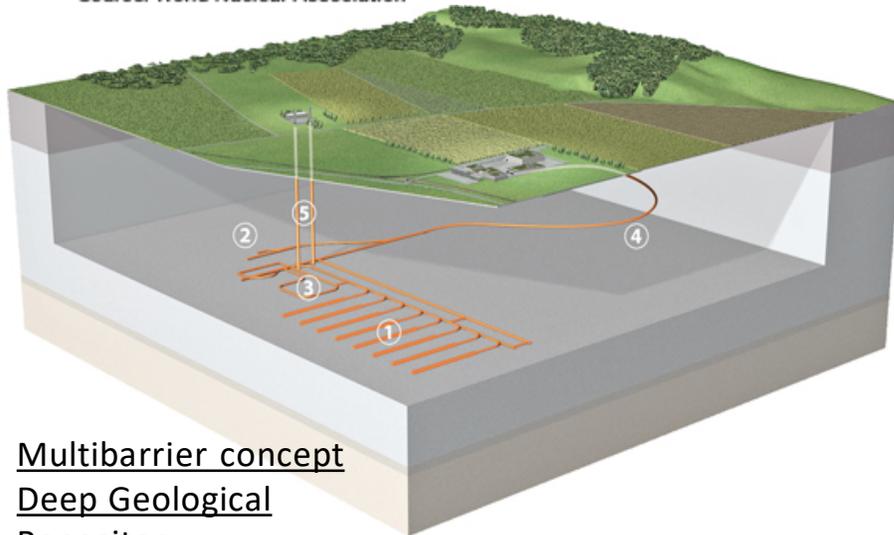
Machine Learning for Digital Twins and multiphysics simulations

