FloodWaive

AI for Rhine Low-Flow Forecasting: Strategic Insights & The Path to Surrogate Models

Ongoing Collaborative Initiative between Rijkswaterstaat and FloodWaive Predictive Intelligence GmbH

Foto: Bezirksregierung Köln

WHO ARE WE?

Pioneers in Operational AI-based Flood Risk Analysis

Dr.-Ing. Julian Hofmann
CEO & Co-Founder

Strategy & Management,
Business Development,
Sales & Customer Success

Adrian Holt
CTO & Co-Founder

Lead Product Development,
Software Front- & Backend,
AI Research & Development

Dr. Sascha Welten
COO

Lead Operations & Processes,
DevOps Management,
Project Management

Key Members

Christian Heinrichs

Interim CFO,
Finance, Strategy

Timon Rochholz

HR &
Accounting

Jonna Hahn

Marketing Lead
Communication

Gregor Johnen

Lead Research &
Developement

Joshua Mader

Hydraulic Engineer
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Full Stack Development
(Front- & Backend)

Marvin Engler

Software Engineer
(Frontend)

Bozhen Zhu

Software Engineer
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Advisory Board

Prof. Dr.-Ing. Schüttrumpf

Head of the IWW
RWTH Aachen

Jr. Prof. Dasgupta, PhD

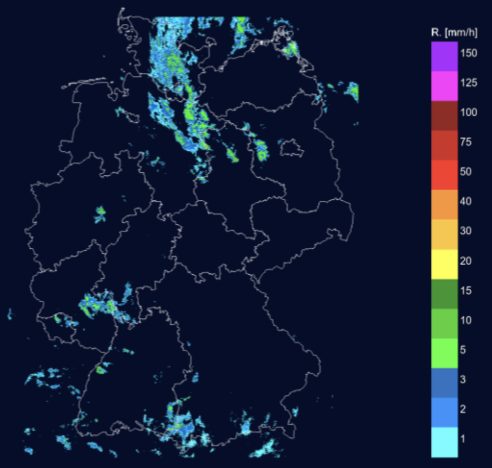
Data-Driven Computing
IWW, RWTH Aachen

Mathis Niederau

Production Engineering
> 5 Years M&A

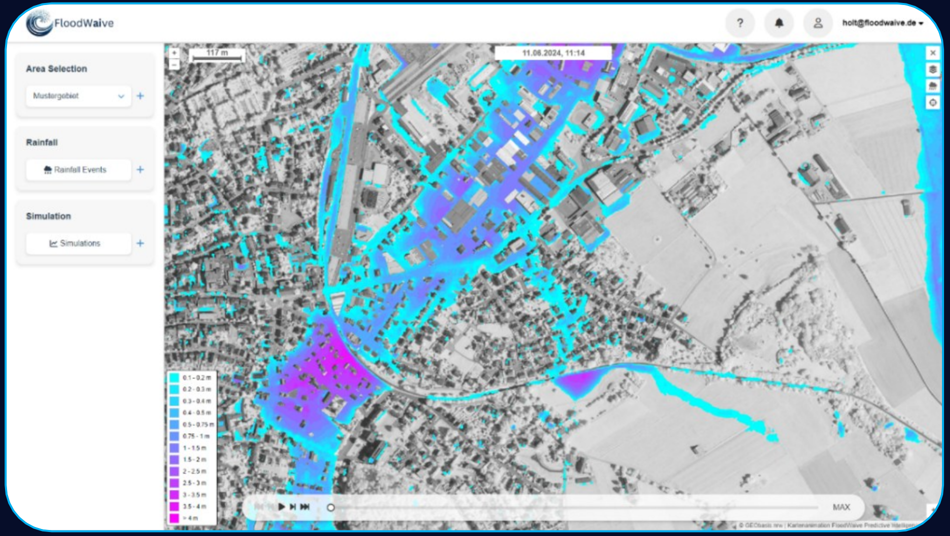
SPECIALISING ON SURROGATE MODELS

DeepWaive: Fusion of Physical-based Models with Deep Learning



Rainfall Forecast

Calculation:
1 second



DeepWaive Flood Forecast | 1m Resolution

DeepWaive is a disruptive breakthrough in flood forecasting technology, enabling highly precise and physically accurate predictions calculated nearly instantly

