Joint training of hydrologic & hydraulic models using deep learning and SWOT PIXC data for Torne river

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EO4FLOOD

1. CONTEXT

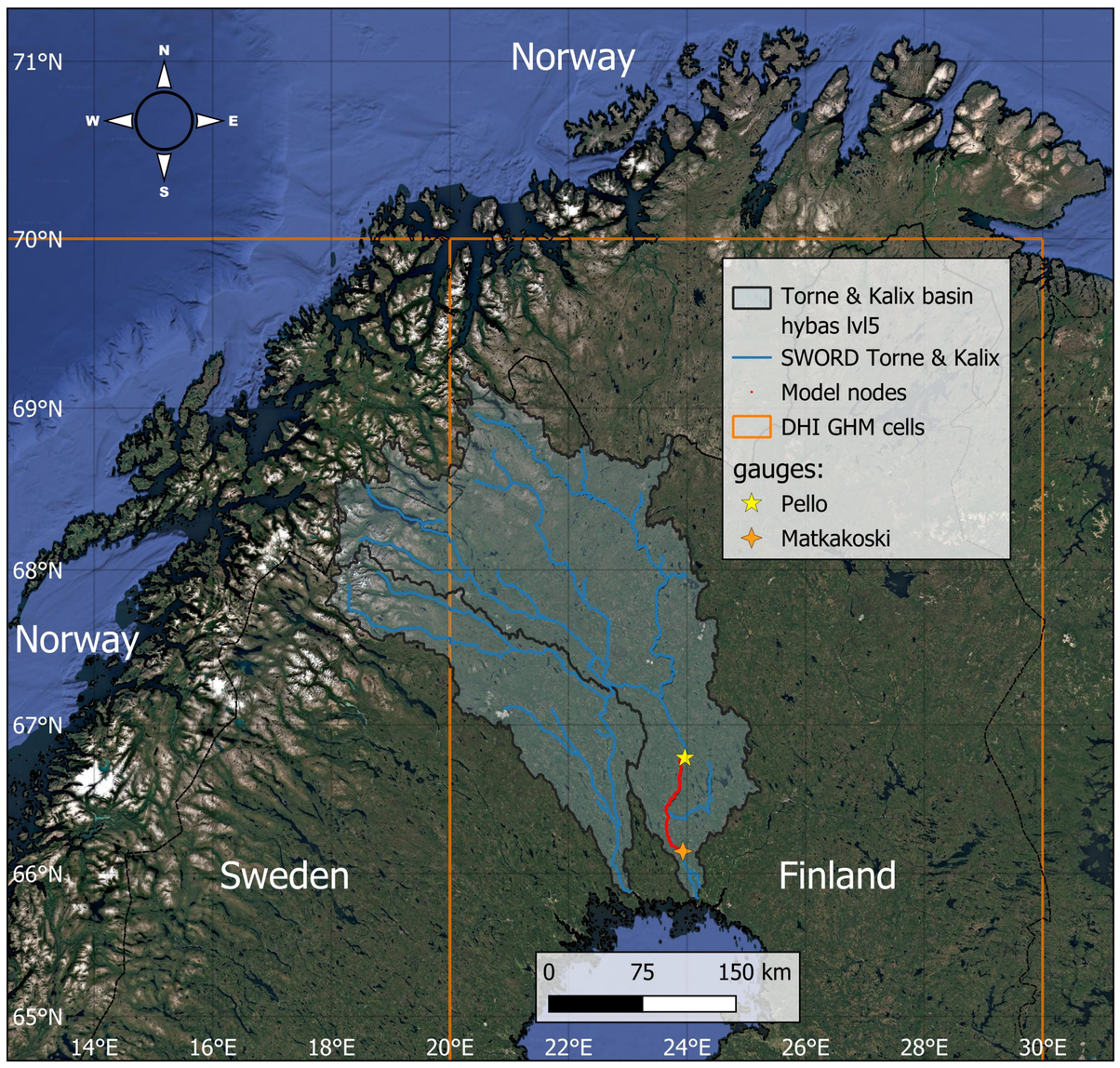

Fig 2: Map of Region of Interest. Background: google earth.

