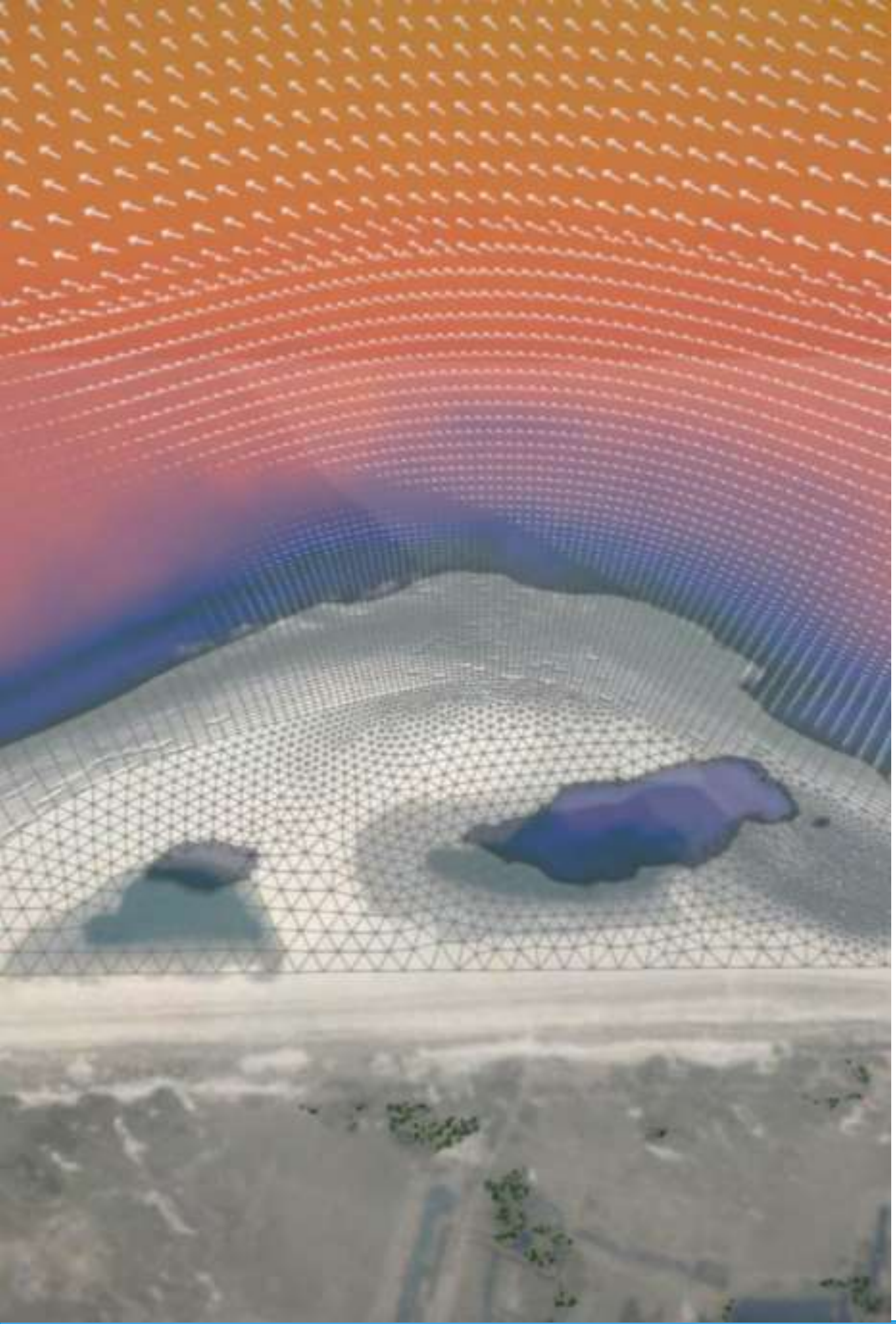


DIGISHAPE
DATASCIENCE FOR DELTAS

NL AI Coalitie

Proeftuin AI in het waterbeheer

OMGAAN MET EXTREMEN

Werksessie 2 juli

Chris Karman - DigiShape
Arnold Lobbrecht - HydroLogic

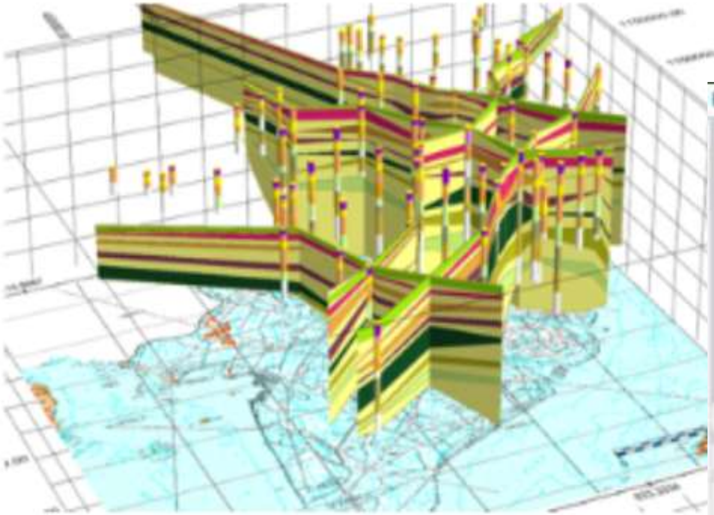
Er komt veel op ons af

Door klimaatverandering hebben we steeds meer te maken met weersextremen

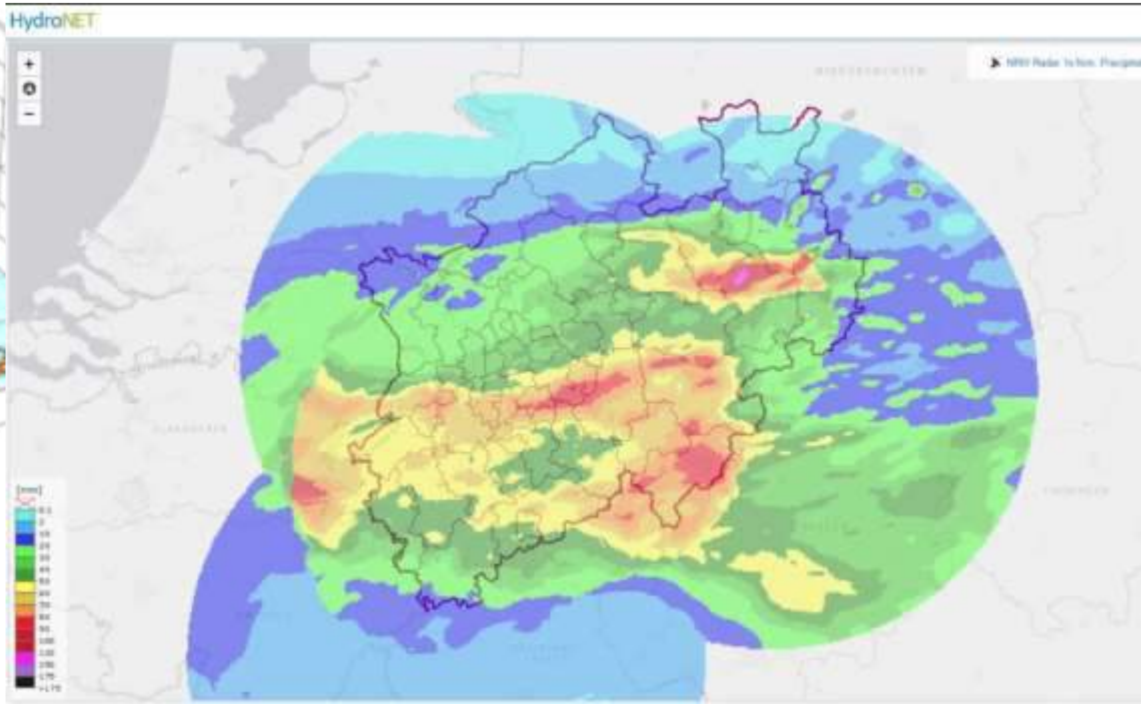
Deze extremen leiden tot droogte, wateroverlast, overstromingen èn daaraan gerelateerde uitdagingen

Sterk in domeinkennis, hybride & data-gedreven modellen

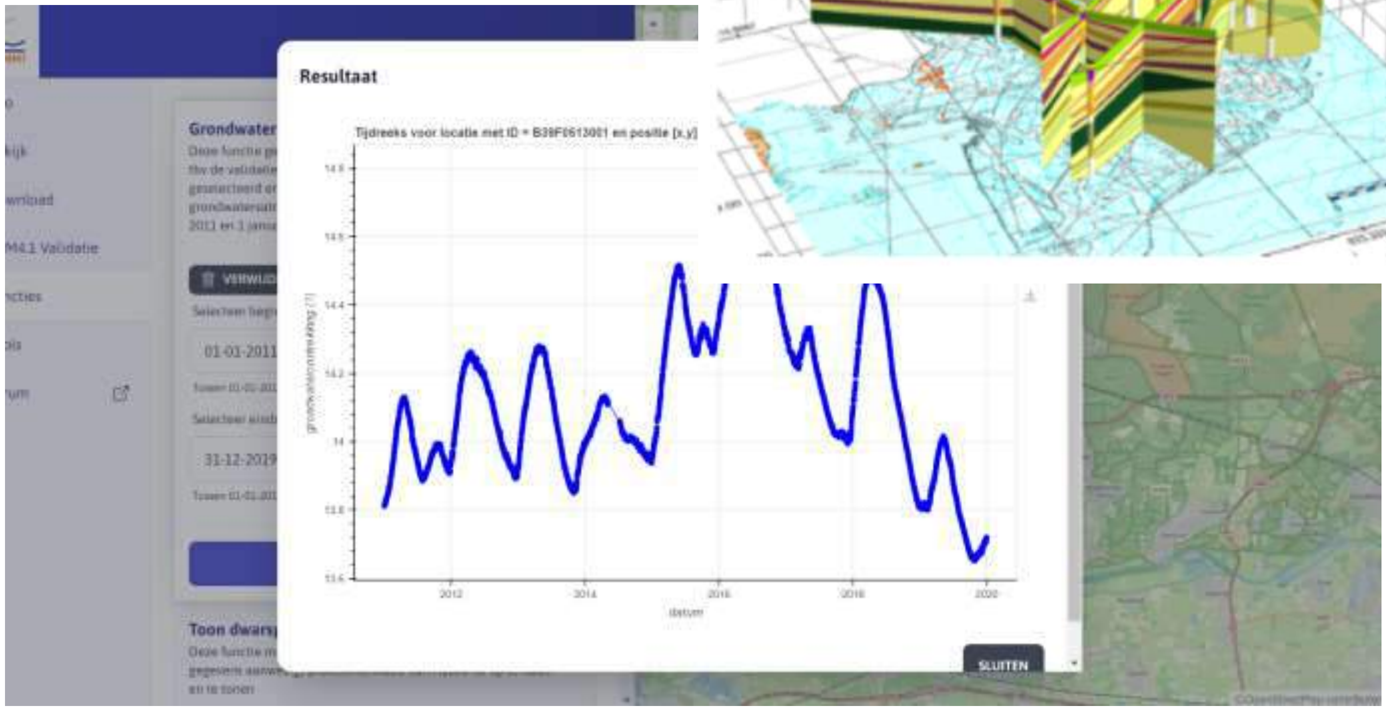
Imod 5.5



HydroNET



Nationaal Hydrologisch Instrumen



Onze uitdaging: complexiteit wordt (te) groot

Het watersysteem is tot de grenzen opgerekt: geen reserves meer

➔ klimaatverandering komt daar bovenop

➔ onze traditionele aanpak werkt niet meer

Behoefte aan real-time informatie en handelingsperspectief:

Open, toegankelijk en uitlegbaar!