# Nuclear Waste Management concept

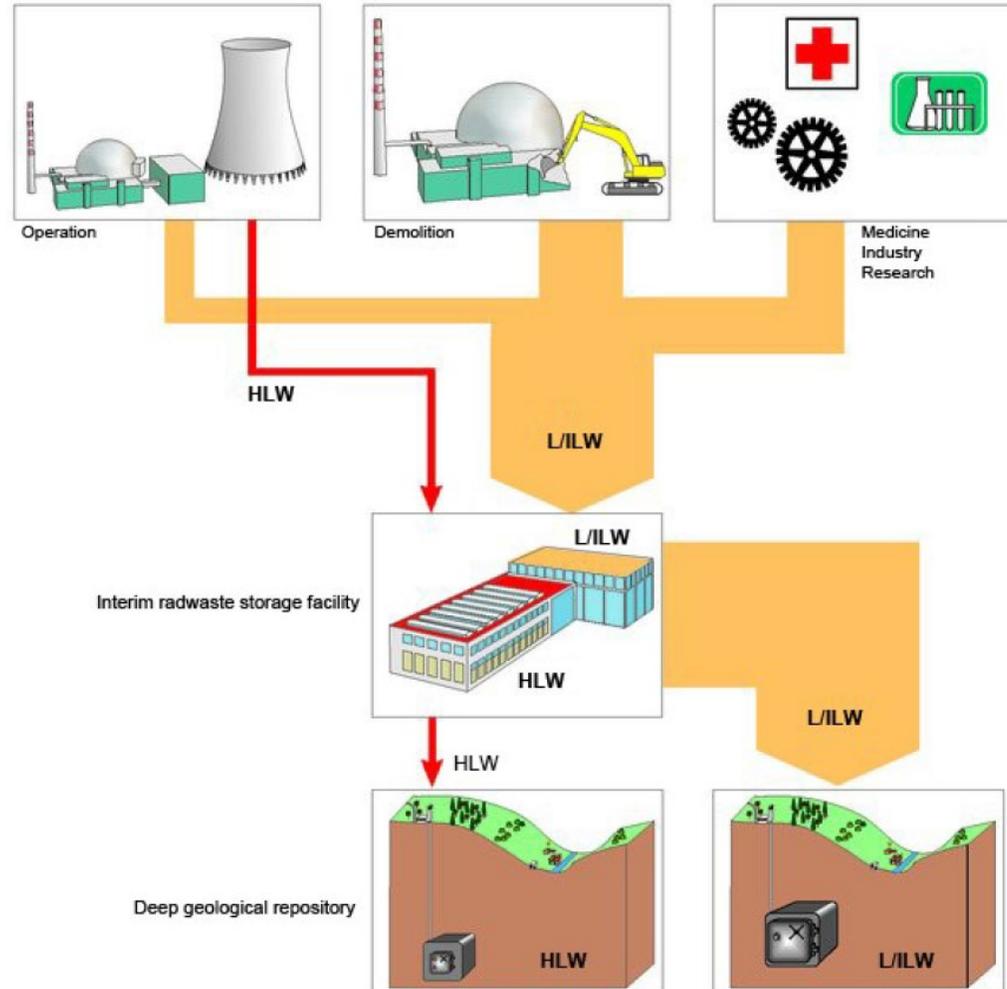
## Nuclear Power Plants in Switzerland



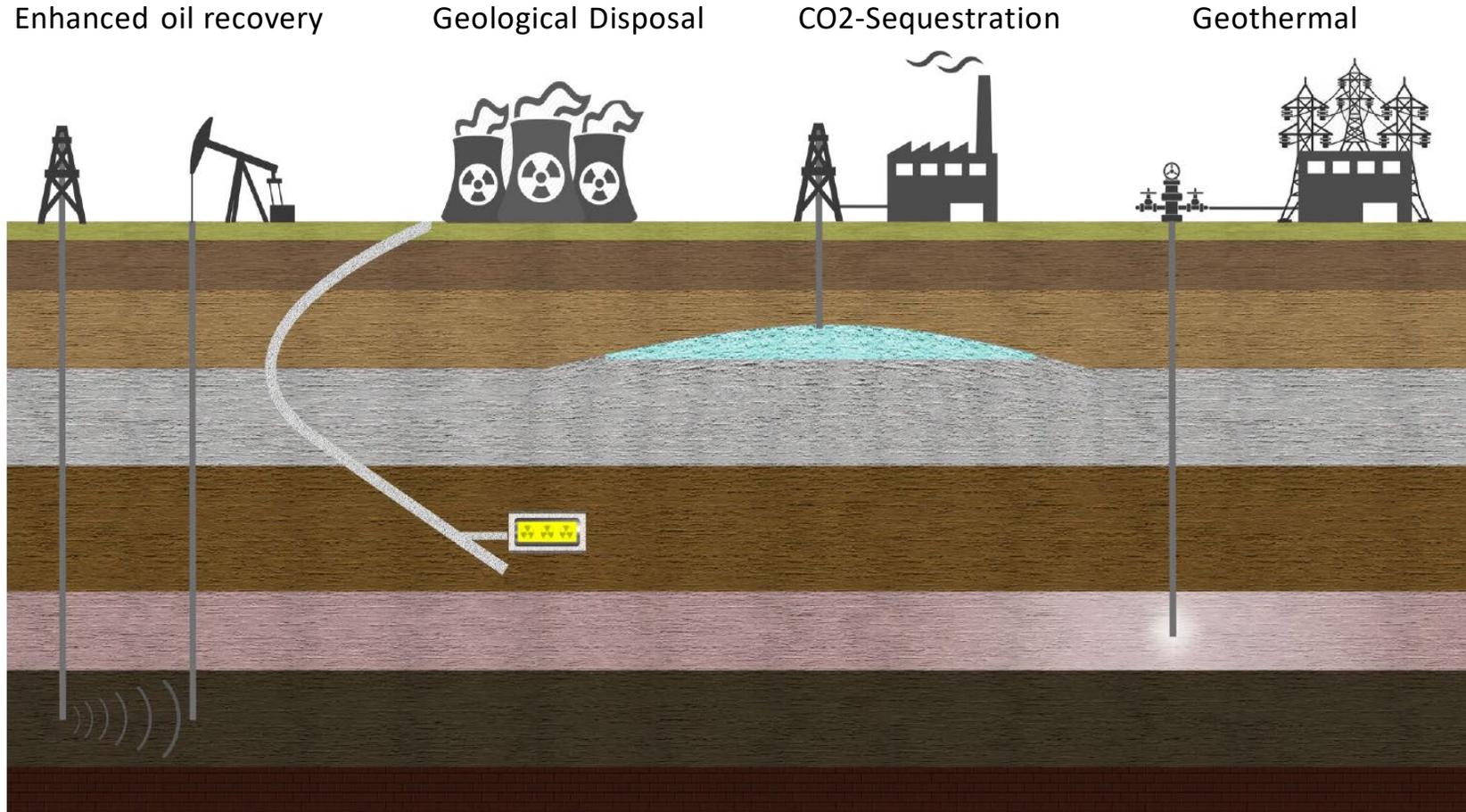
Source: World Nuclear Association



Multibarrier concept  
Deep Geological  
Repository



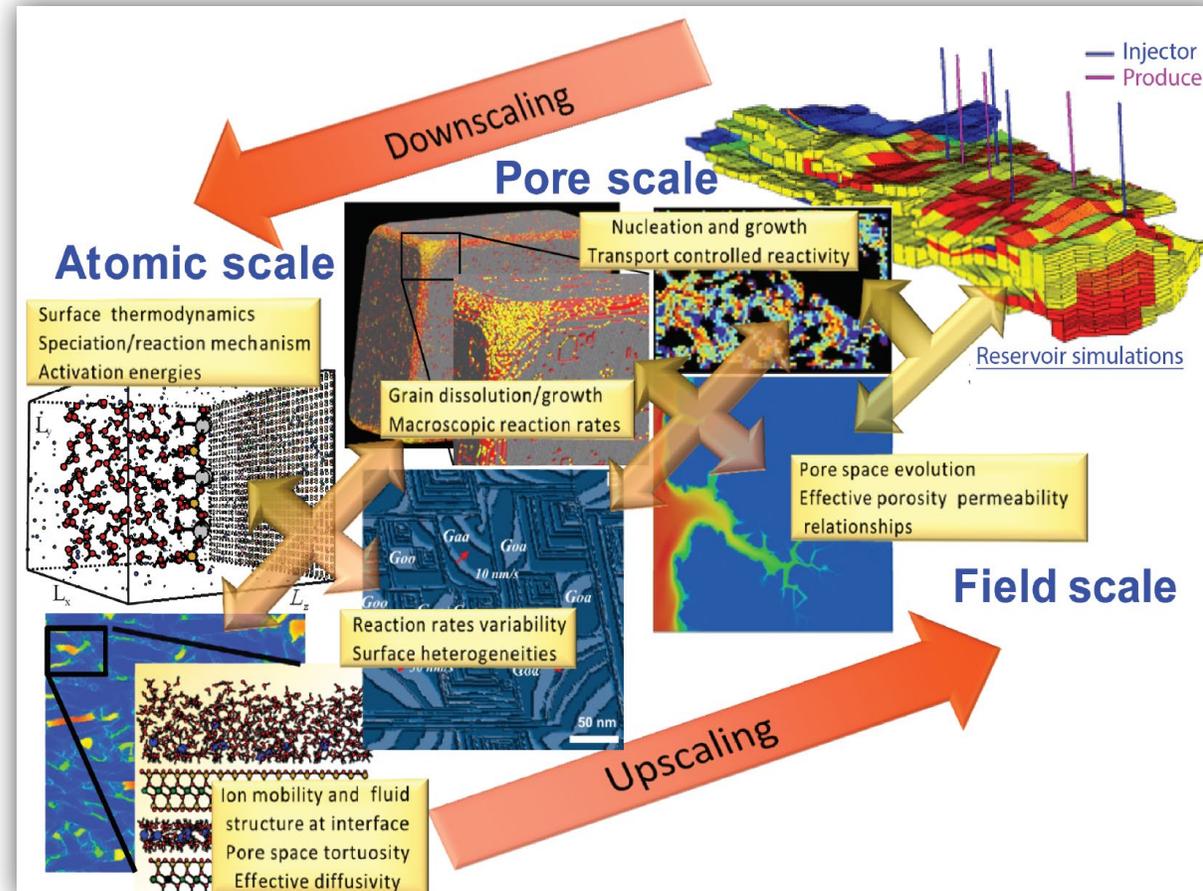
# Subsurface processes are governed by dissolution precipitation processes



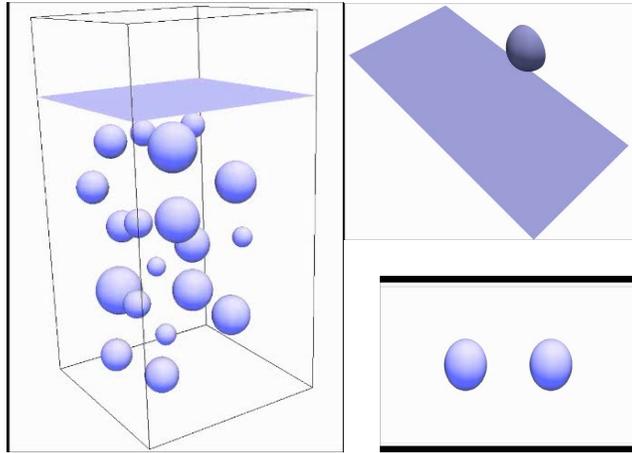
Multiscale description is necessary

# Geochemical evolution of repository is governed by mass transport and phase changes: all scales matter

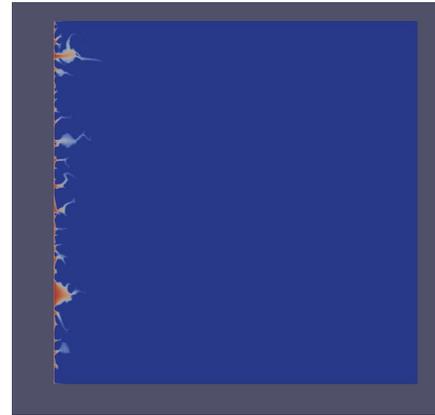
Processes occurring at the atomic- and pore- scale control the evolution of the geochemical systems. Currently, there exist several mature numerical tools, and good process understanding, at each scale.



