From monitoring to understanding

Towards a digital twin for hydrological drought prediction

M. Castelli, M. Claus, A. Crespi, P. Bartkowiak, A. Jacob

Institute for Earth Observation, Eurac Research

Center for Climate Change and Transformation, Eurac Research

EODC Forum 2023

WP4

Co-design and validation with research communities

Objective:

Demonstrate that the Digital Twin Engine can support the implementation of digital twins in different domains.

T4.6 Early Warning for Extreme Events (floods & drought)

Deltares
Eurac Research
TUWien

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Earth observation data and machine learning are not fully exploited for hydrology

Water Resources Research

Technical Reports: Methods | Open Access

Toward Improved Predictions in Ungauged Basins: Exploiting the Power of Machine Learning

Frederik Kratzert, Daniel Klotz, Mathew Herrnegger, Alden K. Sampson, Sepp Hochreiter, Grey S. Nearing

First published: 23 November 2019 | https://doi.org/10.1029/2019WR026065 | Citations: 159

Water Resources Research

Commentary | Free Access

What Role Does Hydrological Science Play in the Age of Machine Learning?

Grey S. Nearing, Frederik Kratzert, Alden Keefe Sampson, Craig S. Pelissier, Daniel Klotz, Jonathan M. Frame, Cristina Prieto, Hoshin V. Gupta

First published: 13 November 2020 | https://doi.org/10.1029/2020WR028091 | Citations: 109

nature > nature communications > articles > article

Article | Open Access | Published: 13 October 2021

From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling

Wen-Ping Tsai, Dapeng Feng, Ming Pan, Hylke Beck, Kathryn Lawson, Yuan Yang, Jiangtao Liu & Chaopeng Shen

Nature Communications 12, Article number: 5988 (2021) | Cite this article

16k Accesses | 30 Citations | 72 Altmetric | Metrics

We want to make good use of available EO data to formulate hydrological predictions.

Deep learning can learn from big data, while hydrological models work better if calibrated locally, on individual basins.

The machine learning and the hydrology communities are still distant, but there is a lot they can gain from each other.

Early Warning for Hydrological Drought

WHAT

Generating a drought early warning system for Alpine catchments

WHY

To support public authorities in water resources management under water scarcity

conflicts on water use for hydroelectric power production and for agriculture, or water use restrictions

HOW

Combining deep learning with the process-based model WFLOW (Deltars) and satellite observations

Space

Time

Past to NRT: reproducing timeseries of hydrological variables, possibly reproducing the current situation in NRT

Near future: predicting hydrological variables and drought occurrence 2 weeks to 2 months in advance based on sub-seasonal climate forecasts