We hebben (heel) veel historische, ruimtelijke data, maar moeten extremen voorspellen waarvoor nog nauwelijks data is:

➔ het onvoorstelbare voorstelbaar maken

➔ dichter bij het 'menselijke gevoel' halen

➔ aanschouwelijk maken

Verbinden van twee ecosystemen: Water en AI

Hoofddoel:

- **Versnelling aanbrengen in de aanpak van een groeiende mondiale uitdaging!**

Opdracht van werkgroep:

- **Hoe laten we de vonk overspringen?**
- **Wat is er nodig voor een constructieve samenwerking?**
- **Samen aan de slag!**

Resultaat:

- **Een krachtige coalitie die innoveert, uitprobeert en exporteert**

Ontwikkelingen naar 2030

- Innovatieagenda bepaald door grote bedrijven
- Onderscheidende rol voor MKB is specialisatie
- Door Cloud en SaaS makkelijker opschalen
- Onze sector wordt kennis-intensiever
- Noodzaak tot het smeden van kennisketens: per land, per stroomgebied, per domein,…

Ontwikkelingen naar 2030

- Innovatieagenda bepaald door grote bedrijven
- Onderscheidende rol voor MKB is specialisatie
- Door Cloud en SaaS makkelijker opschalen
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Tijdlijn

- Whitepaper (jan 23)
- Gesprekken coalitie (mei-sep 23)
- Nieuw toepassingsgebied (nov 23)
- Lancering tijdens jaarcongres NLAIC (apr 24)
- Formuleren concrete cases (juli 24)
- Organiseren financiering (najaar 24)
- Start eerste projecten (voorjaar 25)


AI voor water en klimaat
AI
Proeftuin
Samen werken we met AI aan de oplossing van de water- en klimaat opgave
Zeespiegelstijging
De zeespiegelstijging gaat steeds sneller en bedreigt ons lage land en delta's over de hele wereld
Waterbeschikbaarheid
Steeds lagere afvoeren in de zomer leiden tot slechte waterkwaliteit, minder zoet water voor landbouw en risico op zoutintrusie
Droogte
Lange perioden van droogte zijn een toenemend risico voor natuur, landbouw en veiligheid
Neerslagextremen
Extreme neerslag zoals in 2021 in Limburg leidt tot verstromingen en risico's op slachtoffers

Agenda werksessie

Introductie

Inzichten vanuit de wetenschap

Roberto Bentivoglio (TU-Delft):	Improving fast spatio-temporal flood modelling with multi-scale hydraulic graph neural networks
Hans van Beek (TU Eindhoven):	Examples of TU/e Water & Climate related Math &AI Research. From Topological River Networks to Weather Correlations and Tipping Points

Open Space

- Inventarisatie cases + pitches
- Selectie top 3 cases
- Uitwerking
- Per case: next steps

Afsluiting en borrel

Improving fast spatio-temporal flood modelling with multi-scale hydraulic graph neural networks

Roberto Bentivoglio, Elvin Isufi, Sebastiaan Jonkman, Riccardo Taormina

Delft University of Technology

Motivation

- Accurate numerical models for simulating floods are computationally **expensive**
- Deep learning methods can be used to **accelerate** simulations
- But current deep learning models struggle to generalize to:
  - different **topographies**
  - different **boundary conditions**
  - irregular **meshes**

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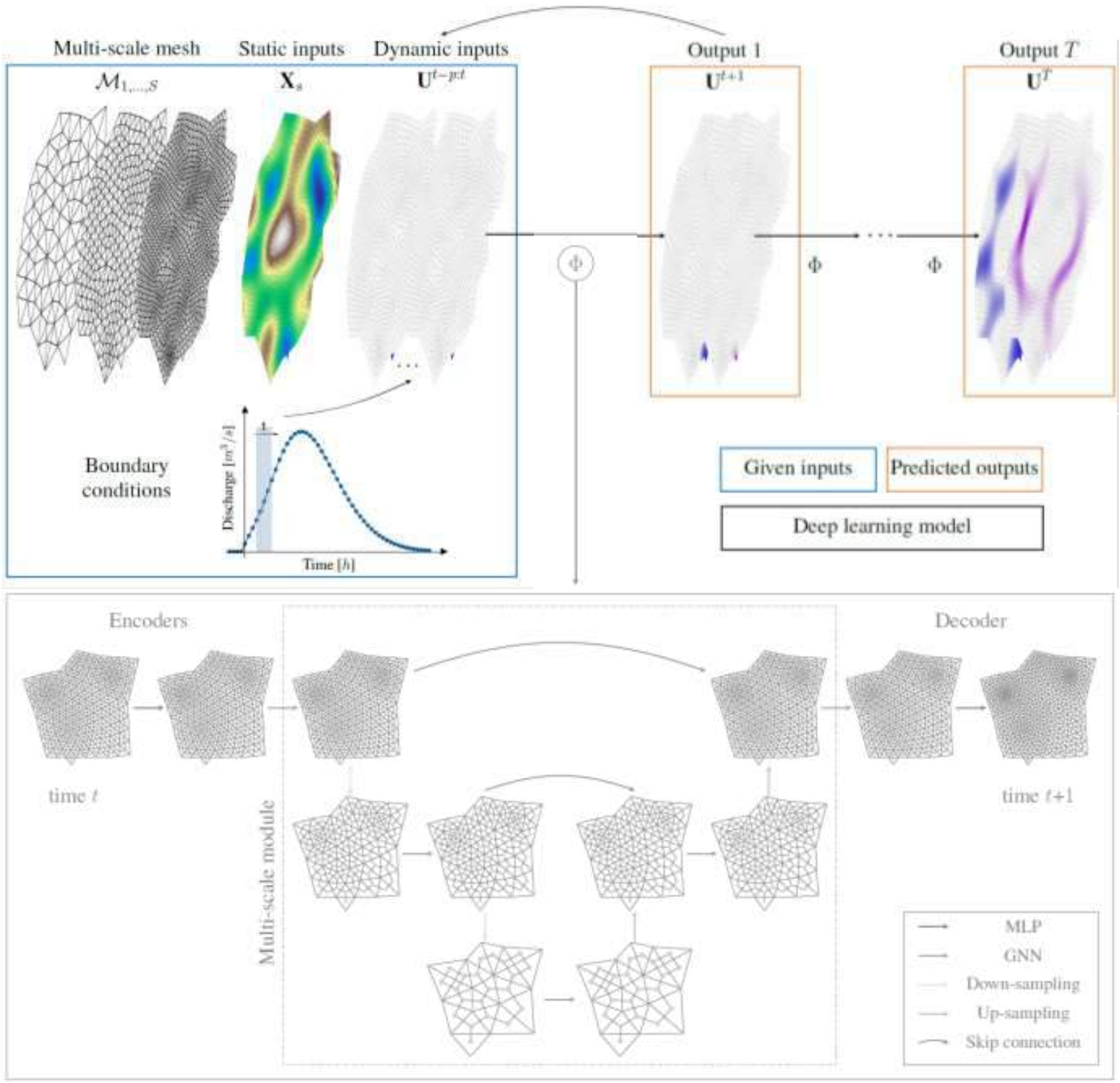
TUDelft

M-SWE-GNN

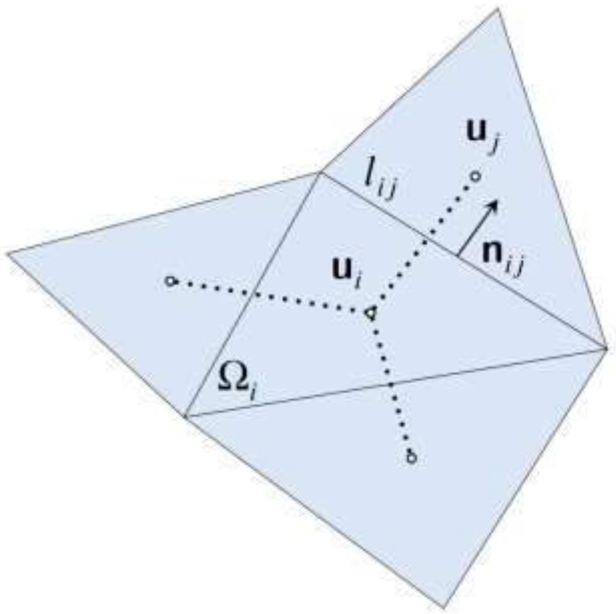
Overview



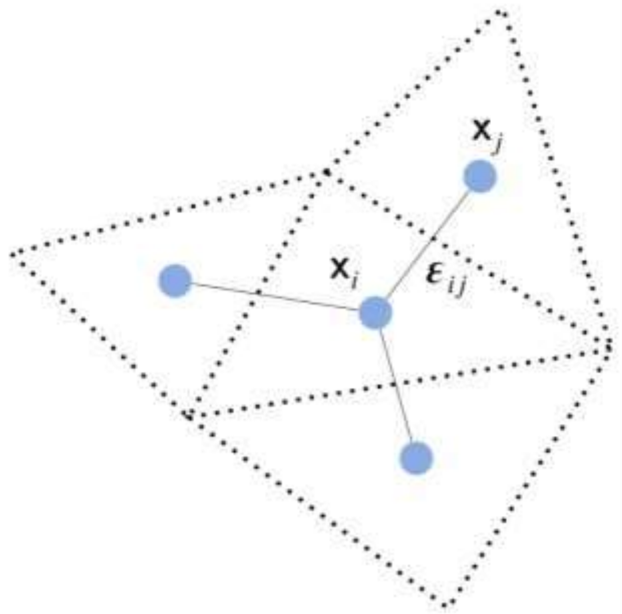
SWE-GNN[1]

Motivation

$$\boldsymbol{u}_i^{t+1} = \boldsymbol{u}_i^t + \sum_{j=1}^{N_i} \left(\boldsymbol{s}_{ij} - (\boldsymbol{F} \cdot \boldsymbol{n})_{ij} \frac{l_{ij}}{\mathrm{a}_i} \right) \Delta t \longleftrightarrow \boldsymbol{x}_i^{t+1} = \boldsymbol{x}_i^t + \sum_{j=1}^{N_i} f(\boldsymbol{x}_i, \boldsymbol{x}_j, \boldsymbol{\varepsilon}_{ij})$$



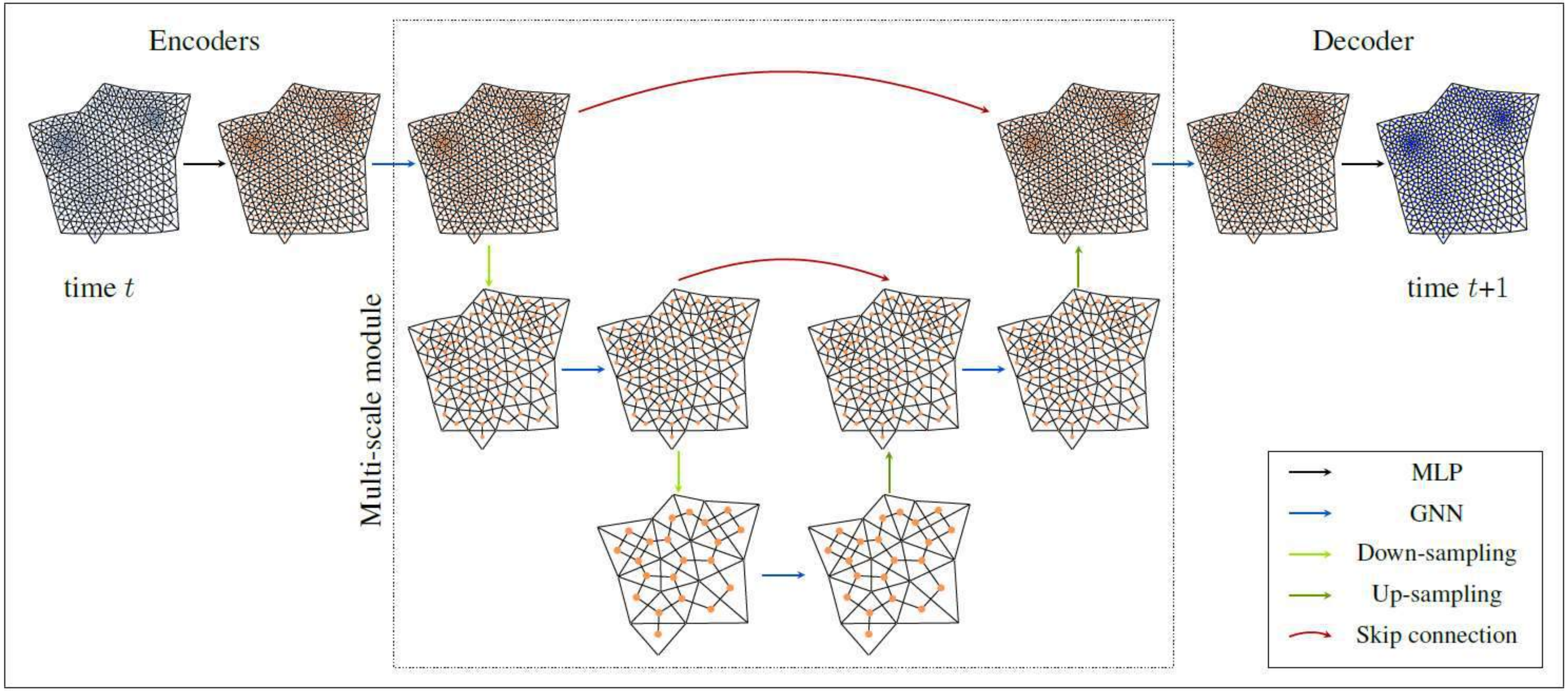
Finite volume mesh



Dual graph

[1] Bentivoglio, R., Isufi, E., Jonkman, S.N. and Taormina, R., 2023. Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks. *Hydrology and Earth System Sciences*, *27*(23), pp.4227-4246.