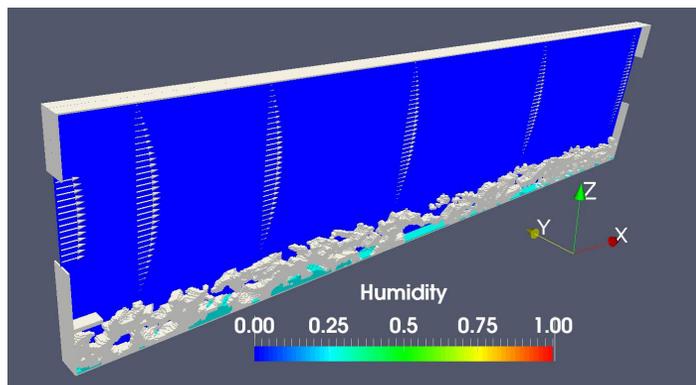
# Lattice Boltzmann activities at PSI



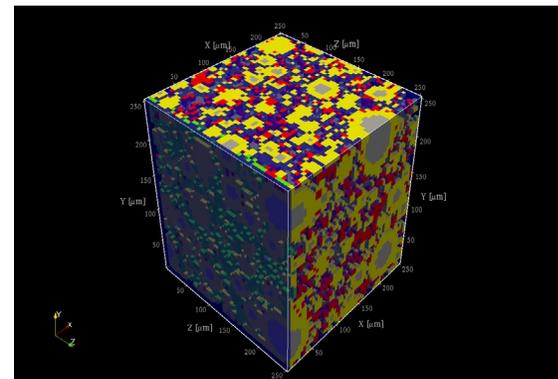
**Multiphase Models  
 (Nuclear reactors, fuel cells)**



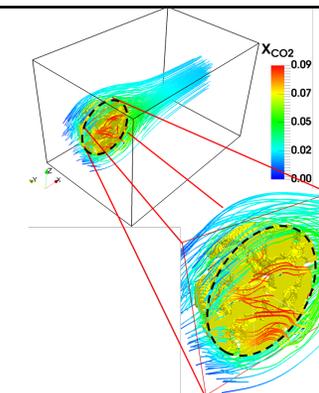
**Geochemical reactions  
 (wormholes during acidification)**



**Evaporation in porous media (fuel cells)**



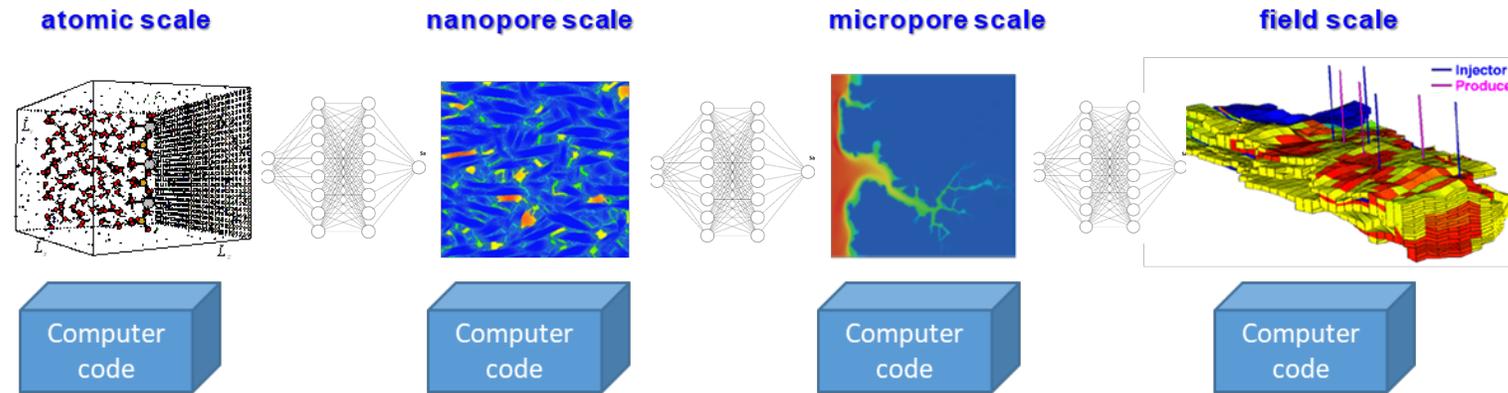
**Cement Evolution**



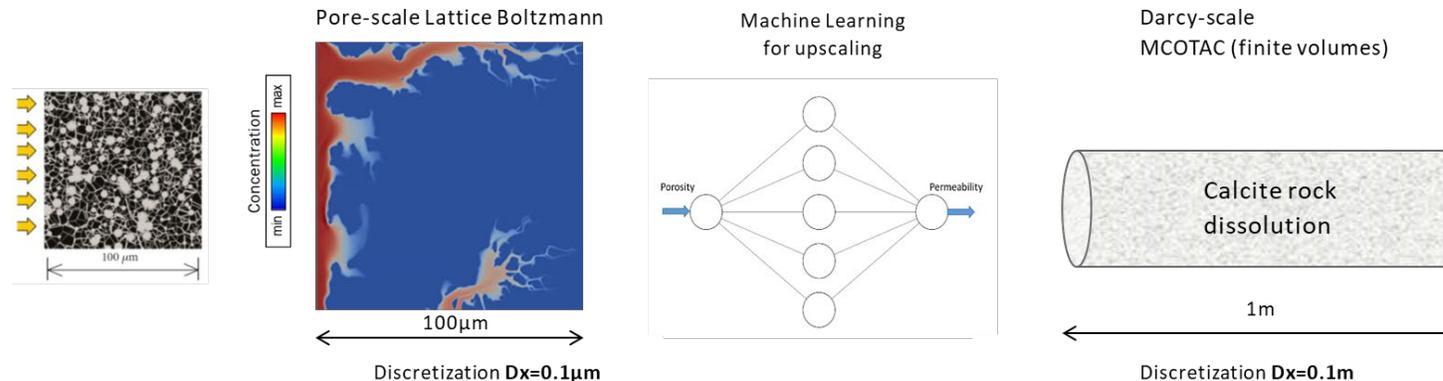
**Catalytic particulate flow**

# Neural network based multiscale modelling for reactive transport simulations

Multiscale modelling is limited by the communication between heterogeneous codes which operate at different scales and physical descriptions. Data driven deep-learning (neural network) framework is proposed and demonstrated