Deep learning in place of traditional calibration for large scale applications

nature COMMUNICATIONS

ARTICLE

Check for updates

https://doi.org/10.1038/s41467-021-26107-z OPEN

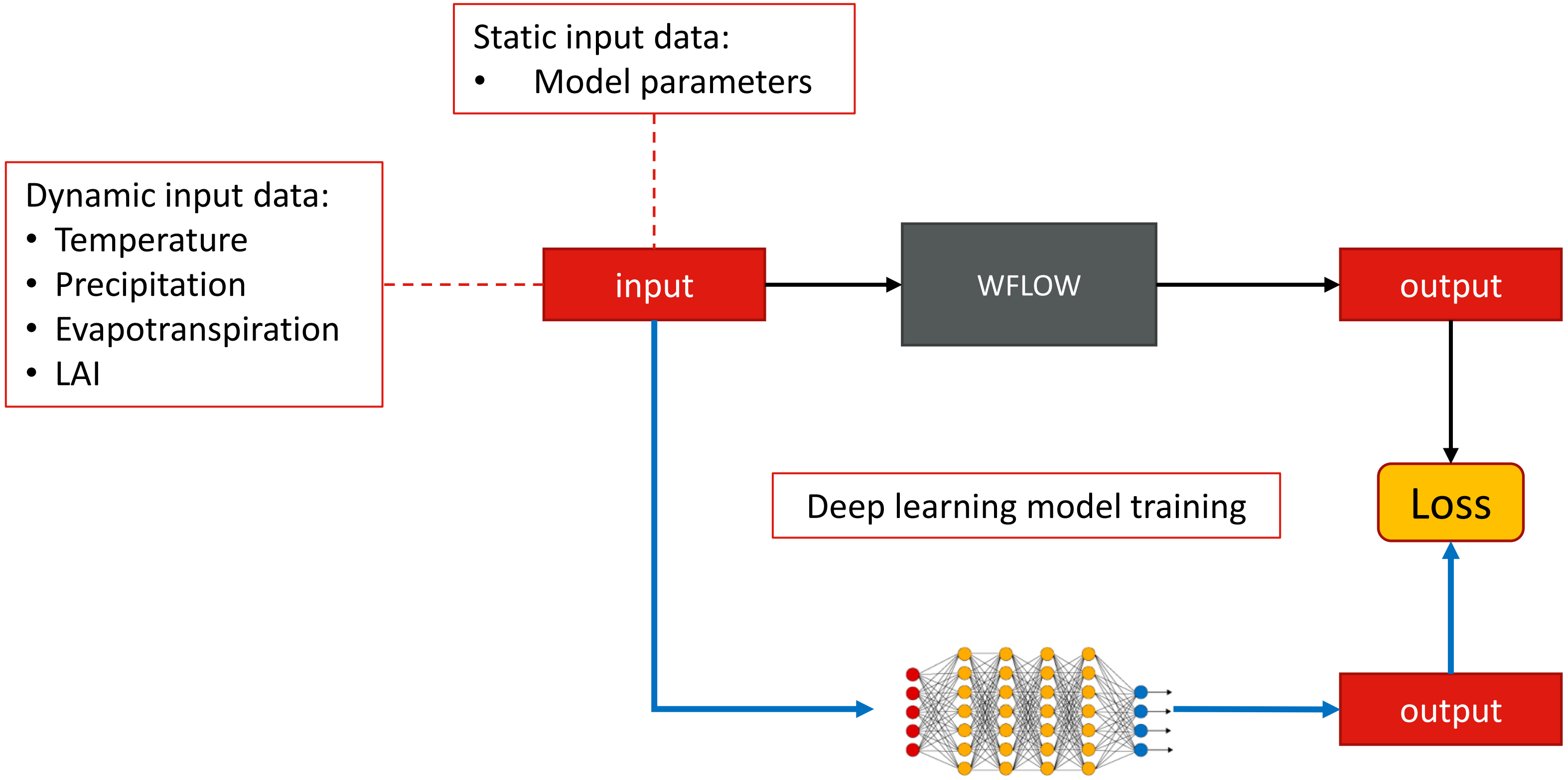
From calibration to parameter learning: Harnessing the scaling effects of big data in geoscientific modeling

Wen-Ping Tsai[1], Dapeng Feng[1], Ming Pan[2,3], Hylke Beck[4], Kathryn Lawson[1,5], Yuan Yang[6,7], Jiangtao Liu[1] & Chaopeng Shen[1,5]✉

- Deep learning can increase the efficiency of model calibration and model generalizability
- The loss function can be defined over the entire training dataset, defining a global constraint
- Deep learning can learn scale dependent input-output relationships from large datasets at large scale