Multi-scale SWE-GNN



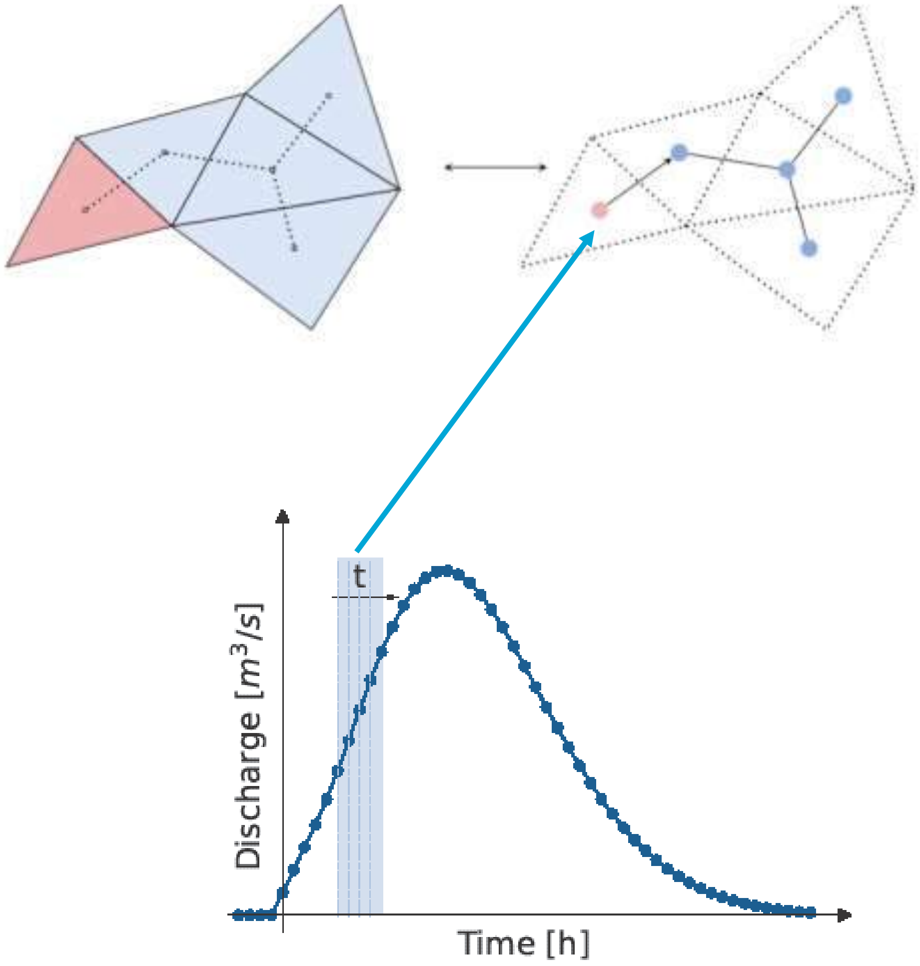
- Idea: each scale propagates water at different speeds

Boundary conditions

- Ghost cells: “fake” cell in correspondence of boundary condition

- Add directed edge in dual graph

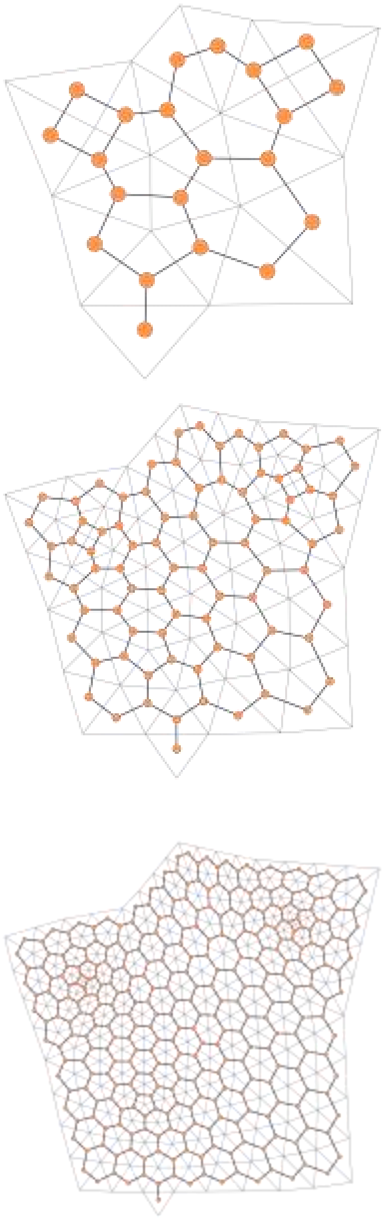
- Assign value to ghost cell at each input time step



Dataset

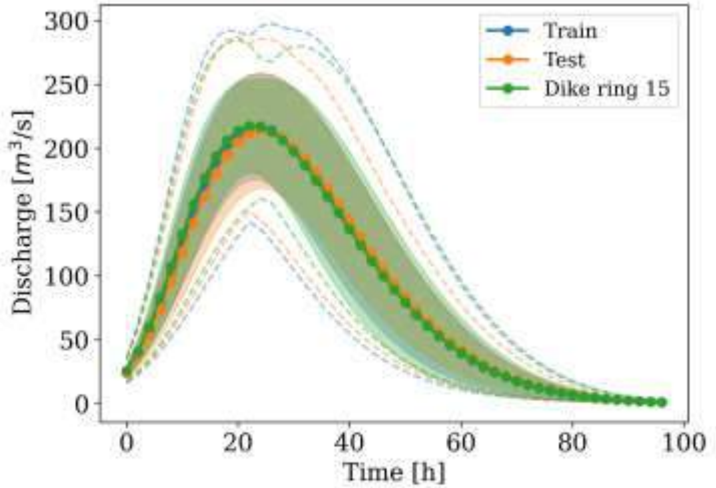
Mesh generation

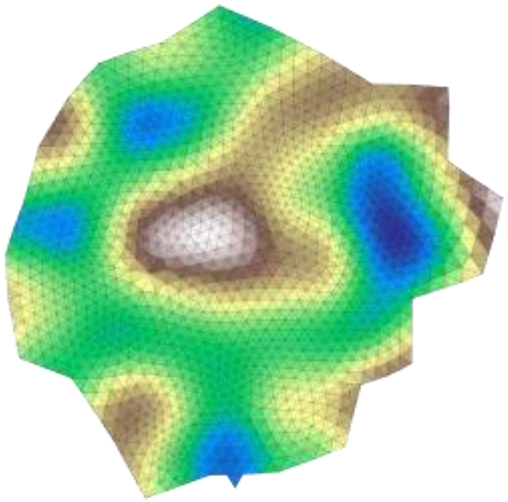
- Random polygons with fixed number of vertices
- Coarse mesh created from polygon
- Finer meshes created via progressive refinement from the coarse mesh
  - (4 total scales in this work)



Dataset

- 60 training, 20 validation, 20 testing simulations (+10 real case testing)
- Varying boundary conditions (peak ranges from 150 to 300 m^3/s)
- Random terrains, random breach location
- 96 hours simulation time, 2h temporal resolution

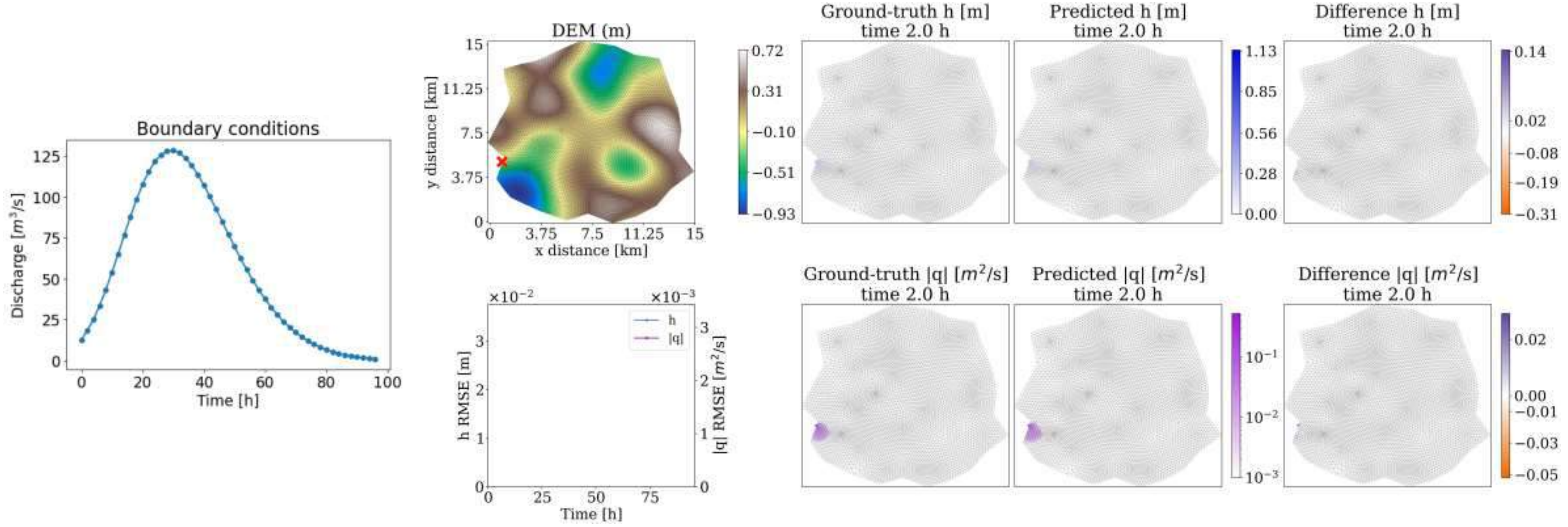




AI ADRO LAB

TU Delft

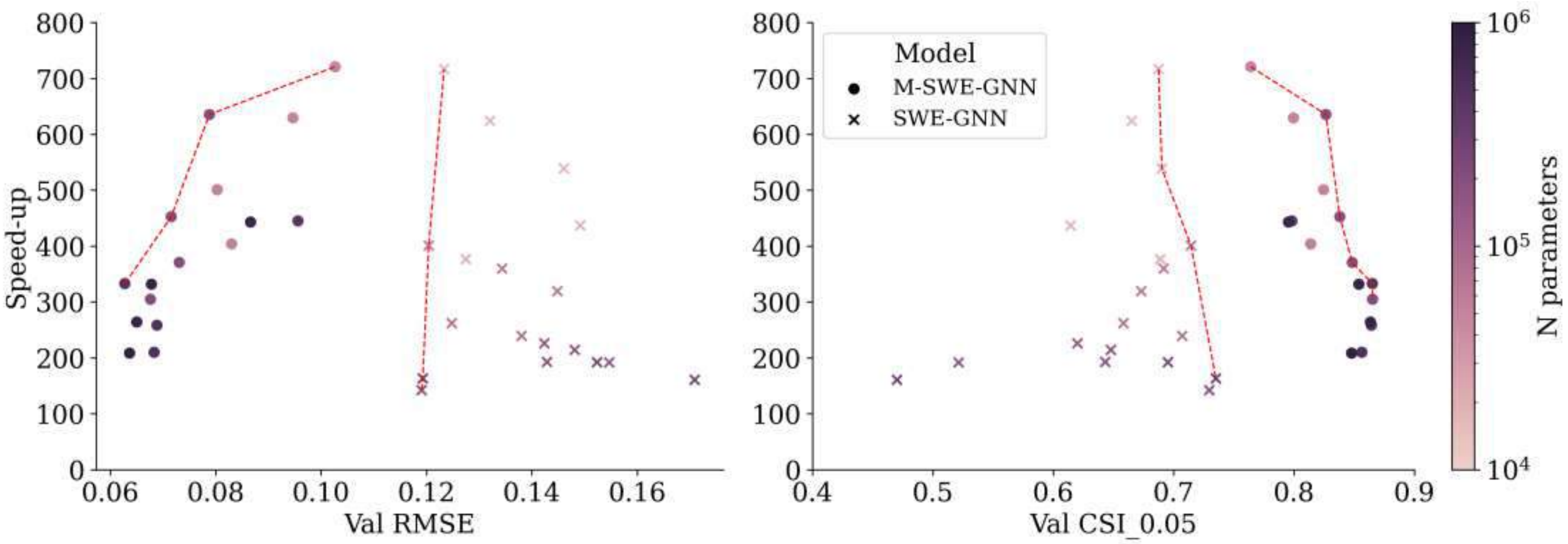
Results



Boundary conditions
Discharge [m^3/s]
Time [h]
DEM (m)
y distance [km]
x distance [km]
h RMSE [m]
|q| RMSE [m^2/s]
Ground-truth h [m]
time 2.0 h
Predicted h [m]
time 2.0 h
Difference h [m]
time 2.0 h
Ground-truth |q| [m^2/s]
time 2.0 h
Predicted |q| [m^2/s]
time 2.0 h
Difference |q| [m^2/s]
time 2.0 h