Computation Time	Resource Efficiency	Accuracy
Up to 1,000,000 times faster than exisiting methods	Reducing simulation costs and overhead by 50%	Highest-fidelity Forecasts at sub-1 meter resolution

OUR SOLUTION

DeepWaive: Risk Analysis and Early Warning with one AI-Model

Potential heavy rainfall scenarios

Rainfall- and hydrological forecasts

DeepWaive Foundation Model

DeepWaive Finetuning
e.g. domain and sensor data

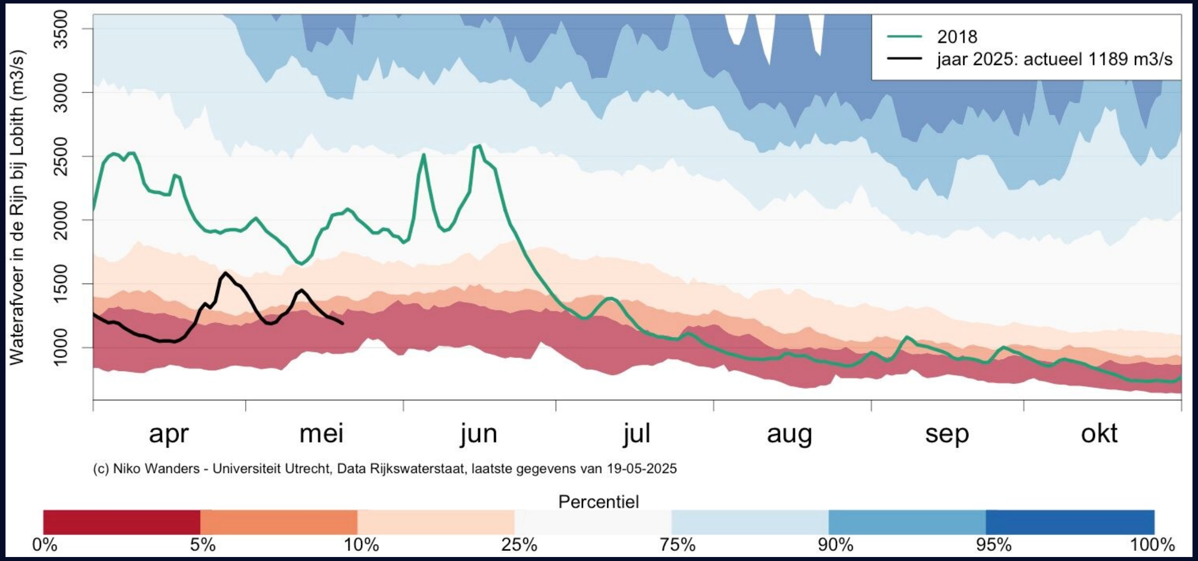
Risk analysis and effectiveness test of flood protection measures

Flood forecasts and early warning

In addition to near-instantaneous flood forecasts and early warnings based on weather forecasts, DeepWaive allows different heavy rainfall scenarios to be modelled, thus enabling proactive risk analysis for the engineering, insurance, and infrastructure sectors

TODAYS FOCUS

Securing Reliable Low-Flow Forecasts for the Rhine (up to 45-day & seasonal)