Use Torne as a well-observed and well-gauged river within the EO4Flood project to produce a joint hydraulic & hydrologic model proof of concept.

- Section between Pello and Matkakoski
- Swedish-Finnish border river
- Gauges in start- and end-point

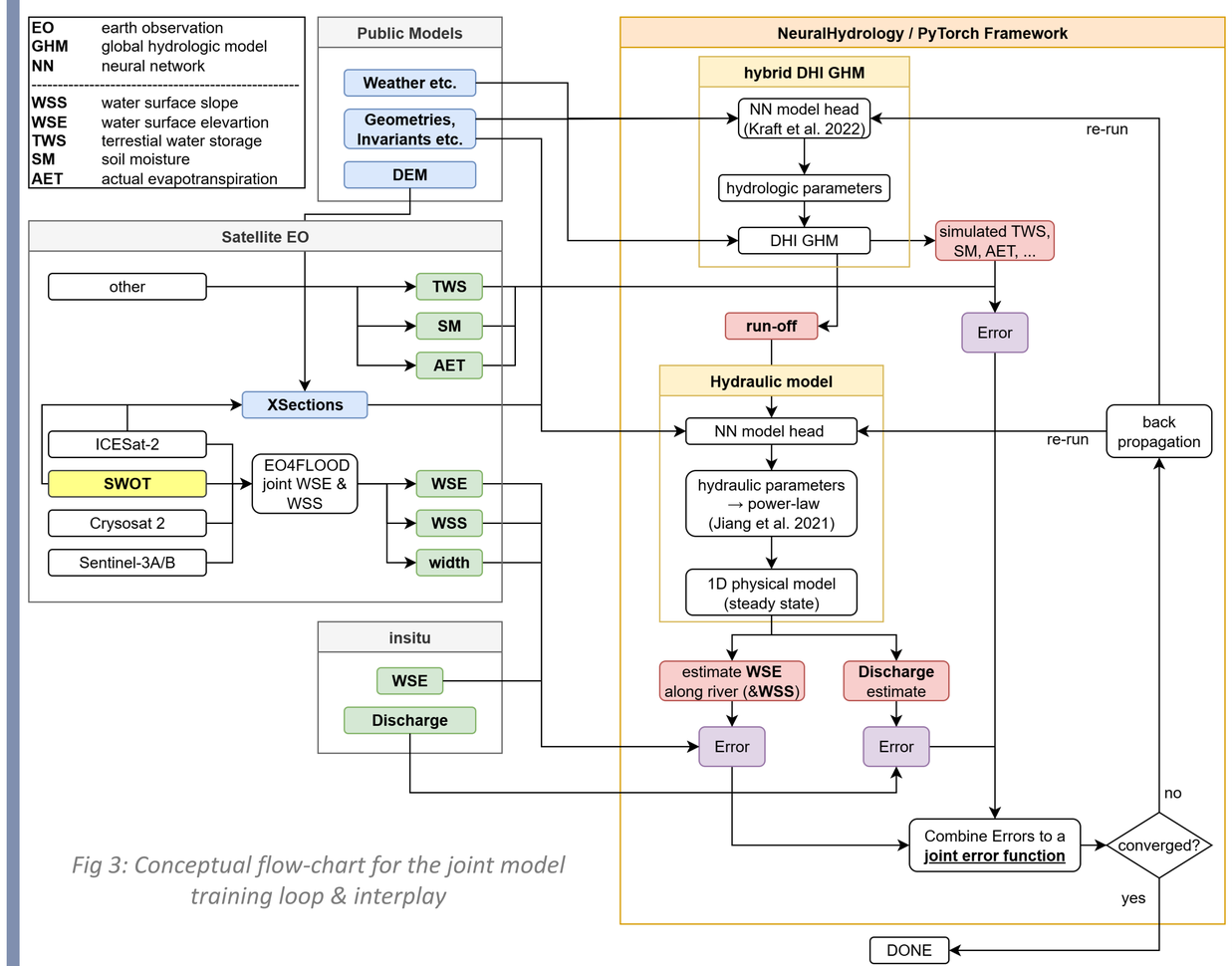

Fig 3: Conceptual flow-chart for the joint model training loop & interplay

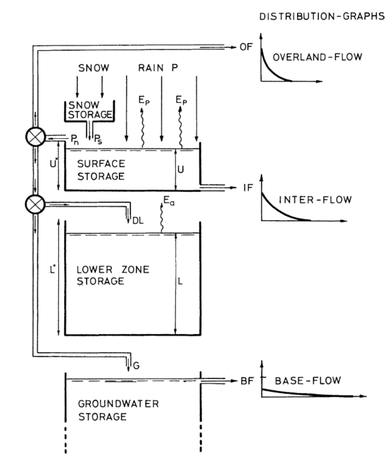

Fig 4: Structure of rainfall-runoff-model NAM, Nielsen & Hansen 1973

Idea:

- Couple hydrologic and hydraulic models
- Hydrologic model's output as input to hydraulic solver
- Use deep learning (DL) models for parameter estimation