Results

Comparison with SWE-GNN



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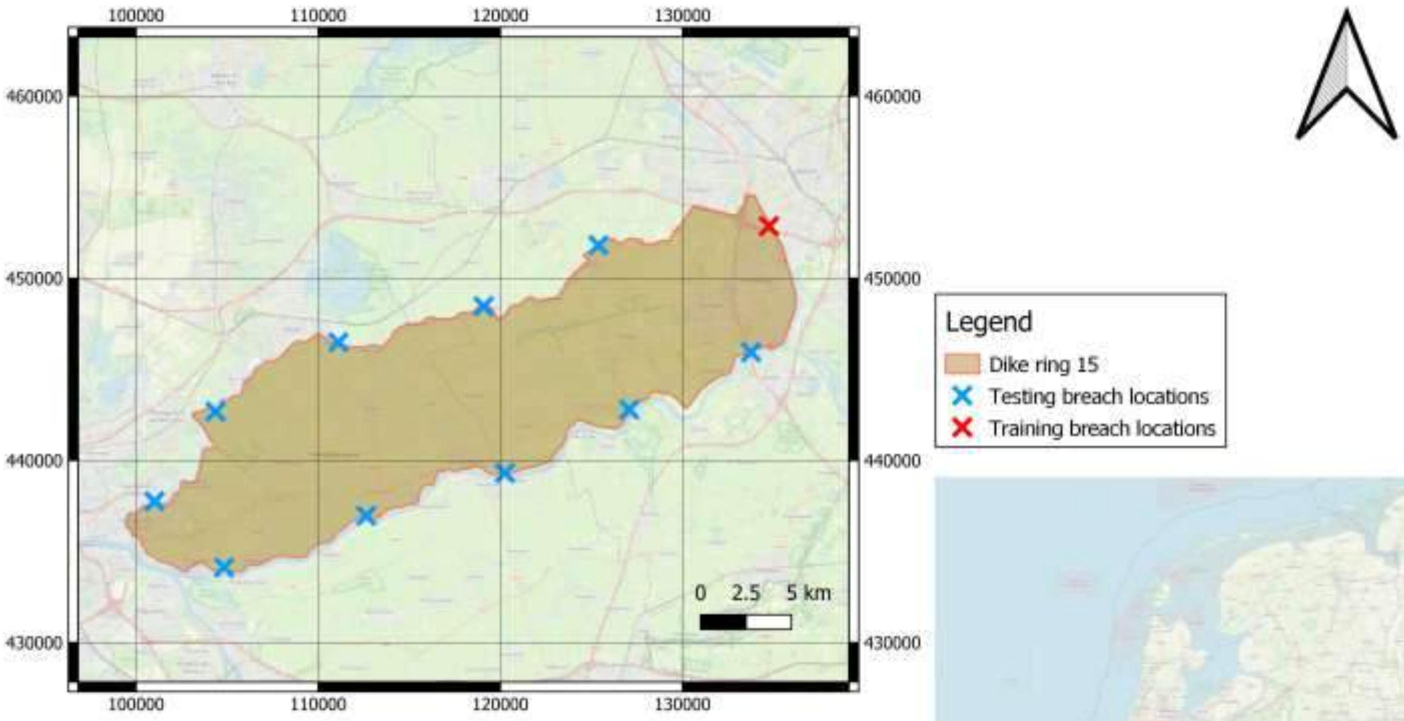
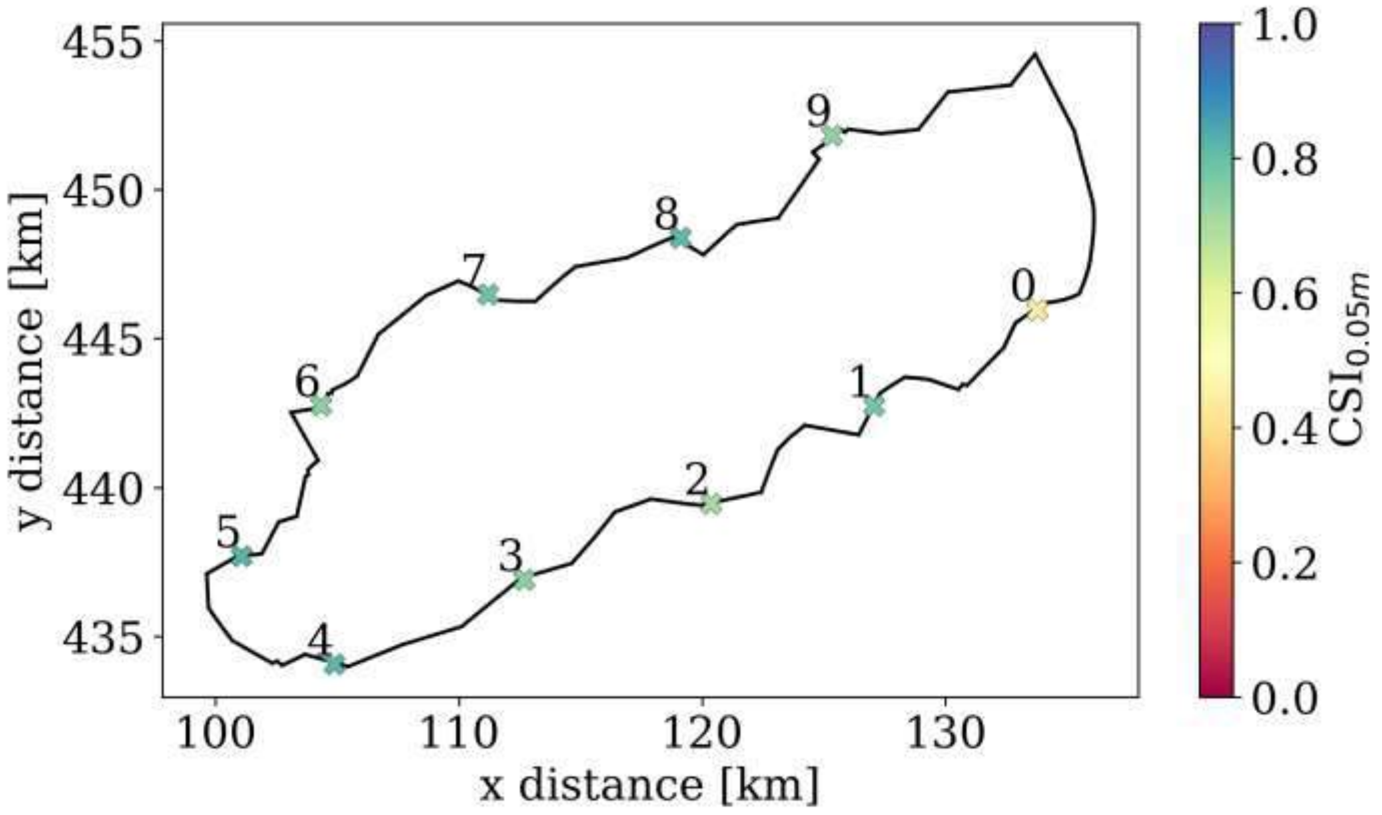
Fine tuning to dike ring 15



Results



455
450
445
440
435
y distance [km]
100
110
120
130
x distance [km]
0
1
2
3
4
5
6
7
8
9
1.0
0.8
0.6
0.4
0.2
0.0
$CSI_{0.05m}$

Conclusions

- We propose a new multi-scale graph neural network model that improves speed and accuracy of its non-multi-scale counterpart
- The model can accommodate multiple time-varying boundary conditions
- Future works should aim to apply the model for probabilistic analyses on real case studies

An ICAI Lab for the water sector

ICAI: **Innovation Center for Artificial Intelligence**

Academia/private/public **partnerships** to advance AI in specific sectors

Minimum 5 PhDs working on related topics, lots of training/dissemination events for partners, joint supervisions, …

TU Delft is leading a proposal with partners in academia, public and private sector.

Contact: Dr Riccardo Taormina, r.taormina@tudelft.nl

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Examples of TU/e Water & Climate related AI & Math Research

From Topological River Networks to Weather Correlations and Tipping Points

2024-07-02 TU/e Hans van Beek

Five examples of how AI and Math can help to

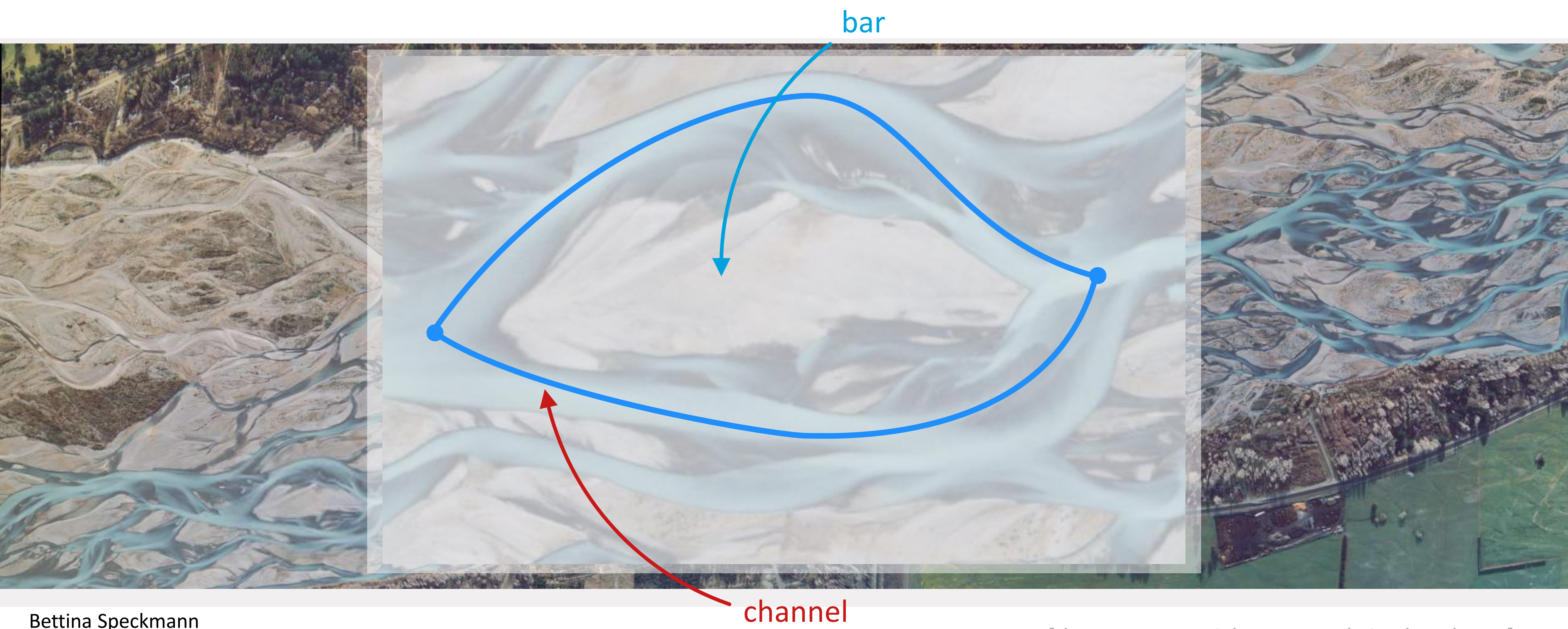
Predict:

1. River Networks:	compute channels in the river automatically
2. Multivariate Correlations Analysis:	predict based on what happens elsewhere
3. Tipping Points:	model and understand tipping dynamics affected by uncertainty

Control:

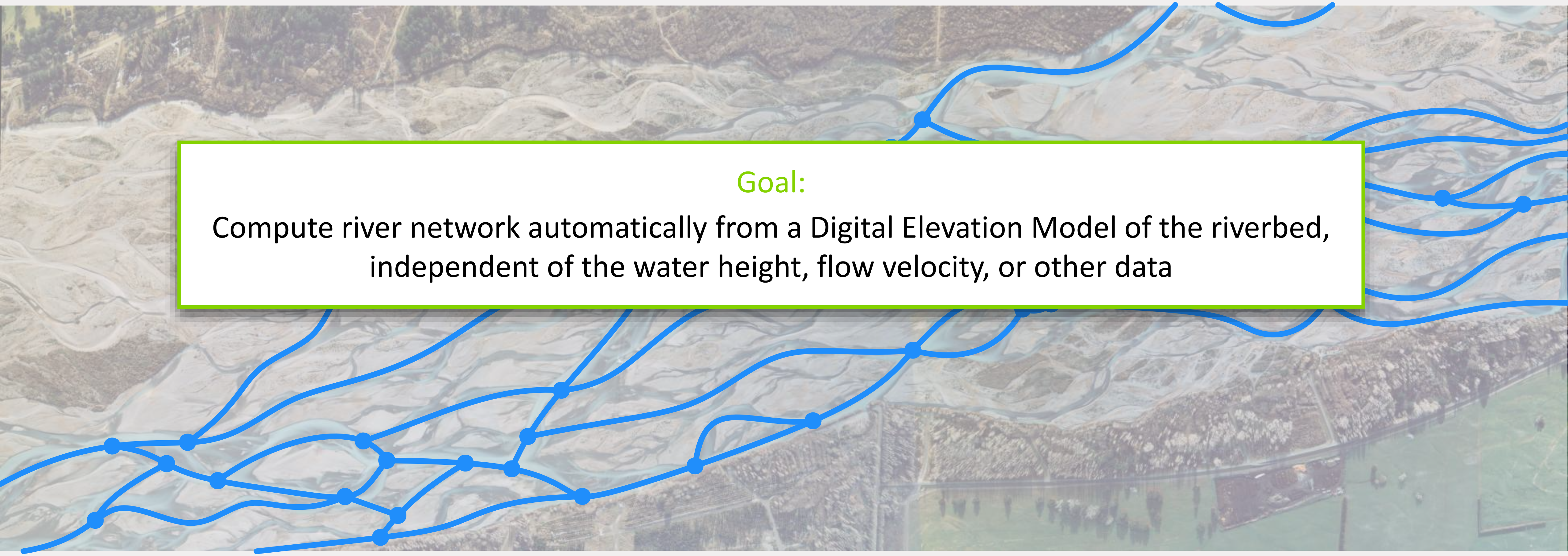
4. Water Distribution Networks:	control water levels
5. Bayesian Automated Inference:	process control in dynamic environments (water & weather?)