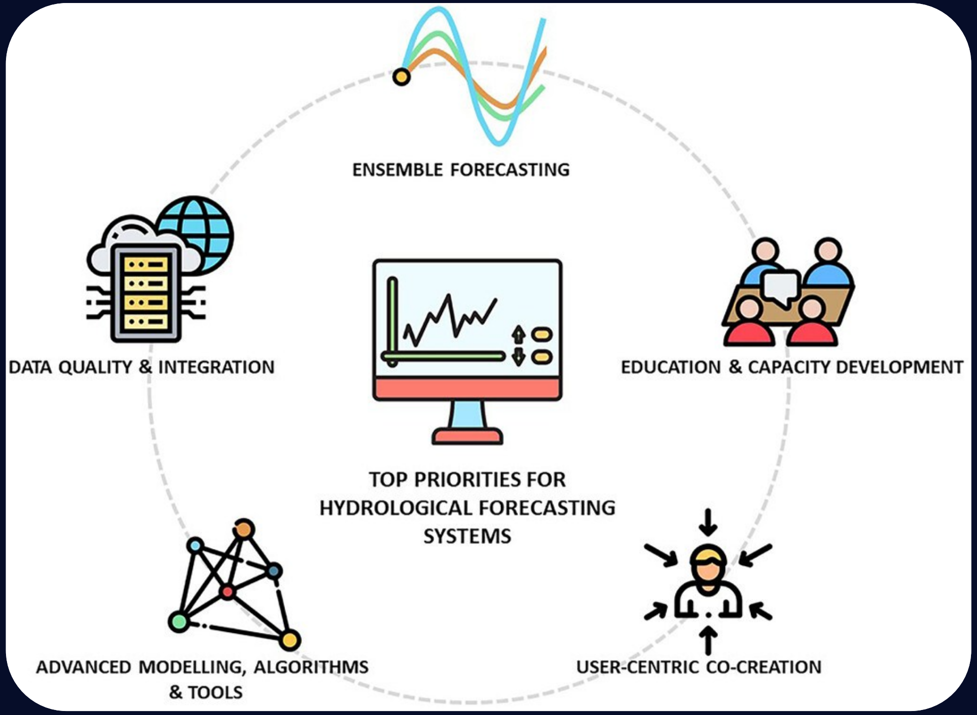
Month	Rhine Discharge at Lobith (daily average in m³/s)
January – April	1000
May	1400
June	1300
July	1200
August	1100
September	1000

THE PROBLEM

Securing Reliable Low-Flow Forecasts for the Rhine

- Rich data landscape at RWS, suitable for ML.
- Key Recommendation: A Proof-of-Concept (PoC) focused on developing an ML-based surrogate model (emulator) for the WFLOW-SBM for basin runoff.
- Primary Goal: Drastically reduce computational runtimes for ensemble forecasting.
- Secondary Benefits: Potential for integrated bias correction and coupling with faster hydraulic surrogates (e.g., for SOBEK sections).
- Hybrid approaches combining physics and ML are deemed most promising for robustness.

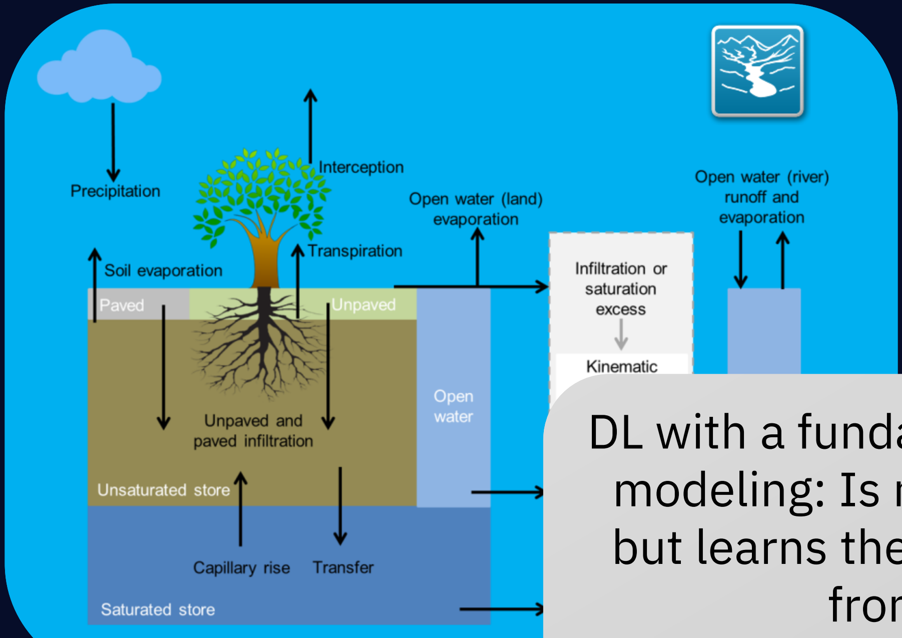
The essence of Operational Forecasting Systems:



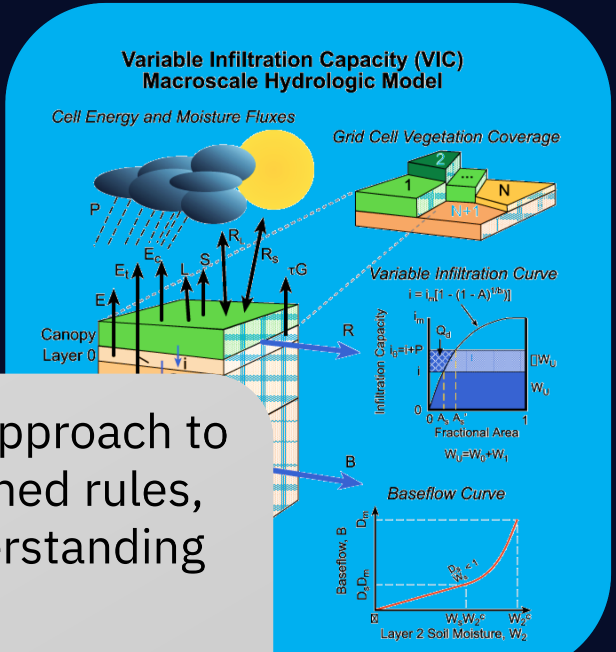
Source: Pechlivanidis et al., 2025. https://doi.org/10.1175/BAMS-D-24-0322.1

INTERIM RESULT

What Should the Low-Flow Surrogate Model Learn?



Source: https://wflow.readthedocs.io/en/latest/wflow



Source: vic.readthedocs.io

DL with a fundamentally different approach to modeling: Is not based on predefined rules, but learns the entire process understanding from the available data.

Data → / Rules → **Classic Modelling** → Targets

vs.

Data → / Targets → **Deep Learning** → Rules

What Should the Low-Flow Surrogate Model Learn?

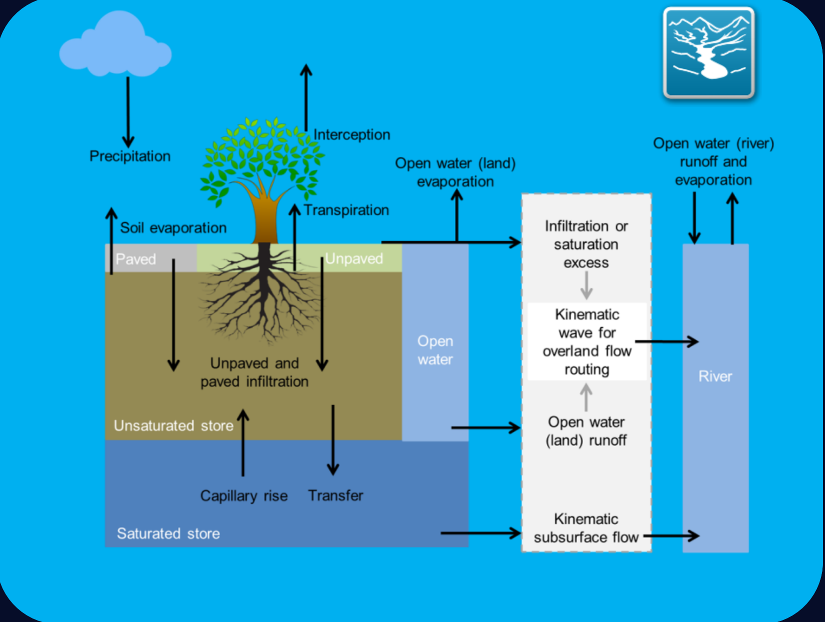
OPTION 1 (RECOMMENDED FOR POC): END-TO-END DISCHARGE EMULATION:

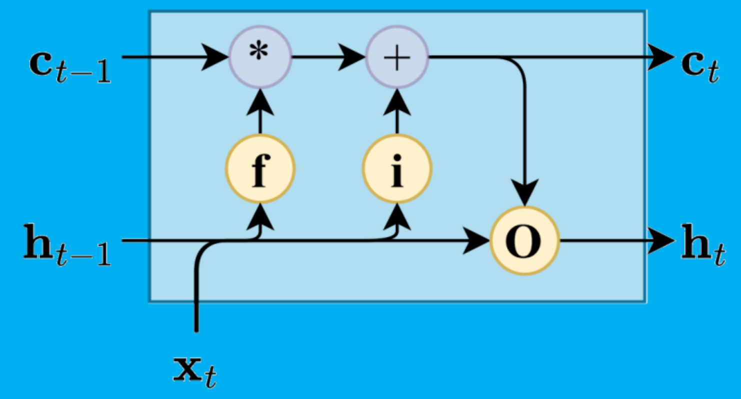
Process Based Hydrological Model

$$s[t] = f(x[t], s[t-1]; \theta_i)$$
$$\hat{y}[t] = g(s[t], \theta_j)$$

LSTM:

$$\{c[t], h[t]\} = f(x[t], h[t-1]; \theta_i)$$
$$\hat{y}[t] = g(h[t], \theta_j)$$