Surrogate model workflow

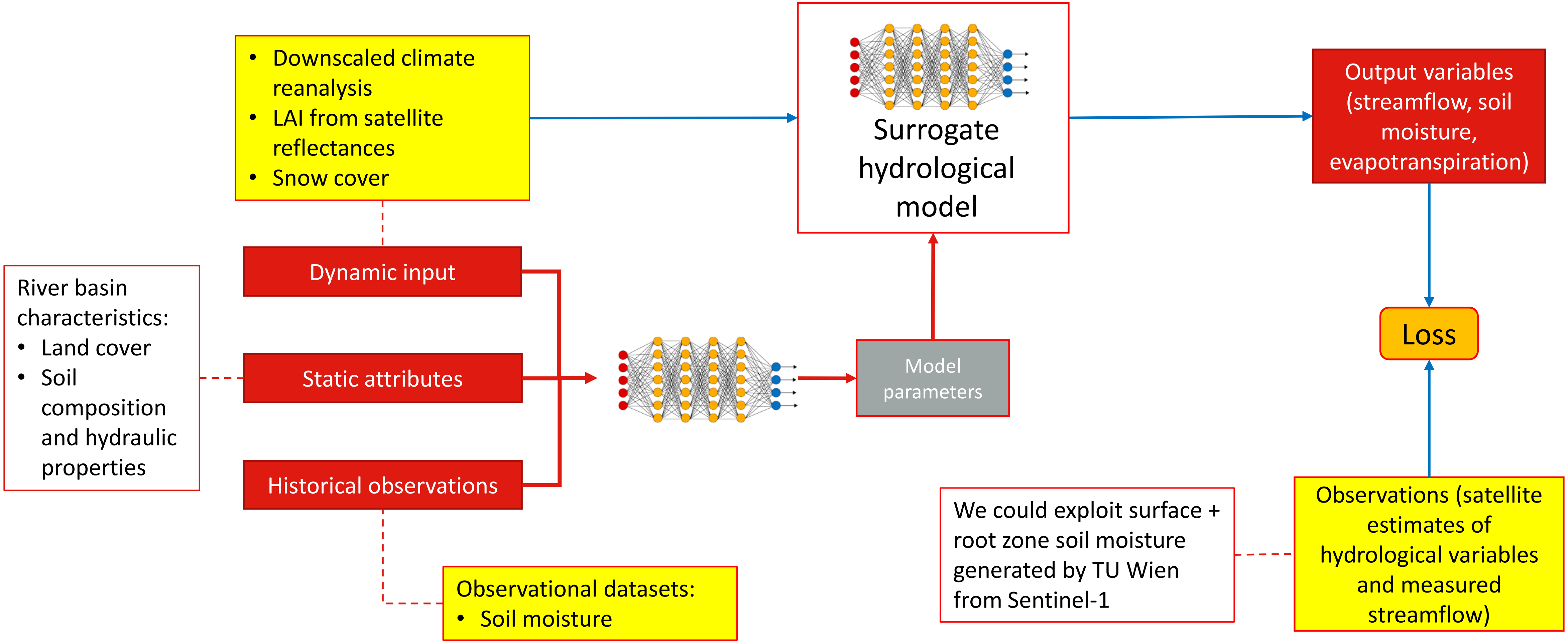
➢ The deep learning model emulates the process-based model, to keep the physics of the model



This step is needed to support a differentiable workflow and to save computational time

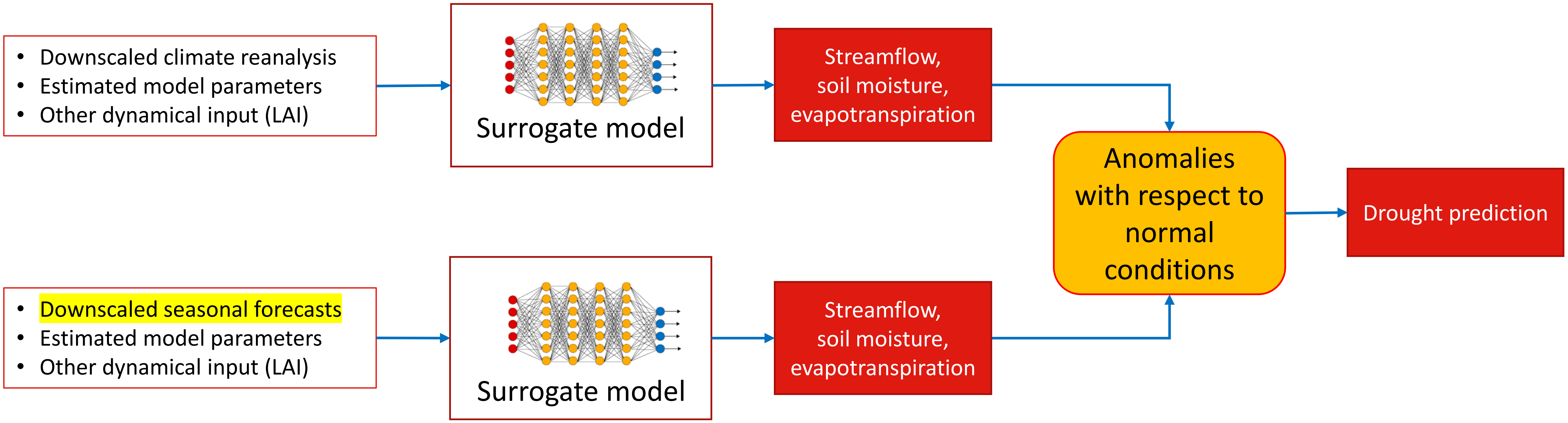
Parameters estimation workflow

➢ The parameters of the hydrological (surrogate) model are estimated based on historical observations and static inputs minimizing a loss function between model output and observations