Flood control and ecosystem health: how do rivers behave?



[data: Murray Hicks, NIWA Christchurch, NZ]

Topological Data Analysis for River Network Analysis

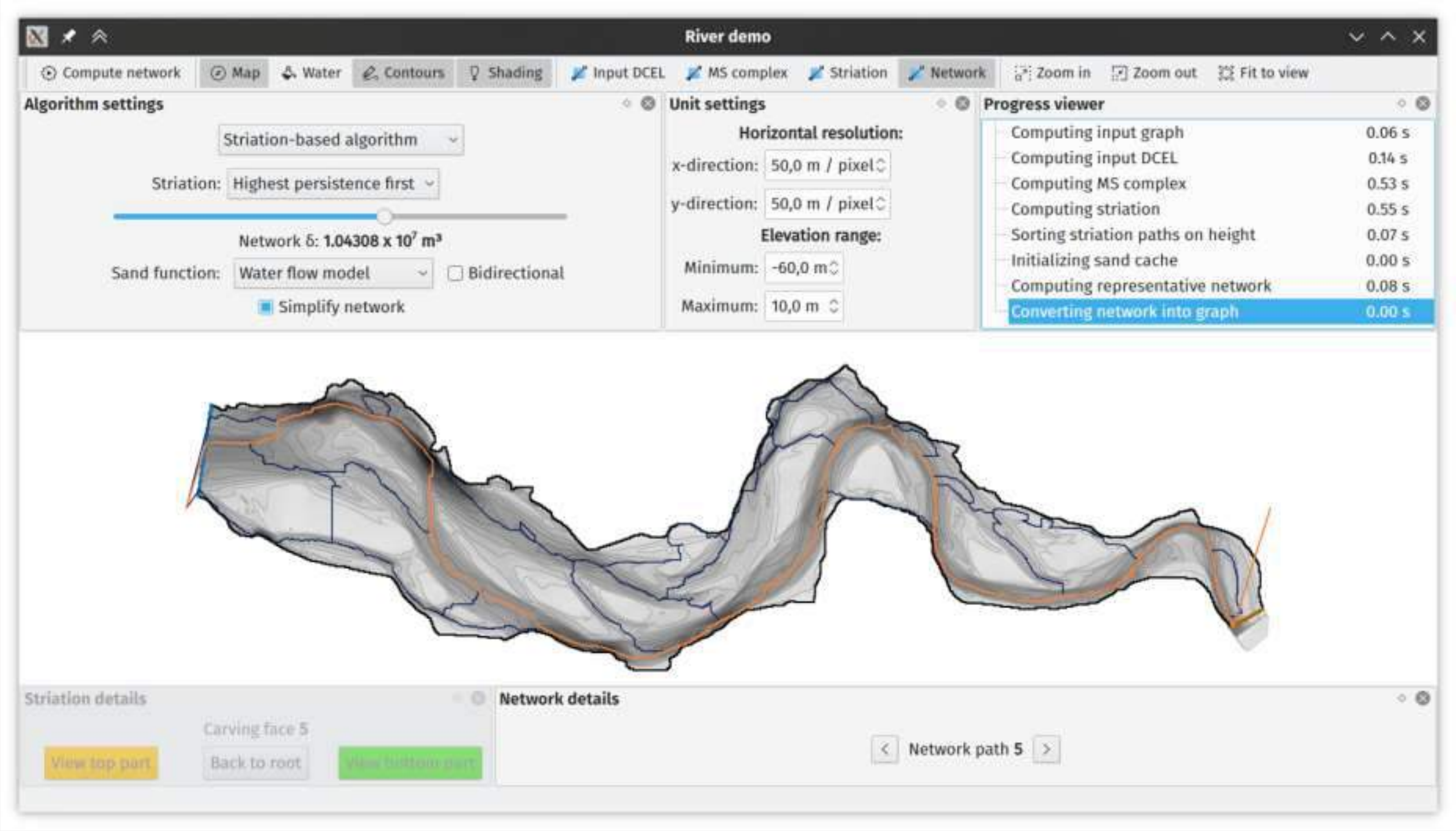


Goal:

Compute river network automatically from a Digital Elevation Model of the riverbed, independent of the water height, flow velocity, or other data


Dordrecht
Biesbosch
Overflakkee
Schouwen-
Duiveland
Oos
Breda
Oosterschelde
Bergen
op Zoom
Walcheren
Roosendaal
Zuid-Bev
Zoom
Zeeuws-Vlaanderen
Ekeren
Brugge
ANTWERPEN
Eeklo

First: Describe Network as a Graph; Next: Predict



How to use all that streaming data to predict what we want to know?

Hundreds/thousands of sensor arrays scattered across Europe
Each sensor collects many readings per minute

Odysseas Papapetrou

Recent publications here: https://www.win.tue.nl/~opapapetrou/publications.html

Multivariate Correlations Analysis

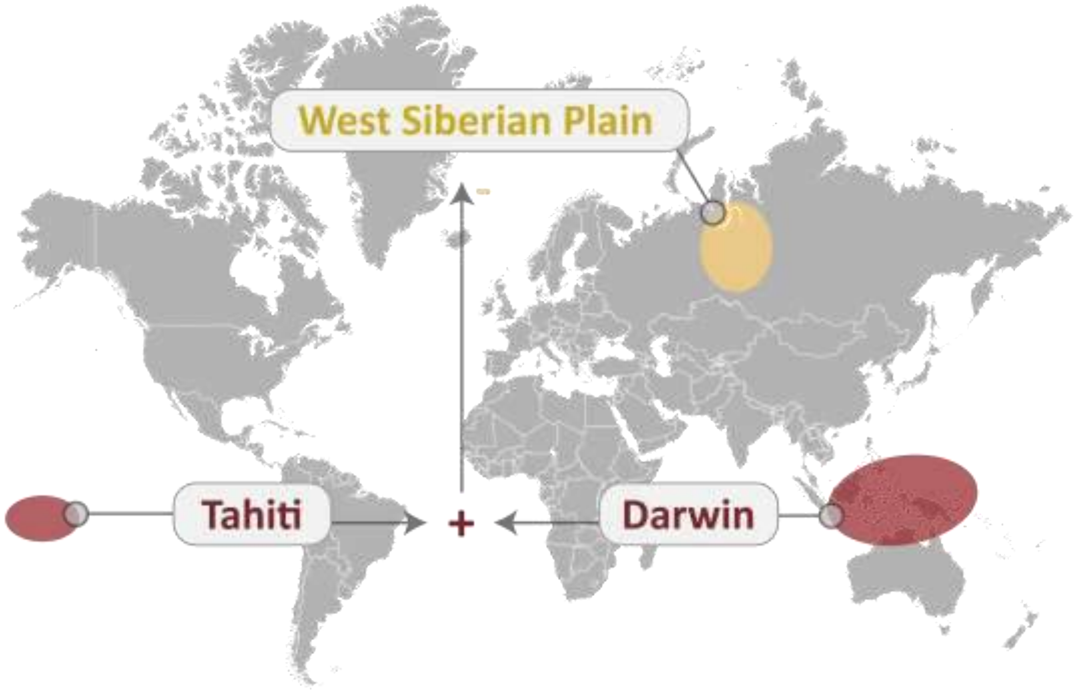
What are multivariate correlations?

Correlation Analysis is a common tool for Complex Data Analysis

Most research has been focused on discovery of **pairwise relations**

Recent work shows importance of **multivariate correlations**

Example: ternary relationship between Sea-Level pressures;



Website and demo here: https://correlationdetective.com

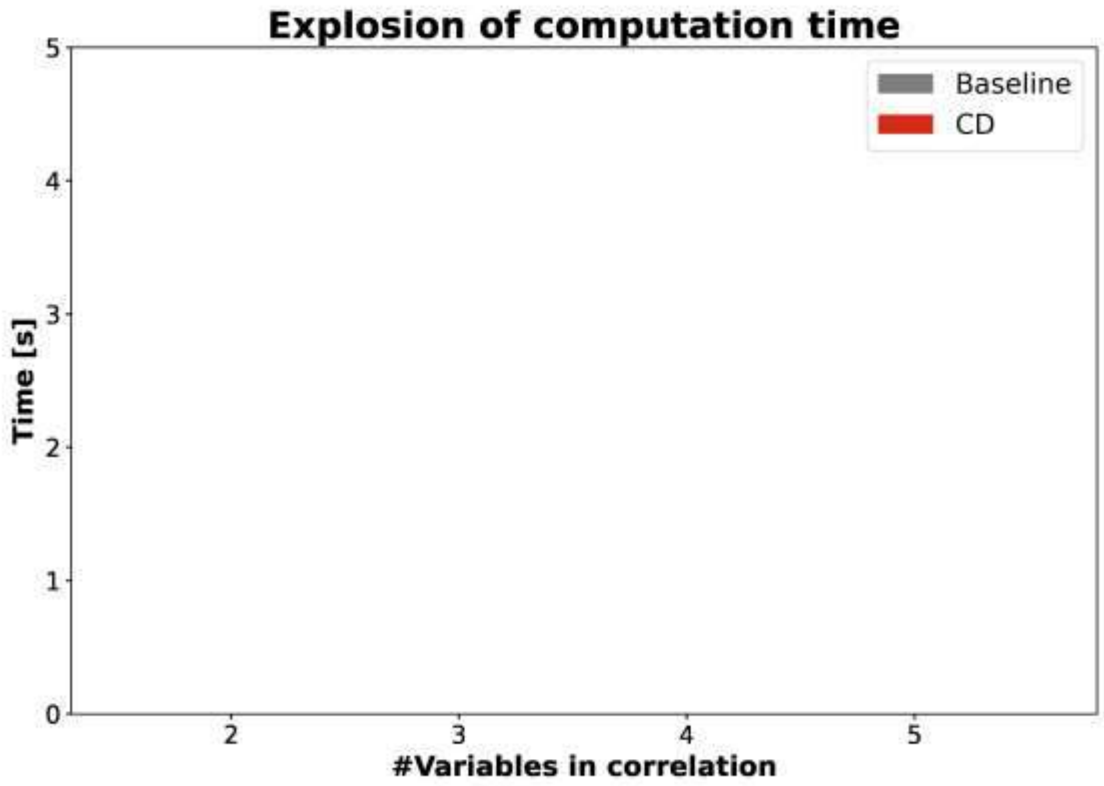
Multivariate Correlations Analysis

The Correlation Detective algorithm

Problem: exhaustive computation of all possible correlations is expensive due to number of possible combinations

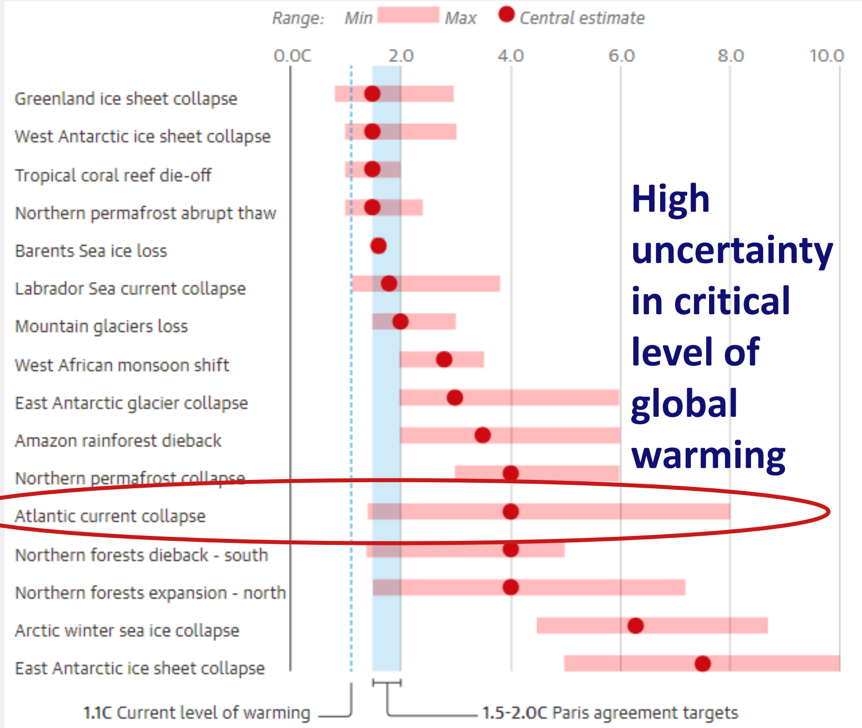
Solution: Correlation Detective, which reduces time by two orders of magnitude

Supports: 4 different correlation measures, 2 query types and 2 optional constraints



Visit: https://correlationdetective.com

How to identify the Tipping Points for Climate & Water?