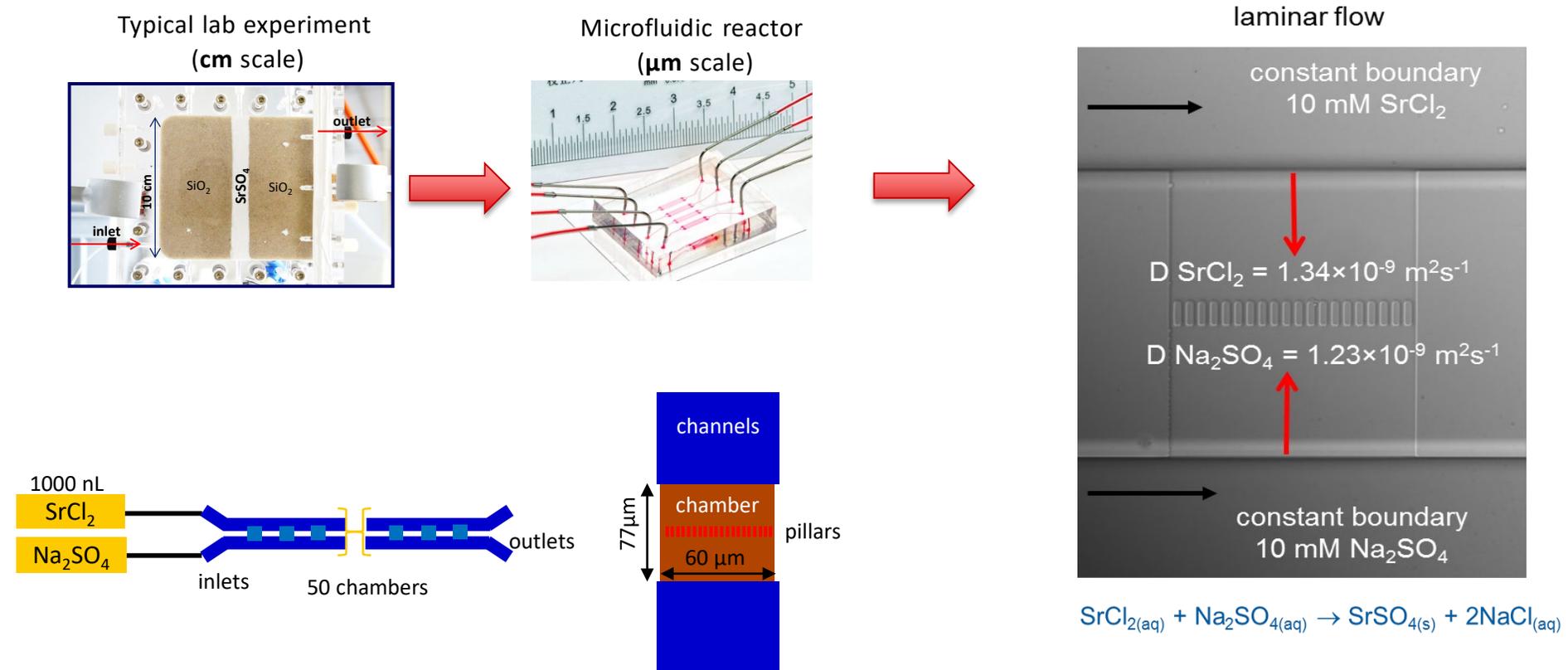


**Demonstration:** Pore-scale Lattice Boltzmann simulations provide the porosity permeability correlations in reactive environment (micrometer level). e.g. calcite rock dissolution due to acidification. Simulation output was encoded in a neural network and integrated in a finite element solver (meter level).



**Advantages:** miniaturized environment, shorter time-scales, small quantities of reactants, continuous monitoring, parallel

**Challenges:** in-situ conditions of flow and chemistry unknown, control of experiment, manufacturing, design of experiment



# Digital Twin and Numerical diagnostics

Augmented reality by combining cross scale lattice Boltzmann modelling diagnostics. Numerical model includes: a classical nucleation theory (CNT) implementation (nanoscale processes), multicomponent transport, kinetic reactions.

Injection of 10 mM  $\text{SrCl}_2$  and 10 mM  $\text{Na}_2\text{SO}_4$  → celestine precipitation, crystal growth

## Layers of diagnostics

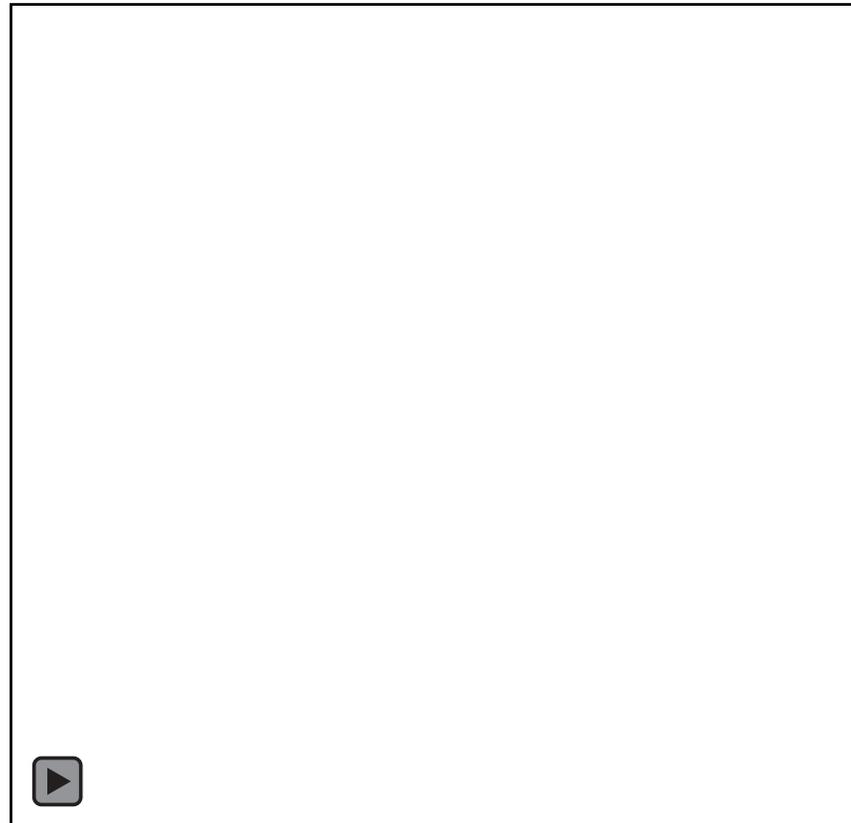
Evolution of experiment (camera)

Local flow-field and streamlines visualization  
(numerically calculated, experimentally verified).