* No need to decide which hydro-logical processes are important

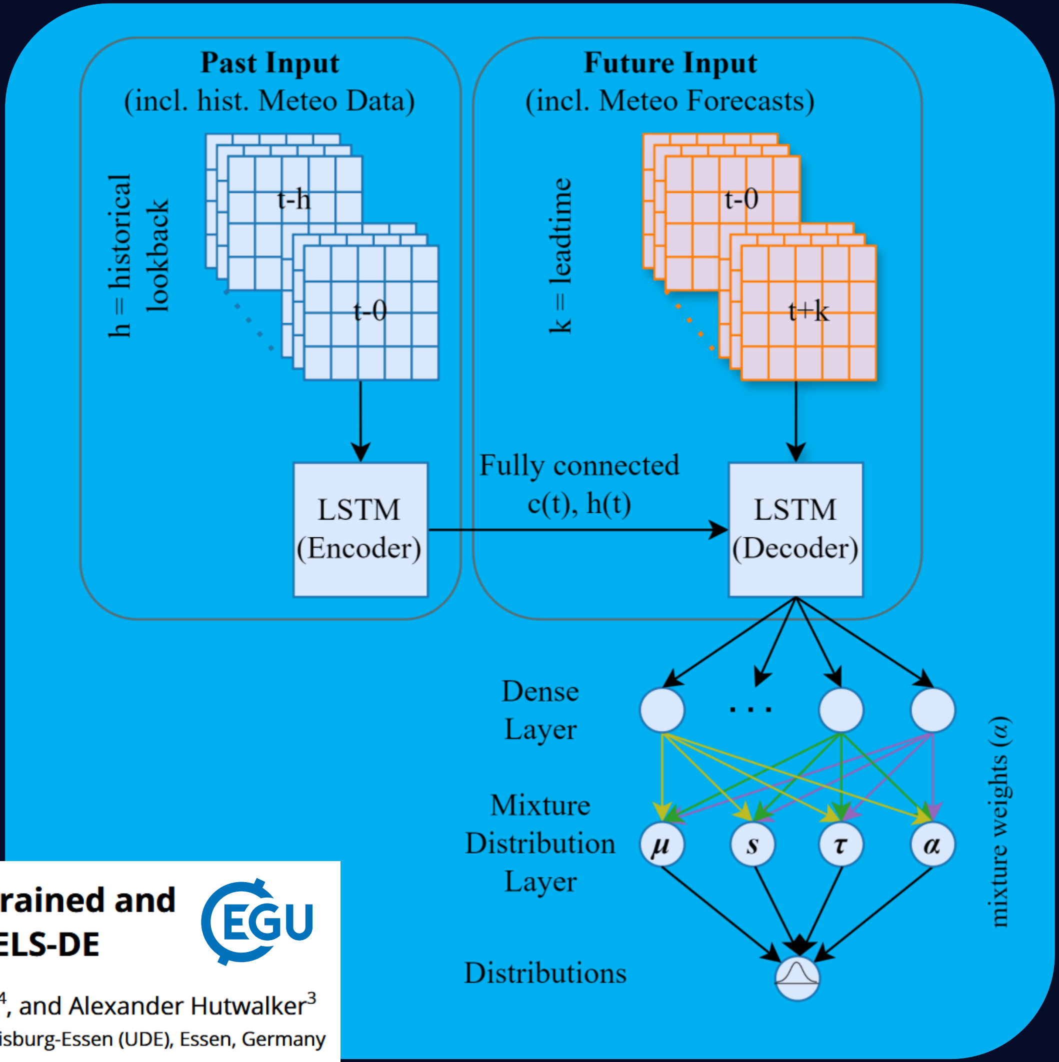
Pro: Directly addresses the primary forecast need, offers significant overall runtime reduction and derives uncertainties intrinsically.

Choice Implication: Requires a comprehensive training dataset from diverse catchments and respective static attributes of them.

INTERIM RESULT

Probabilistic LSTMs

- Model processes both historical data and (multiple) forecasting products (ECMWF-ENS, ECMWF-SEAS, ICON (DWD), GloFAS (potential)).
- Classical models often require additional mechanisms for probabilistic estimates, e.g. pre-/post-processing, data assimilation or Monte Carlo sampling.
- Output are time-variable & conditional probability density function.
- **Architectural variability meets model performance!**



Forecasting Reservoir Inflows Using Regionally Trained and Finetuned LSTM Models: A Case Study with CAMELS-DE

EGU

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[2]FloodWaive Predictive Intelligence GmbH, Aachen, Germany