Drought prediction

➢ Drought indices estimated from river discharge and soil moisture will be used to predict drought conditions

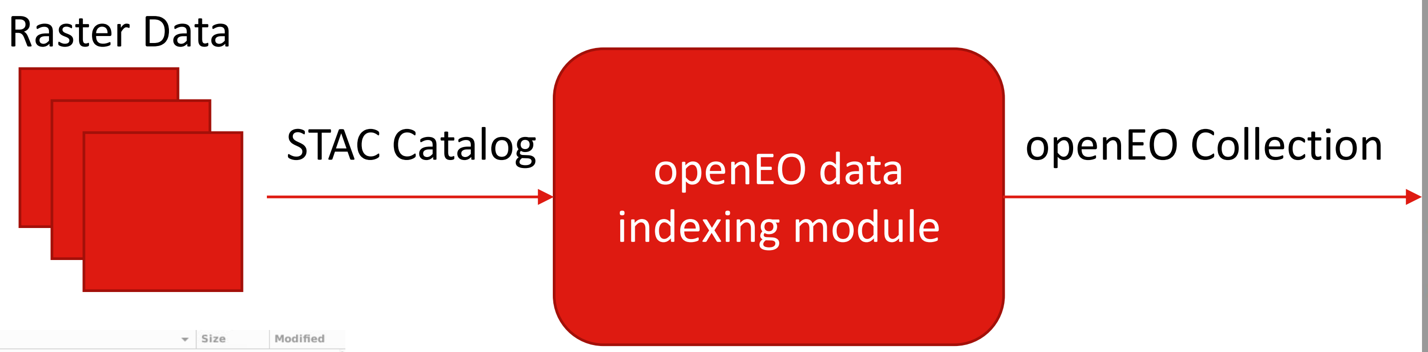


WP7 – T7.5 thematic modules

The InterTwin thematic module T7.5 Earth Observation Modelling and Processing will develop the necessary building blocks to run Digital Twins based on EO data, with openEO as the driving technology.

openEO data indexing module

➢ Create a well define component capable of indexing datasets generated by other components of the Digital Twin Engine (DTE) or coming from project partners.



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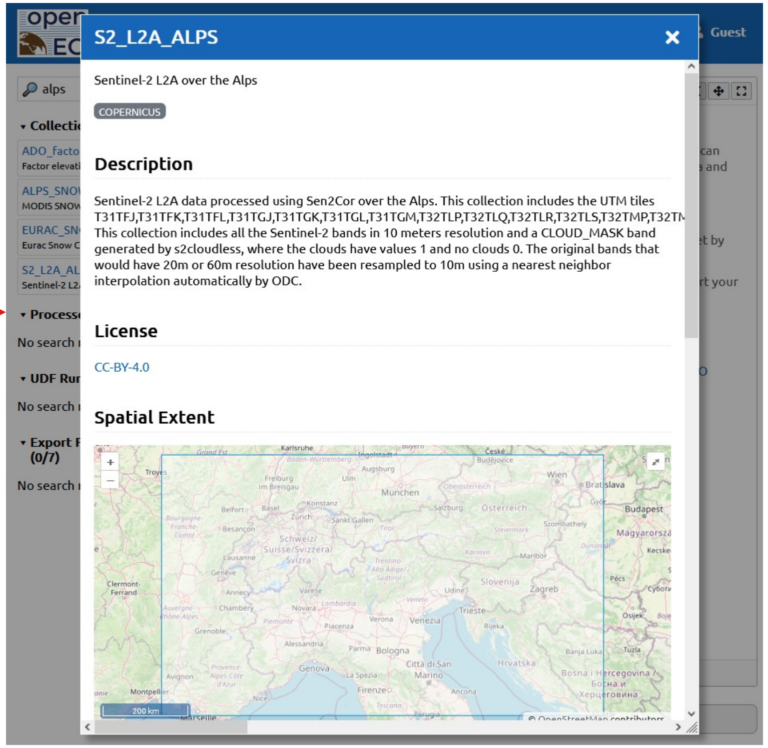