Spatial resolution of velocity field at different stages of  
the experiment (numerically calculated)

Local species concentrations, saturation ratio  
(numerically calculated, interplay of advection/diffusion)

Local precipitation rates at fluid-solid interface,  
prediction of directional differential growth  
(numerically calculated, color: precipitation rate)



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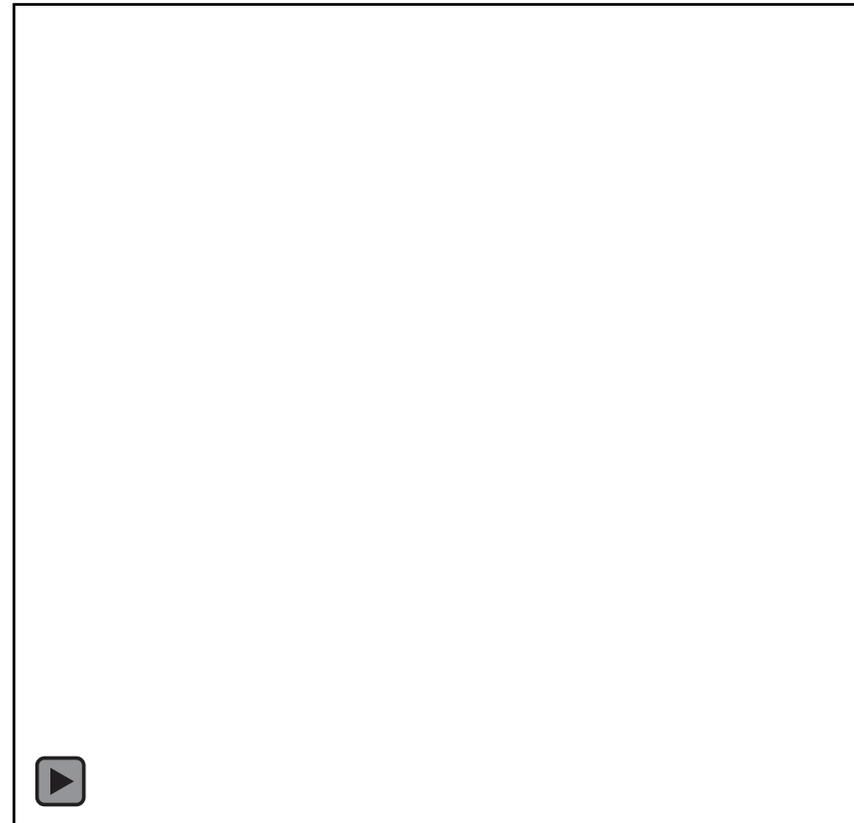
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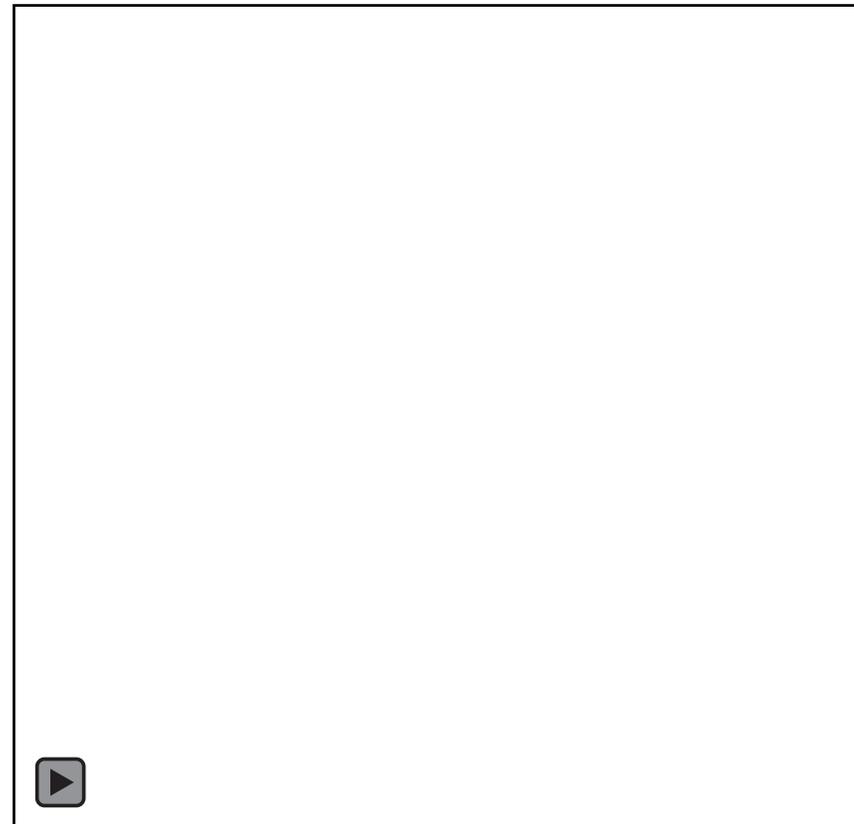
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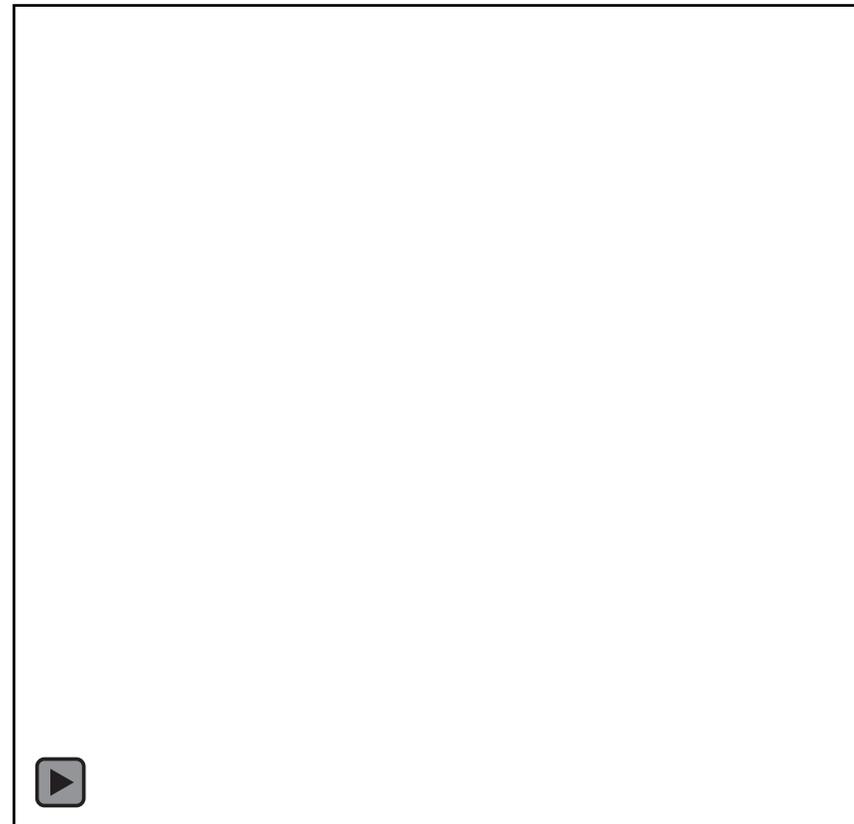
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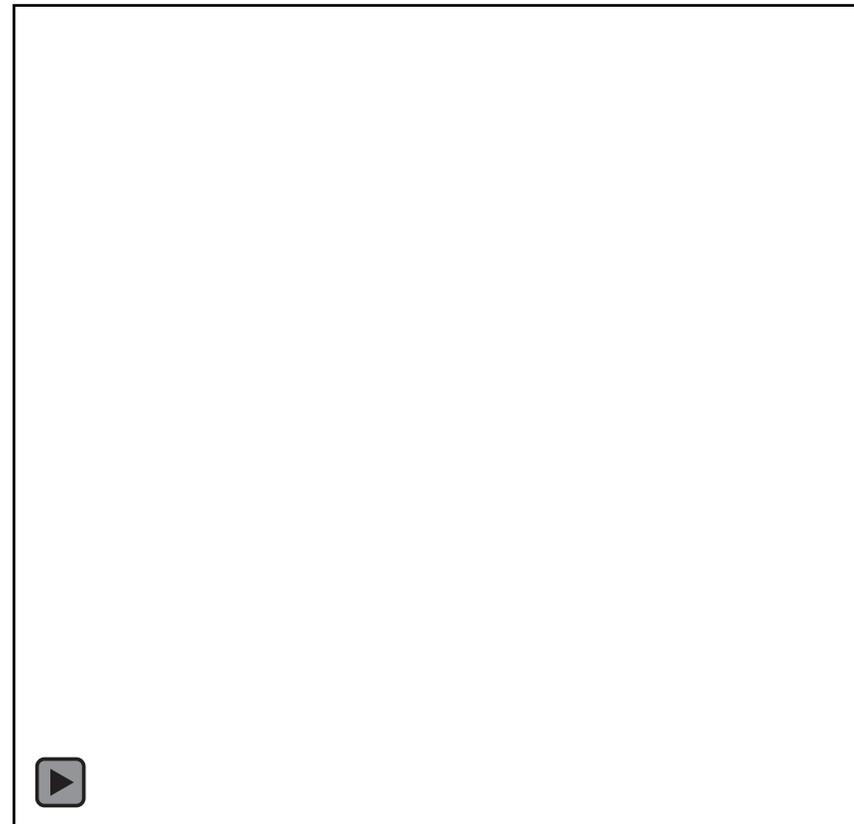
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## Introducing GEMS™