- Physics based models for physical consistency
- Joint training of both models in one loop

Means:

- Differentiable programming using PyTorch
- DHI GHM (Murray et al. 2023) uses NAM as rainfall-runoff-model (RR)
- Steady, gradually-varied flow solver

Benefits:

→ Both models benefit from SWOT

→ Potentially other state variables

→ Almost independent from gauges

→ Independent of rating-curves

3. DATA

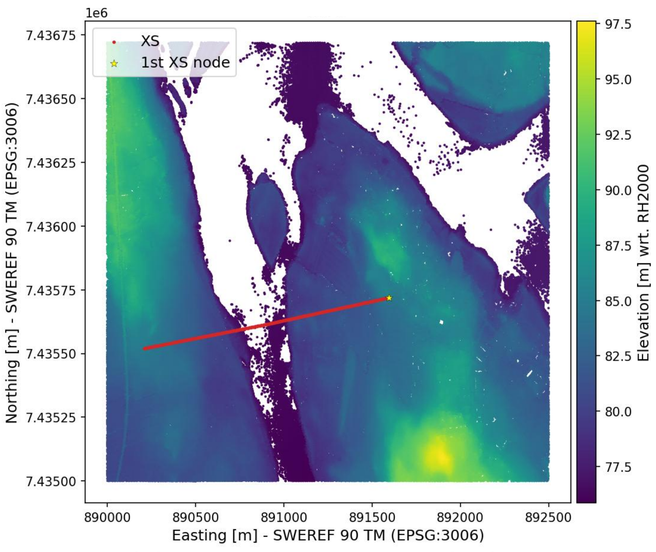

Fig 5: Swedish topographic LIDAR point-cloud over Pello

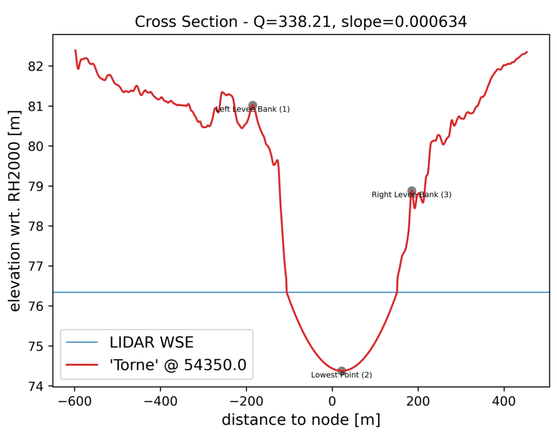

Fig 6: Cross-section from topographic LIDAR with estimated submerged section.