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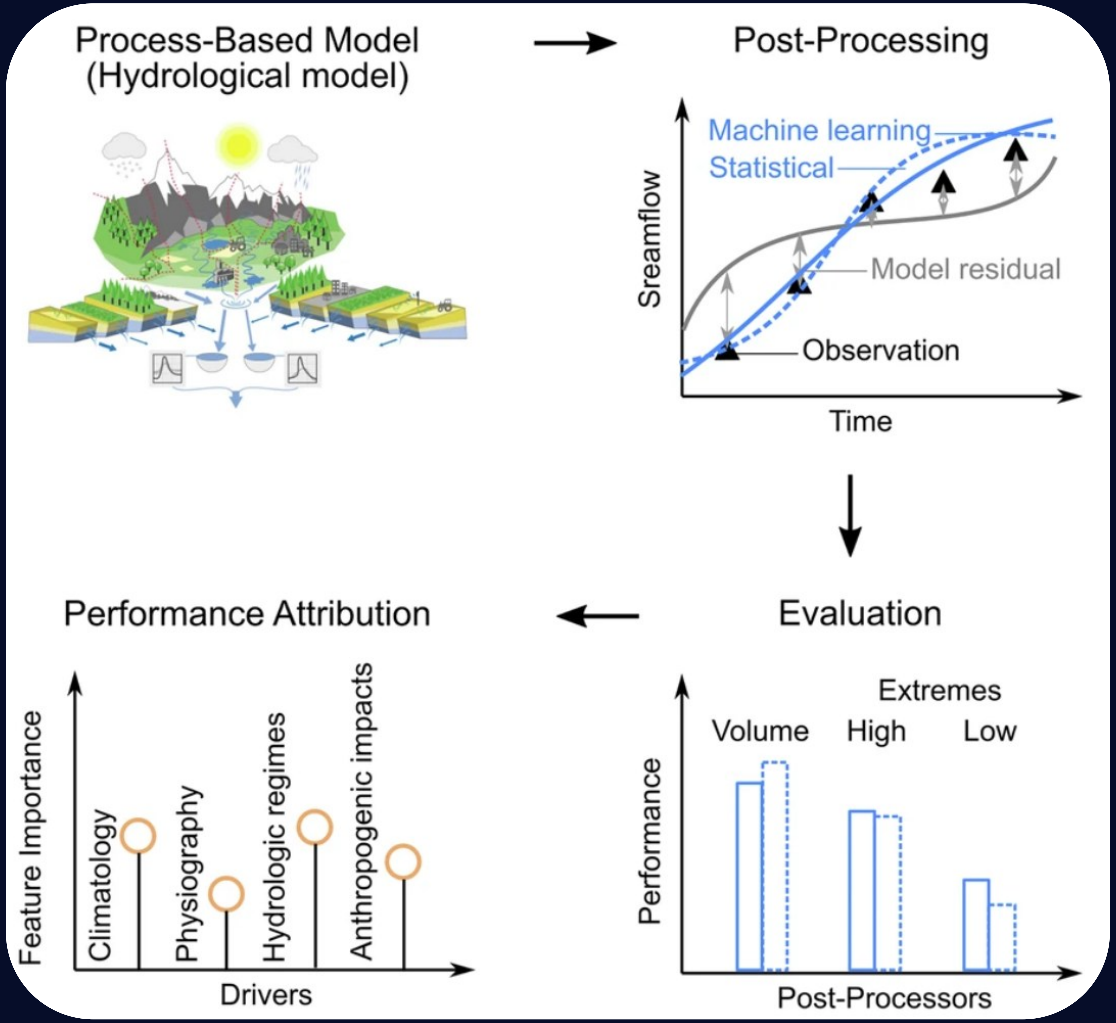
Source: Johnen et al. 2025
[10.1007/s35152-025-1982-z](https://doi.org/10.1007/s35152-025-1982-z)

What Should the Low-Flow Surrogate Model Learn?

OPTION 2 (Future Consideration): Component-Based Emulation:

Emulate specific, computationally intensive sub-modules within WFLOW-SBM (e.g., snowmelt, routing).

Pro: Could offer targeted speed-ups.
Choice Implication: More complex integration with the WFLOW-SBM framework.



Source: Du & Pechlivanidis, 2025
https://www.nature.com/articles/s43247-025-02324-y

Physical plausibility and extremes: the crucial role of data and validation

Extrapolation & Physical Consistency:

Physically implausible results
→ Incorporating physics-informed inductive biases (e.g. mass conservation)

Inheriting Input Data Biases

Different distributions in historic and forecast data
→ Critical importance of access to long forecasting archives

Training Data Needed:

Training Data of one catchment not enough to extrapolate
→ Make use of large sample-hydrologic datasets

Evaluation Metrics:

How do we define "success" for the surrogate
→ Apply multimetric approach suitable for probabilistic models and drought conditions (e.g. drought occurrence probabilities in Lobith)