**GEMS development team**  
11 participants from 6 Institutions



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 **44+** national and international research projects use GEMS

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 **>10M** CHF related third-party funding

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 **>36** PhD and Postdocs at PSI, Empa, ETHZ

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 **> 4400** Downloads

 **>210** peer-reviewed publications (163 after 2013)  
**>30** reports at ETH domain

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 **>300** active users worldwide

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 **3-5** day trainings with 12-60 trainees around the world

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 **Open Source**

dmitrii.kulik@psi.ch

<http://gems.web.psi.ch/>



Example: **GEM-Selektor** full speciation for **sea water** at 1 bar and 80°C. Concentrations are in molar (mol/L) scale, and only species with concentrations > 10<sup>-10</sup> M are shown.

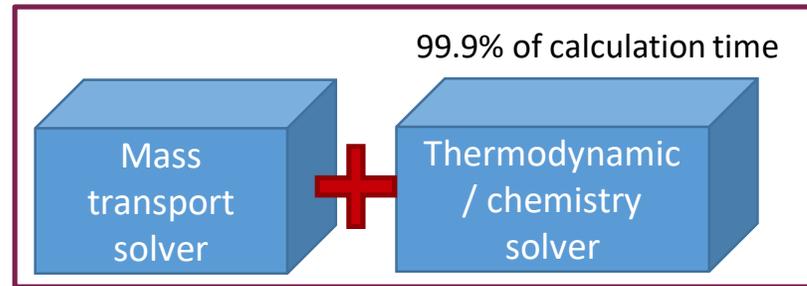


a aq_gen	54.66756	K(SO4)-	0.000229486	Na(CO3)-	1.09E-05	NO3-	1.00E-09
Cl-	0.54518692	Na(HCO3)@	0.000187894	HSiO3-	7.12E-06	Li+	9.87E-10
Na+	0.45936644	Mg(HCO3)+	0.000176174	NaOH@	2.70E-06	HPO4-2	9.41E-10
Mg+2	0.047302479	SiO2@	0.000142668	CaOH+	2.10E-06	Sr+2	8.97E-10
SO4-2	0.014423941	MgOH+	0.000100842	Mg(HSiO3)+	1.74E-06	B(OH)3@	8.86E-10
K+	0.009948141	Mg(CO3)@	5.18E-05	MgSiO3@	1.16E-06	Ba+2	7.94E-10
Ca+2	0.009408134	Ca(HCO3)+	3.63E-05	Ca(HSiO3)+	2.31E-07	F-	5.50E-10
Na(SO4)-	0.007373634	CO3-2	2.96E-05	KOH@	4.79E-08	MgF+	3.55E-10
MgSO4@	0.005341611	Ca(CO3)@	2.92E-05	HSO4-	2.77E-08	Ba(SO4)@	2.01E-10
HCO3-	0.001318276	CO2@	2.91E-05	H+	2.61E-08	BO2-	1.14E-10
Ca(SO4)@	0.000778619	N2@	2.74E-05	CaSiO3@	1.83E-08	Sr(SO4)@	9.74E-11
O2@	0.000244295	OH-	1.97E-05	SiO3-2	2.95E-09		

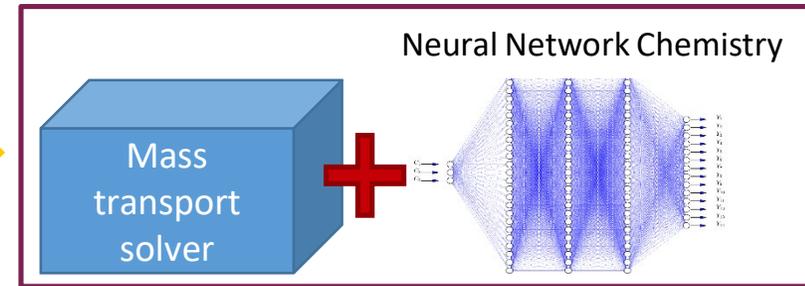
# Neural network based process coupling and code acceleration in reactive transport simulations

In reactive transport simulation a transport and a chemical solver are usually coupled. The thermodynamic/chemical calculations consume > 99.9% of the total simulation time. Data-driven acceleration of the geochemistry at practically zero loss in accuracy was demonstrated