The hydraulic model requires the following input data

Geometry:

- Use topographic lidar if available, else ICESat-2
- Estimate submerged section (Musaeus et al. 2023)
- Slope from LIDAR / SWOT
- Q from gauge or RR-model

Water Surface Elevation:

- SWOT
- Custom PIXC processing
- RiverSP from Hydrocron

Run-off:

- DHI GHM (here un-tweaked)
- Routed through hydro-basin lvl 12
- Good initial agreement with gauge in Pello

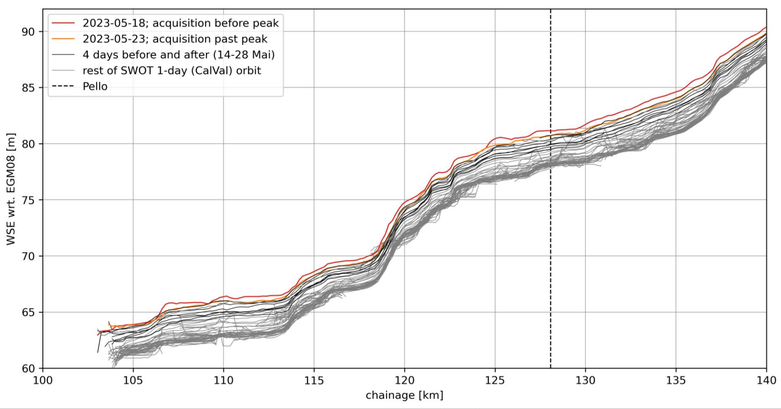

Fig 7: SWOT projected to centerline for flood in 2023 around Pello.

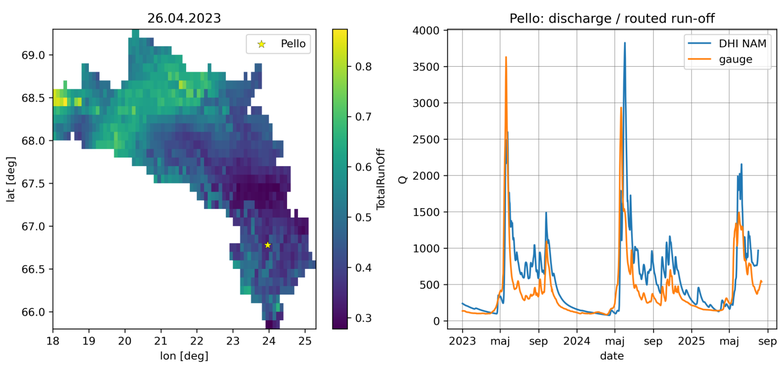

Fig 8: DHI GHM routed run-off

4. CONCLUSION & TAKE-AWAYS

Floods are among the most devastating natural disasters, affecting both developed and developing regions. However, developing countries often lack sufficient monitoring and early warning systems, making them more vulnerable. Within the ESA EO4FLOOD project, we introduce a novel, joint modelling framework that couples hydrologic and hydraulic models using a deep learning (DL) approach to reduce model reliance on insitu measurements and facilitate cross-learnings.

Main Points:

- Topographic LIDAR allows high quality cross-section construction
- A joint hydrologic and hydraulic model offers high independence from in-situ gauges & both models are calibrated with SWOT
- SWOT resolves changing river features with unprecedented details and allows for instantaneous slope estimates
- SWOT based modelled discharge shows good results in a preceding study over the same area

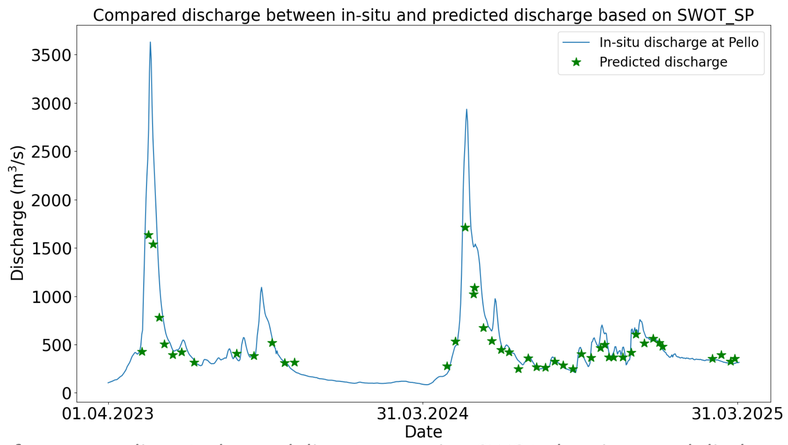

Fig 9: Results from preceding study, modeling Torne using SWOT showing good discharge (Q) results.