Guardian graphic. Source: Armstrong McKay et al, Science, 2022. Note: Current global heating temperature rise 1.1C Paris agreement targets 1.5-2.0C

High uncertainty in critical level of global warming

Simulated impact of Atlantic current collapse on British water balance

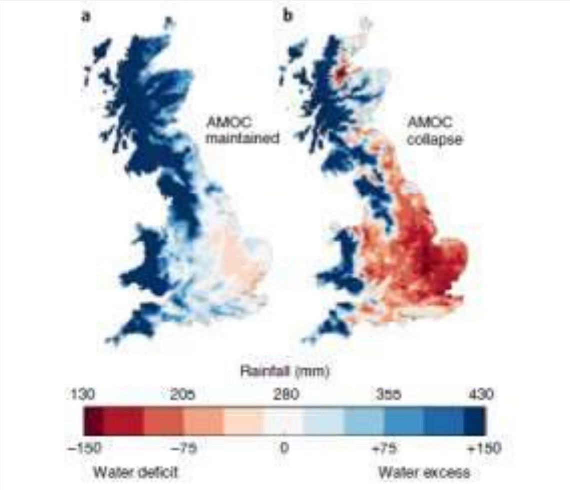
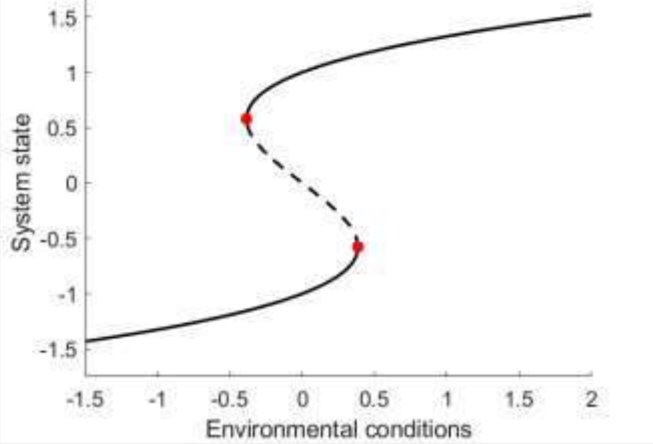


Fig. 4 | British water balance in 2080 during the growing season, with irrigation available, under the climate scenarios for which the AMOC is either maintained or collapsed. a,b, Water deficits (<280 mm) during the growing season (April to September) where irrigation occurs (red), and areas with excess water (>280 mm) (blue), during the growing season when AMOC is maintained (**a**) or collapsed (**b**).

„A key challenge for water is the difficulty in long-term planning for adaptation, ***due to large uncertainties*** *in regional climate changes“ [1, p. 189]*

Need for Uncertainty Quantification of Tipping Dynamics (see next slide)

Illustration of Tipping Dynamics



Possible impacts of Tipping Points on Water Security (see [1]):

- Changes in regional rainfall & reduced river flows
- Salination of groundwater in coastal regions
- Reduced water quality through release of contaminants

Kerstin Lux-Gottschalk

[1] Lenton, et al. (2023): “The global tipping points report”, *University of Exeter*, https://global-tipping-points.org/

[2] Ritchie, et al. (2020): “Shifts in national land use and food production in Great Britain after a climate tipping point”, *Nature Food 1, 76–83*, https://www.nature.com/articles/s43016-019-0011-3

Tipping Dynamics under Uncertainty

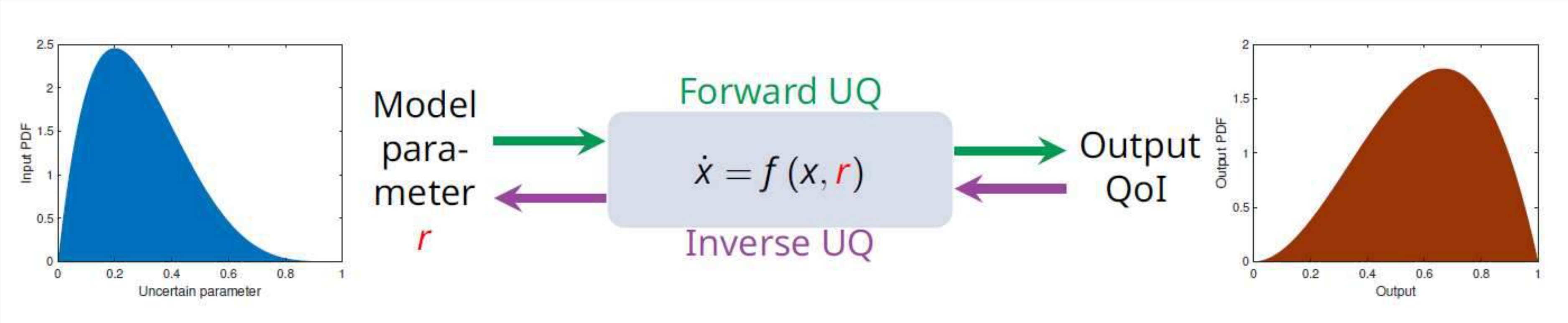
Uncertainty Quantification (UQ)

+

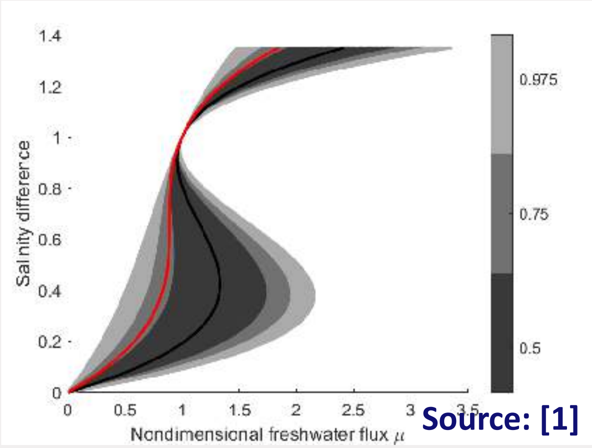
Random Differential Equations

+

Bifurcation Theory

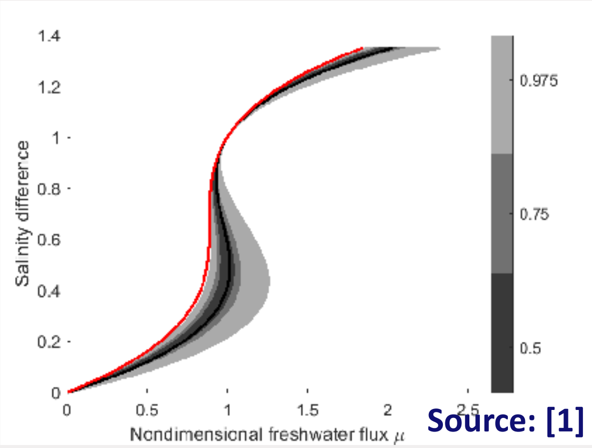


- How can **model parameters be inferred** from measurement data? How can uncertainty be propagated through nonlinear dynamics?
- How are **tipping dynamics affected by uncertainty**?



Bayesian parameter inference and forward UQ for bifurcation curves

Result: drastically narrowed down range of tipping

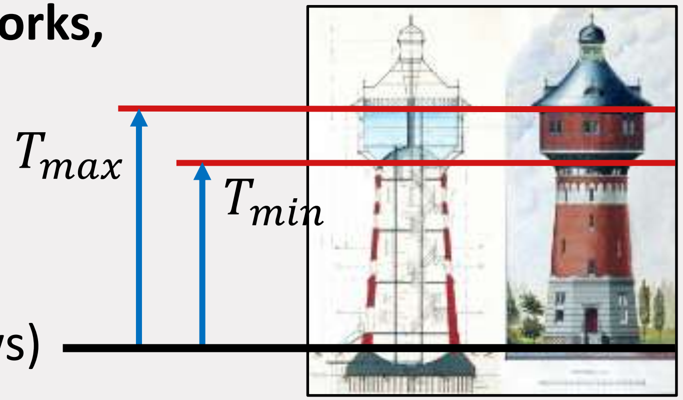


[1] Lux, Ashwin, Wood, Kuehn (2022): "Assessing the impact of parametric uncertainty on tipping points of the Atlantic meridional overturning circulation", *Environ. Res. Lett. 17 075002* 90:301–328, https://iopscience.iop.org/article/10.1088/1748-9326/ac7602/meta

How to control Water Distribution Networks?
(without having physical models of these networks)

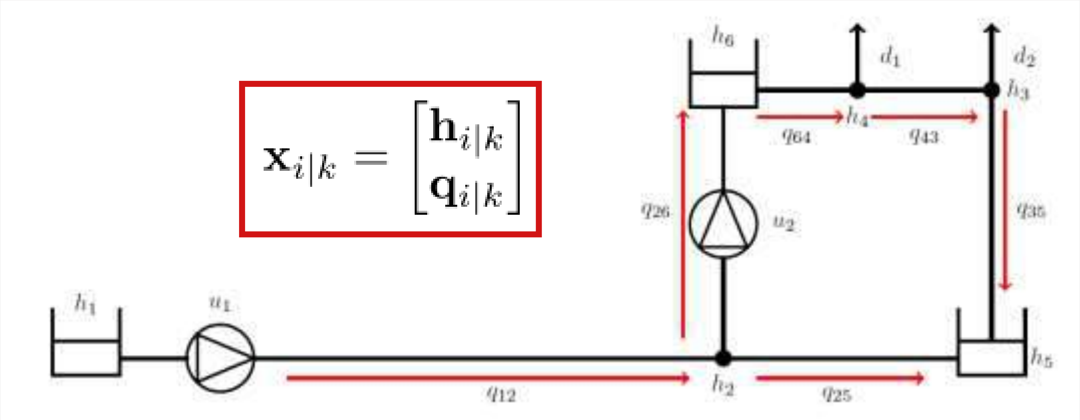
To use data-driven predictive control methods in water distribution networks, we need:

1. Network topology
2. Physical network limits (like tank limits)
3. Measured network data (pressure, flows, pump settings, demand flows)



Simple water network with one loop, containing:

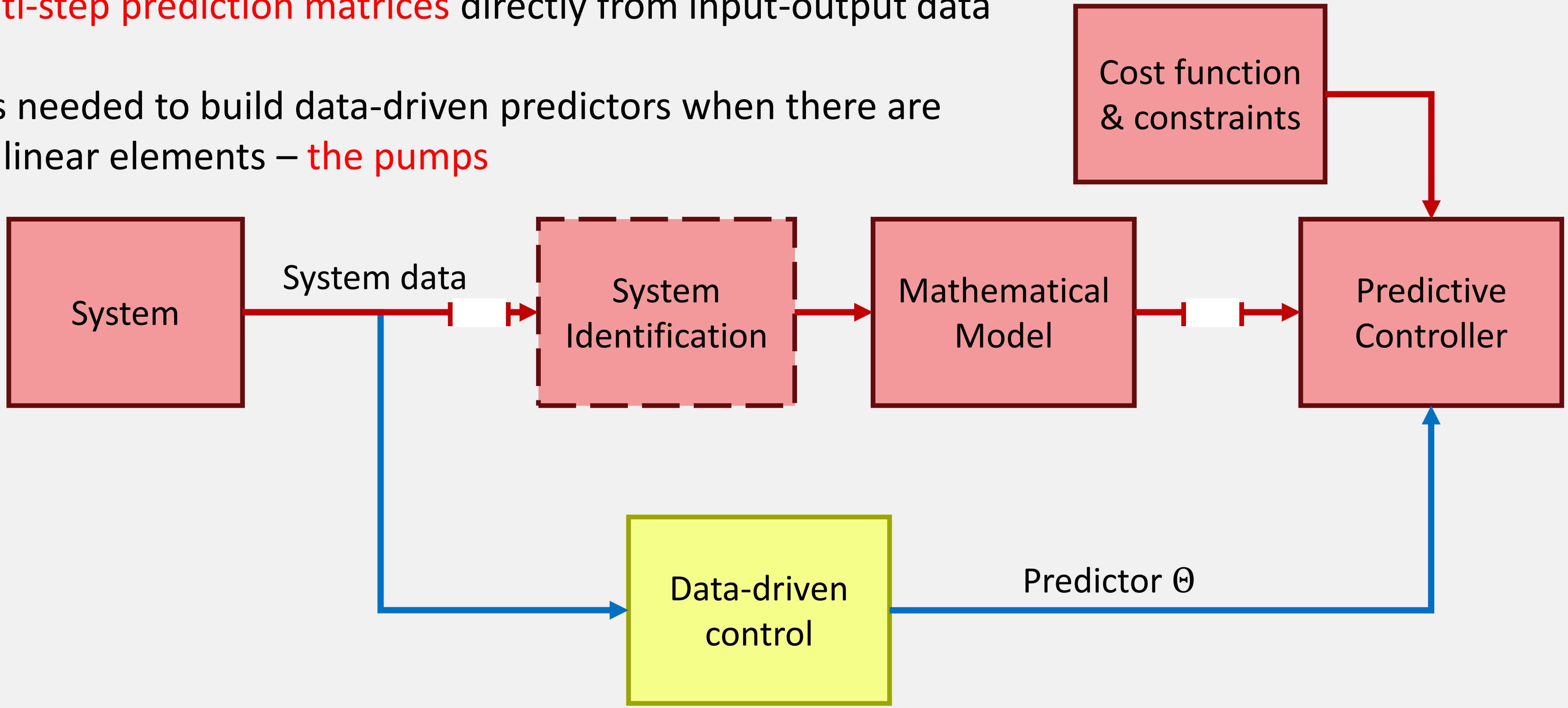
$\boldsymbol{h}(k) =$ 3 tanks h_1, h_5, h_6
$\boldsymbol{q}(k) =$ 4 uncontrollable flows $q_{25}, q_{35}, q_{43}, q_{64}$
$\boldsymbol{u}(k) =$ 2 controllable flows q_{12}, q_{26}
$\boldsymbol{d}(k) =$ 2 demand outflows d_1, d_2



AI and data-driven predictive control

Data-driven control eliminates the need to construct a prediction model and instead estimates multi-step prediction matrices directly from input-output data

AI is needed to build data-driven predictors when there are nonlinear elements – the pumps

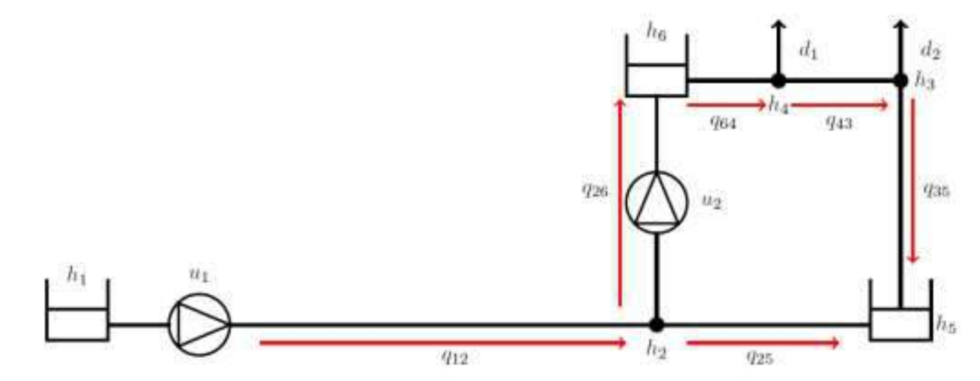


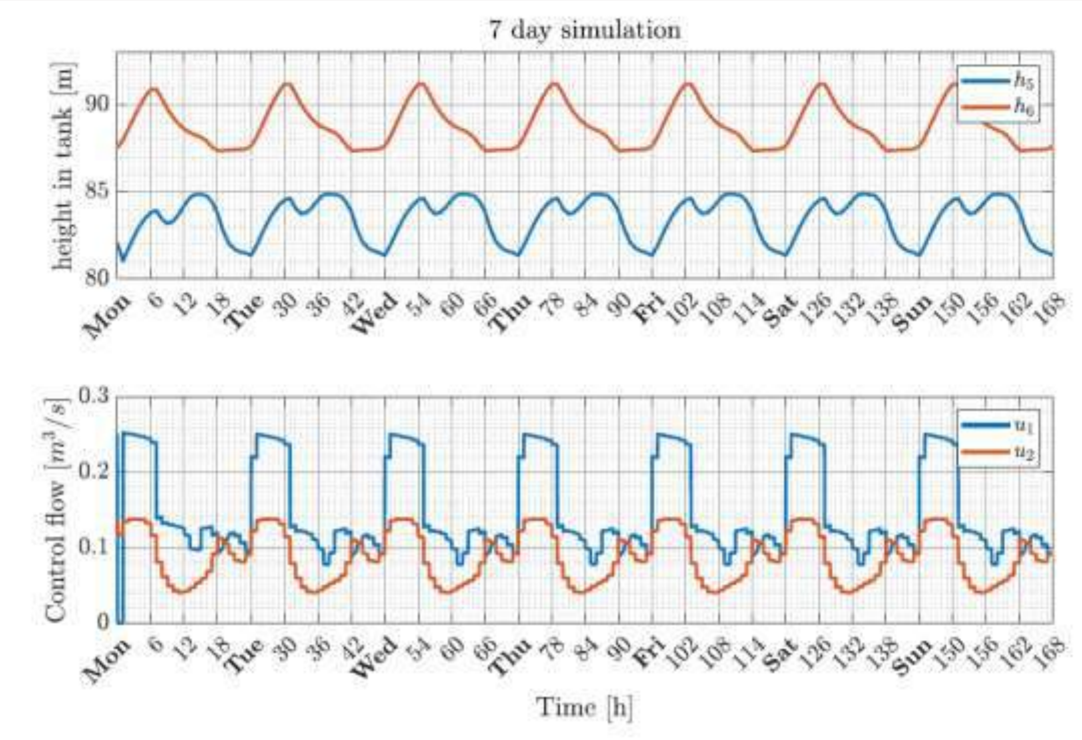
P.C.N. Verheijen, M. Lazar (Control Sys.) *(m.lazar@tue.nl)*
D. Goswami (Electronic Sys.), EE, Aquaconnect NWO

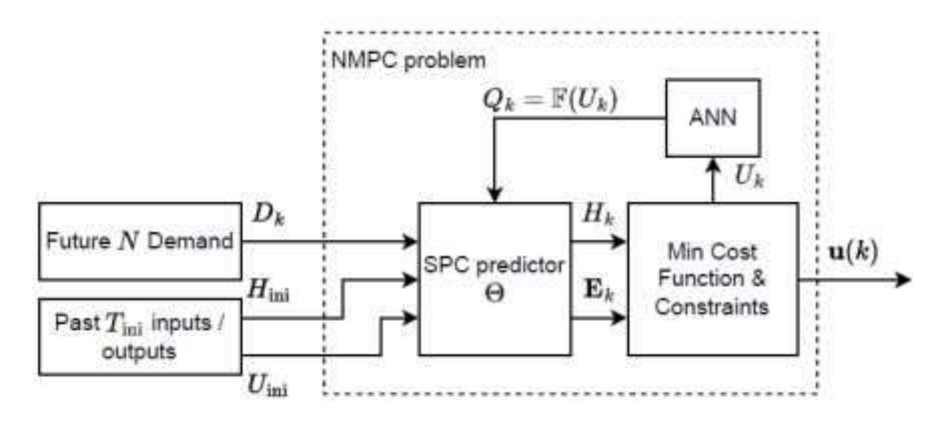
Water Distribution Networks

With virtually no exact physical model we can:

- Accurately control the water level in the tanks
- Save money by operating the pumps when electricity is cheap







Result:

Much

better

Verheijen et al., *"Nonlinear Data-driven Predictive Control design for Water Distribution Networks," submitted to IEEE CDC 2024.*

BIASlab – Bayesian Inference

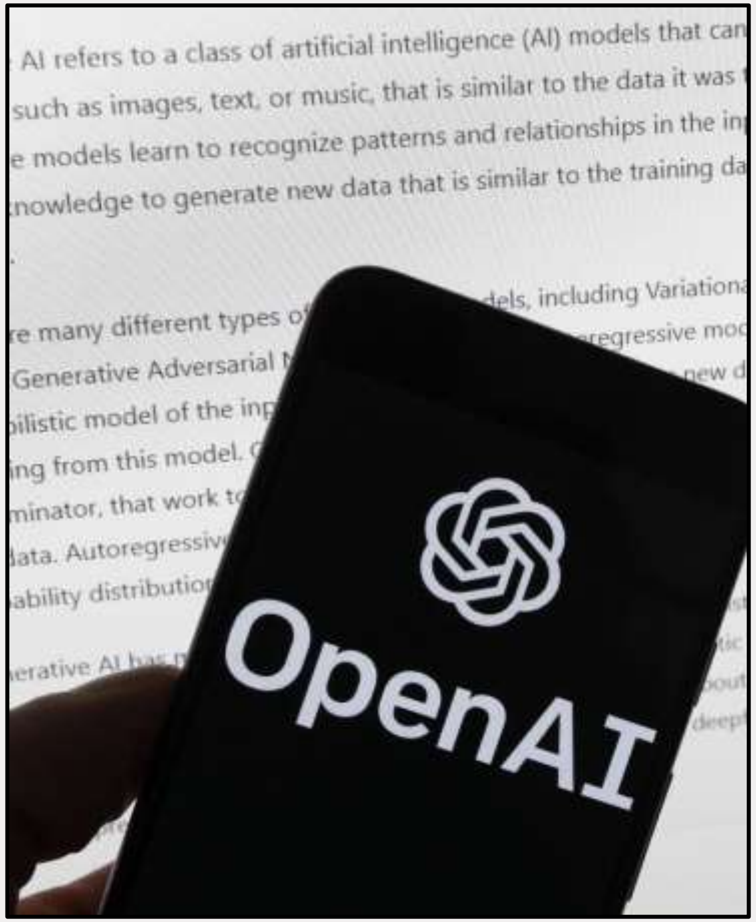
How to steer control in dynamic environments?

Bert de Vries

Generative AI

Natural Intelligence

Natural AI



no real-time learning	real-time learning
hallucination	corrected hallucination
resource-hungry	0 engineers, 20 watts
black box	explainable