Typical reactive transport solver

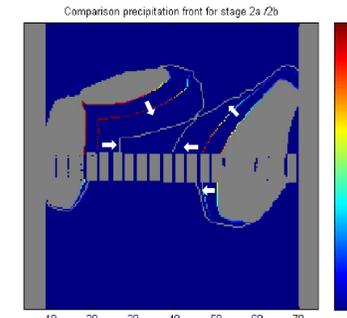
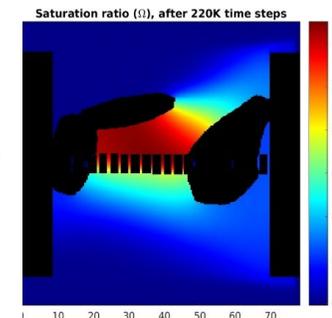
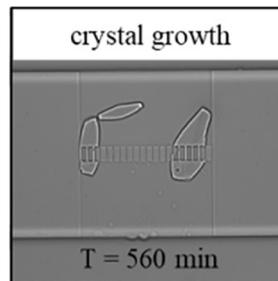
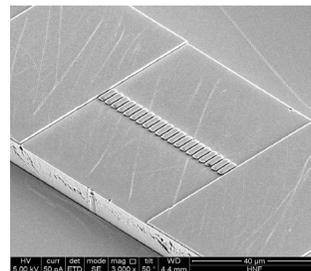
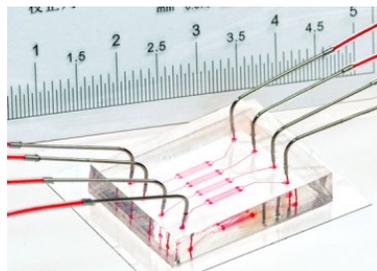


Machine learning assisted reactive transport solver



First tests show a **10'000x** acceleration of the chemical solver, without loss in accuracy and an overall speed up > **1000x**

**Demonstration:** This acceleration was an enabling step for the realization of the digital twin and modelling diagnostics including crystal growth prediction of microfluidic experiments (FZ-Julich)



Microfluidic Experiment

Digital Twin and modelling diagnostics

# Supercomputing: Transport is fast, chemistry is slow, hybrid computer architecture

Current supercomputers allow to simulate geometries with > 10 billion voxels (grid points). Most advanced systems have hybrid CPU/GPU computational nodes. Transport and chemical calculations take place at every voxel, at every timestep

Swiss Supercomputing Center (CSCS)  
Piz Daint Nvidia Tesla P100 GP-GPUs



X-ray tomogram  
(1 Billion Voxels)

## Comparison of Calculations per second

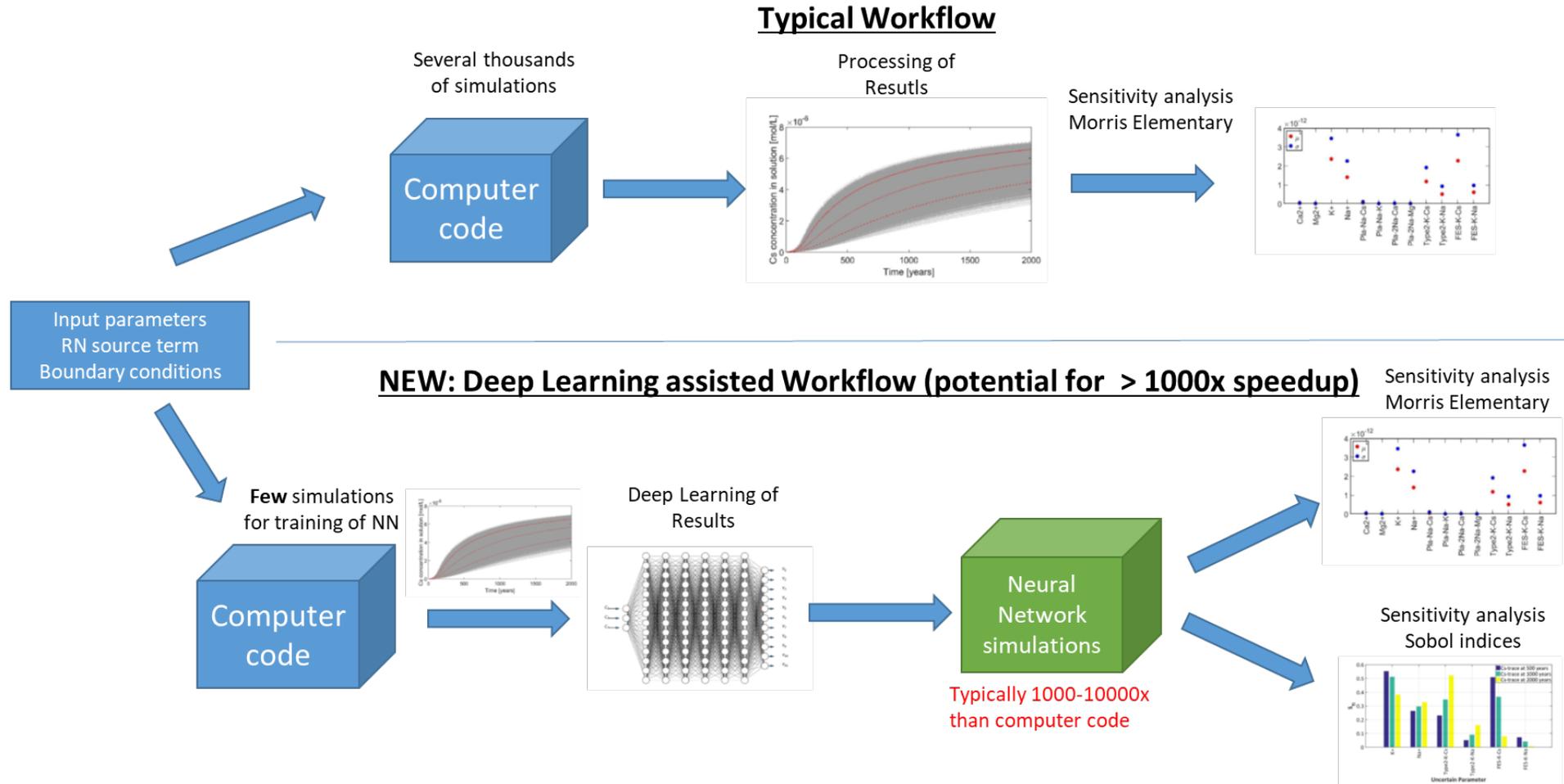
<u>Chemistry</u> GEMS / PHREEQC	<u>Transport (flow)</u> Lattice Boltzmann	<u>Chemistry</u> Neural Network
1 CPU-core ~ 1'000/s	1 CPU-core, 4 species ~ 1'000'000/s	1 CPU-core (depending on system) ->more than 1'000'000/s
1 GPU -> <b>Impossible</b> <b>Code not available</b>	1 GPU, 4 species -> 100'000'000/s	1 GPU -> Expected speedup 10-100 times the CPU



For high performance computing, where problem can be solved entirely in parallel GPU setup (Lattice Boltzmann), **surrogate modelling is an enabling step.**