ROADMAP

Moving Forward: From Strategic Advice to Practical Development

- The Phase 1 advisory has laid the groundwork, identifying WFLOW-SBM emulation as a high-impact path.
- We Propose (Phase 2): Initiate the Proof-of-Concept project with RWS.
- Key PoC Activities:
  - Detailed planning and generation of the WFLOW-SBM training data corpus.
  - Development and training of the initial WFLOW-SBM ML surrogate based on large sample datasets (https://arxiv.org/abs/2411.09459).
  - Rigorous validation against historical data and assessment of computational gains (Hindcast).
  - Exploration of complementary surrogate modeling of SOBEK hydraulic rating sections
  - Scoping for integration into a FEWS sandbox environment:

Cloud API
Pro: Auto scaling, MLOps infrastr., GPU on demand
Cons: Network dependency, Data sec. concerns

On-Premise HPC
Pro: Control and security, Latency, GPU-power
Cons: Investment, Maintanance overhead

Python Package
Pro: FEWS-Integration, On-prem. excec., Low latency
Cons: Dependency management, Ltd. scalability

Docker Container
Pro: Repr. Env., Easy deployment, Version control
Cons: Orchestration complexity, Resource overhead

- FloodWaive is prepared to collaborate closely with RWS on this exciting next phase.

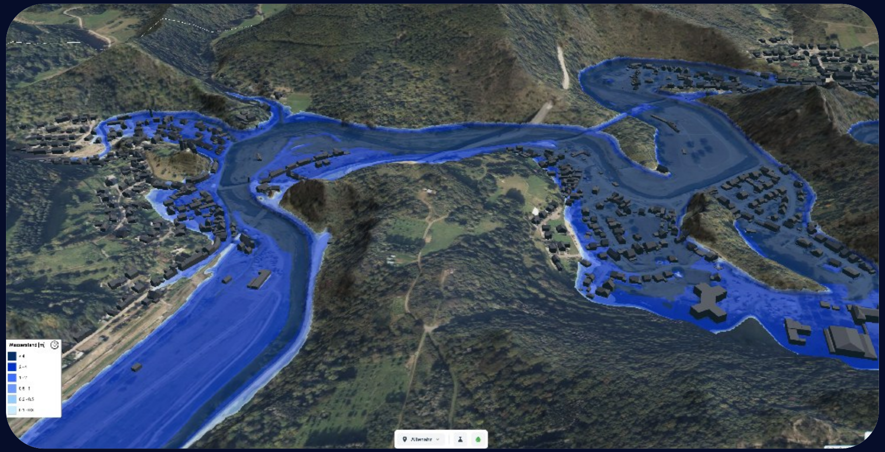
Take Home Messages & Outlook

1. KEY TAKEAWAYS

- **ML can transform Rhine low-flow forecasting** - Addressing critical water scarcity challenges while overcoming computational bottlenecks
- **Rich data foundation already exists** - Extensive historical records, meteorological datasets (E-OBS, HYRAS), and large sample DS provide solid ML training basis
- **Hybrid approach is essential** - Combining physics-based understanding with ML pattern recognition ensures robust, interpretable forecasts (e.g. DeepWaive)
- **FEWS integration is feasible** - Multiple host/deployment options available (Cloud API, Docker, Python) to fit RWS infrastructure

2. OUTLOOK

- **Phase 2 PoC Launch (6-9 months)** - Develop and validate WFLOW-SBM emulator with complementary components
- **Vision: Resilient water management** - ML-enhanced forecasting system protecting Dutch water security in changing climate



FloodWaive

Revolutionizing Flood Risk Intelligence

We translate weather into impact, protecting lives and reducing costs.

DeepWaive RiskAnalyzer
Object-level hazard, mitigation analyses & risk profiles in seconds

DeepWaive Forecast
Impact-based and probabilistic flood forecasting & warning

DeepWaive Operations
Operational decision support & measure analyses during emergency operations

Foto: Bezirksregierung Köln