Music, text, video generation

productivity

Assets, machines

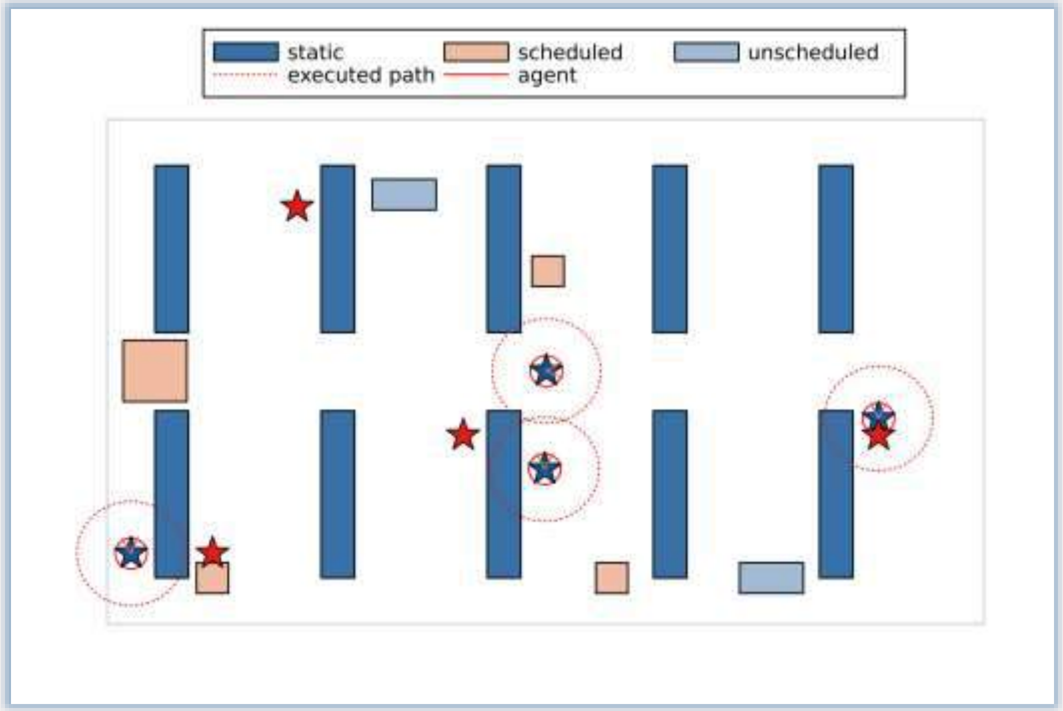
Autonomous control

Smart infrastructure

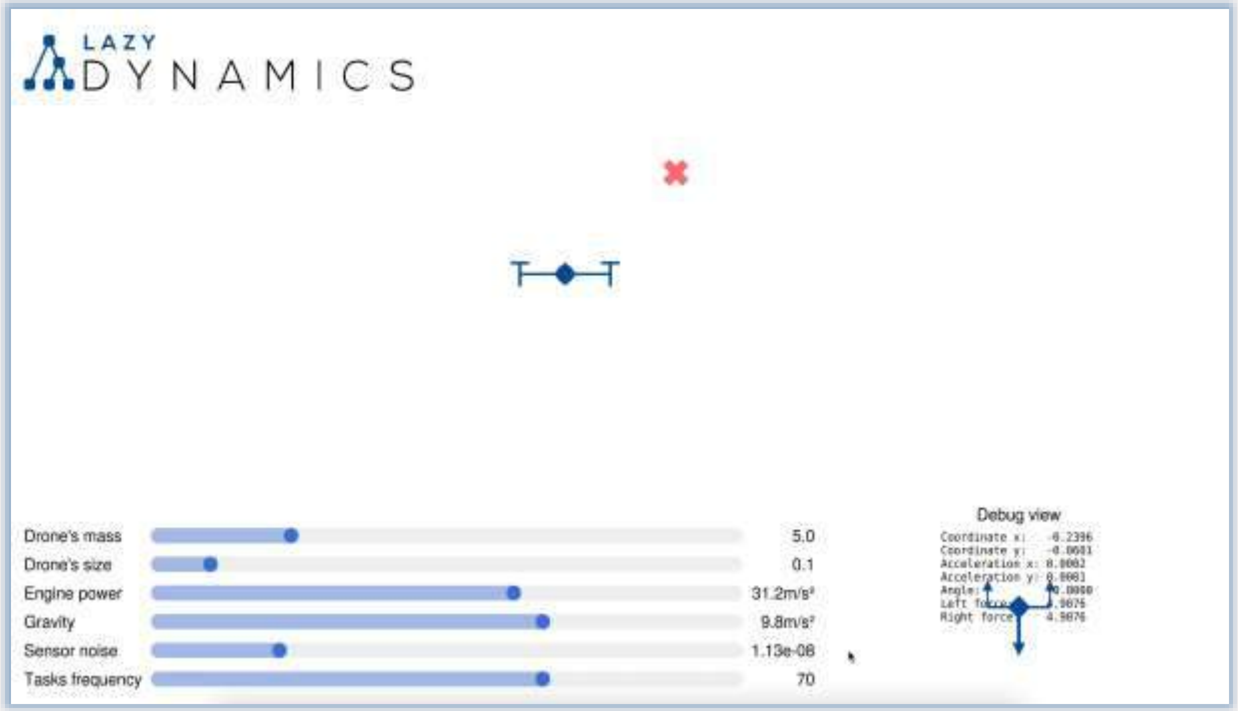
Water management

Bayesian Inference Toolbox: RxInfer

Automated inference in dynamic environments



WAREHOUSE NAVIGATION

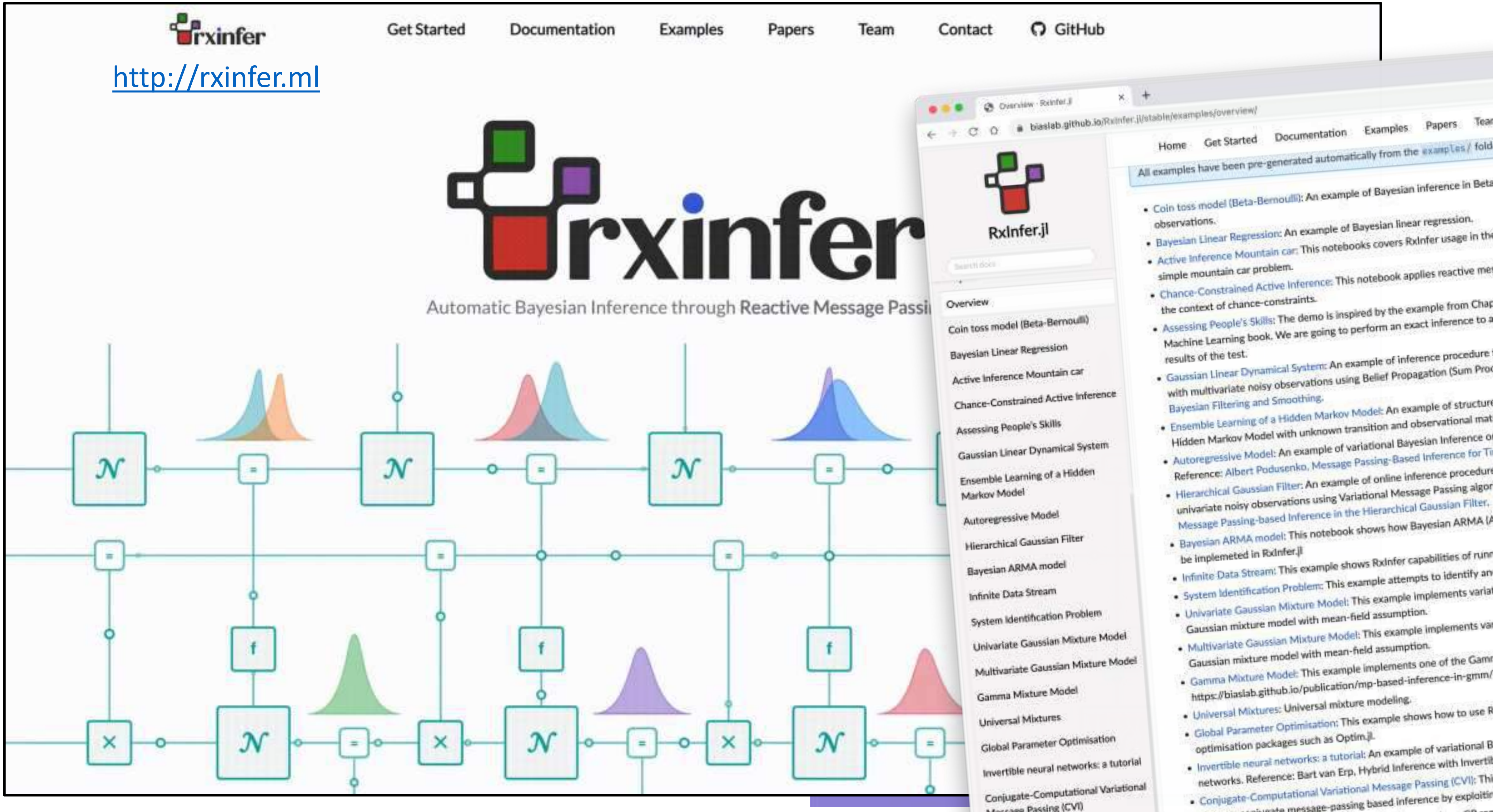


DRONE CONTROL

Just the tip of the iceberg…

A Software Toolbox for Scalable, Real-time, Automatic Bayesian Inference

http://rxinfer.ml



Thanks to some of our Researchers

River Networks:	Bettina Speckmann *(Math & Computer Science – Applied Geometric Algorithms)*
Multivariate Correlations Analysis:	Odysseas Papapetrou *(Math & Computer Science – Database Group)*
Tipping points:	Kerstin Lux-Gottschalk *(Math & Computer Science – Computational Science)*
Water Distribution Networks:	Mircea Lazar *(Electrical Engineering – Control Systems)*
Bayesian Automated Inference:	Bert de Vries *(Electrical Engineering – Signal Processing Systems)*

Thank you for your attention.

Hans van Beek (h.v.beek@tue.nl)

Agenda werksessie

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Roberto Bentivoglio (TU-Delft):	Improving fast spatio-temporal flood modelling with multi-scale hydraulic graph neural networks
Hans van Beek (TU Eindhoven):	Examples of TU/e Water & Climate related Math &AI Research. From Topological River Networks to Weather Correlations and Tipping Points

Open Space

- Inventarisatie cases + pitches
- Selectie top 3 cases
- Uitwerking
- Per case: next steps

Afsluiting en borrel

Uitwerken cases (hulpvragen)

Gewenst resultaat

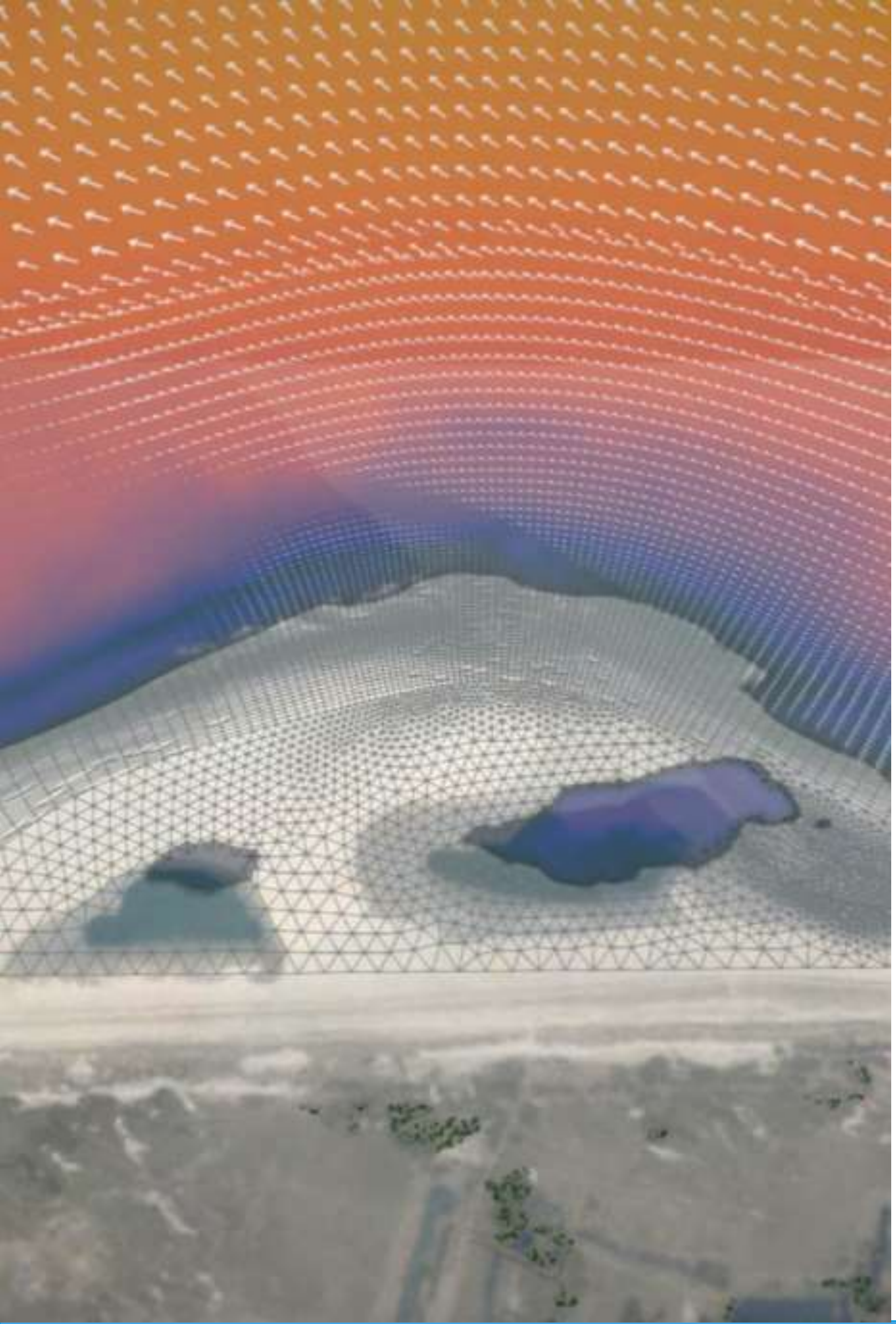
Wat is er nodig om tot realisatie te komen?

Waarom belangrijk?

Welke partners hebben we nodig?

Toegevoegde waarde voor eindgebruiker

Wanneer kunnen we starten? Wat is de looptijd?



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DATASCIENCE FOR DELTAS

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Bedankt

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Op de hoogte blijven?

- Schrijf je in voor de nieuwsbrief op www.DigiShape.nl
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