**Challenge: Train surrogate models for input dimension >4 e.g. 10 and maintain accuracy**

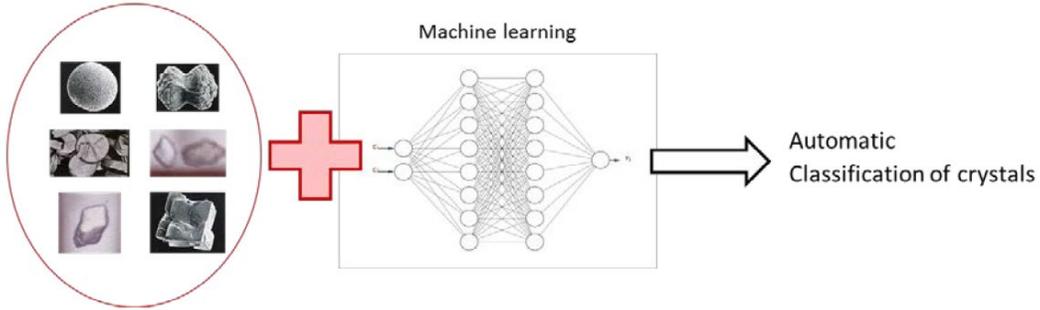
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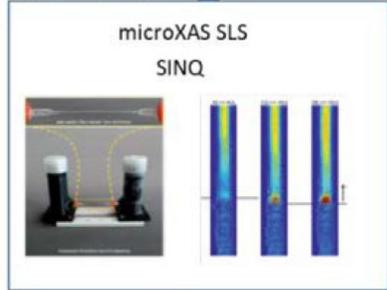
**Challenge: Train surrogate models for input dimension >4 e.g. 10 and maintain accuracy, training dataset might be scarce ?**

# Deep Learning for characterization of X-ray tomography output (beamlines PSI, CROSS project)

Training Database /  
Scientist input during experiment

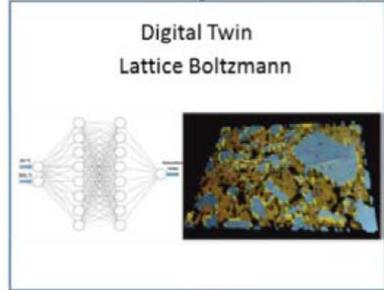


Experiments



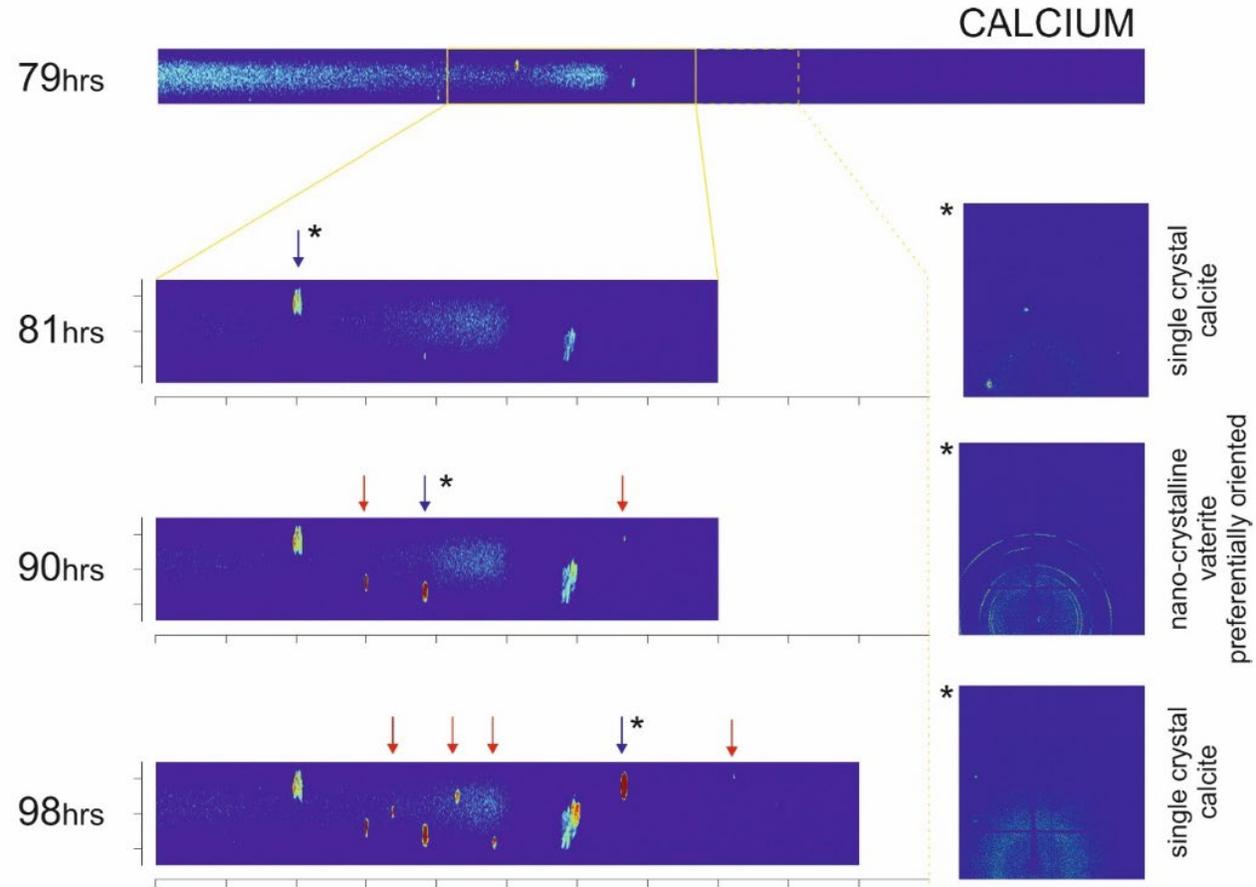
model validation,  
structures and dynamics of process,  
Identification of relevant processes

Modelling



predictions,  
parametrization of experiment,  
process understanding

Machine Learning



Multidimensional Data, Chemical Imaging

1) Surrogate modelling, data driven interfaces between heterogeneous codes → Accelerate Geochemistry, cross platform (2019-2023, EURAD, Nagra)

**Challenge: Train surrogate models for input dimension >4 e.g. 10 and maintain accuracy. Optimum training dataset to represent multidimensional spaces**

2) Metamodelling for sensitivity analysis (2021- ...)

**Challenge: Can a metamodel be trained in a smaller number of costly numerical simulations and achieve similar accuracy at sensitivity analysis studies? Can be used for intensified design of experiment?**

3) Image recognition, classification of X-ray multidimensional chemical data (e.g. microXAS beamline at PSI) for characterization, digital Twin (CROSS project at PSI, 2021-2025, PhD search is ongoing)

**Challenge: Classification of multidimensional data, use small sample of input images, couple with reactive transport solvers for real-time predictions**

Thank you