openEO executor module

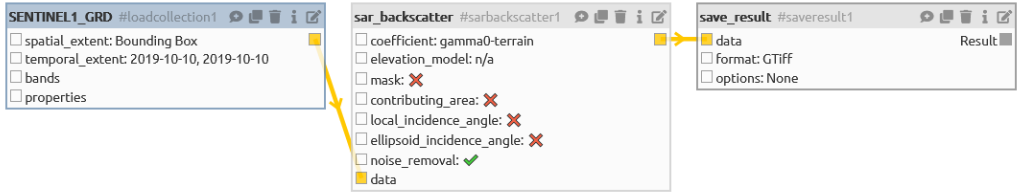
openEO will be used in different digital twins and for different objectives.
Need to define how the openEO workflows interact with the other components of InterTwin.
For this reason, we need a thematic module specialized in running openEO process graphs.

JSON process graph

Run openEO process graph

Processed result

The result could be used as input of the indexing module, becoming a new openEO collection

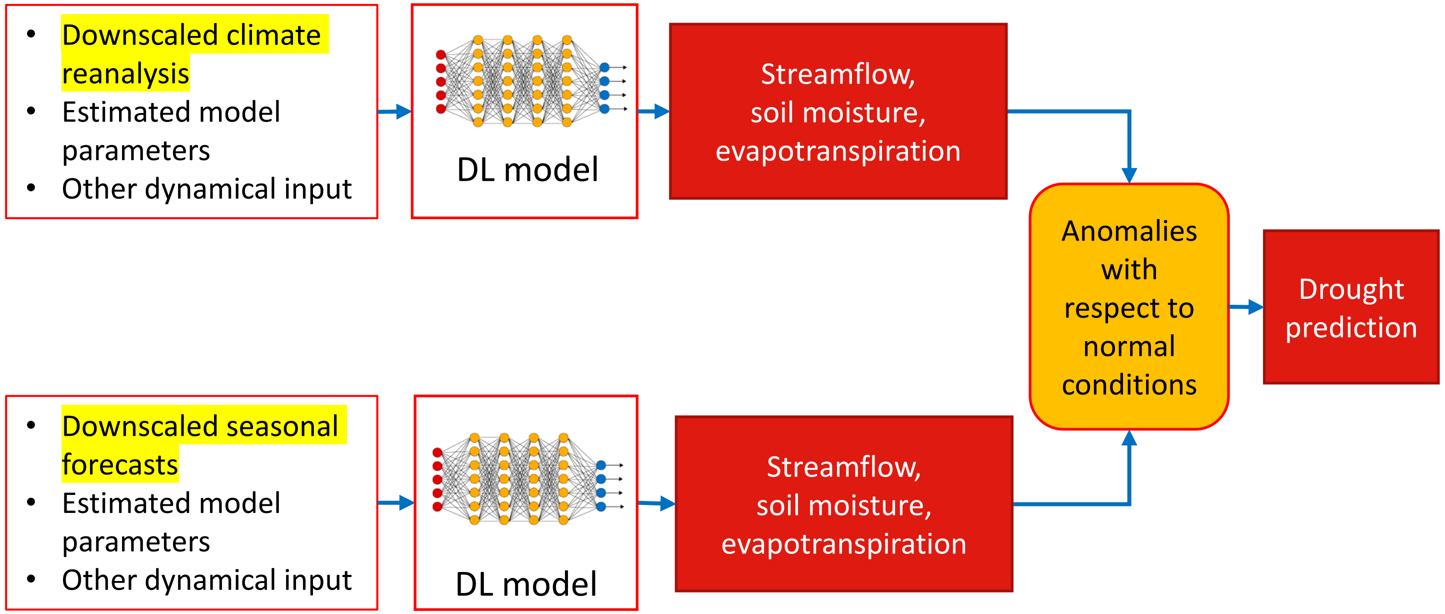


A possible workflow defined as an openEO process graph could be Sentinel-1 backscatter generation, starting from GRD data.

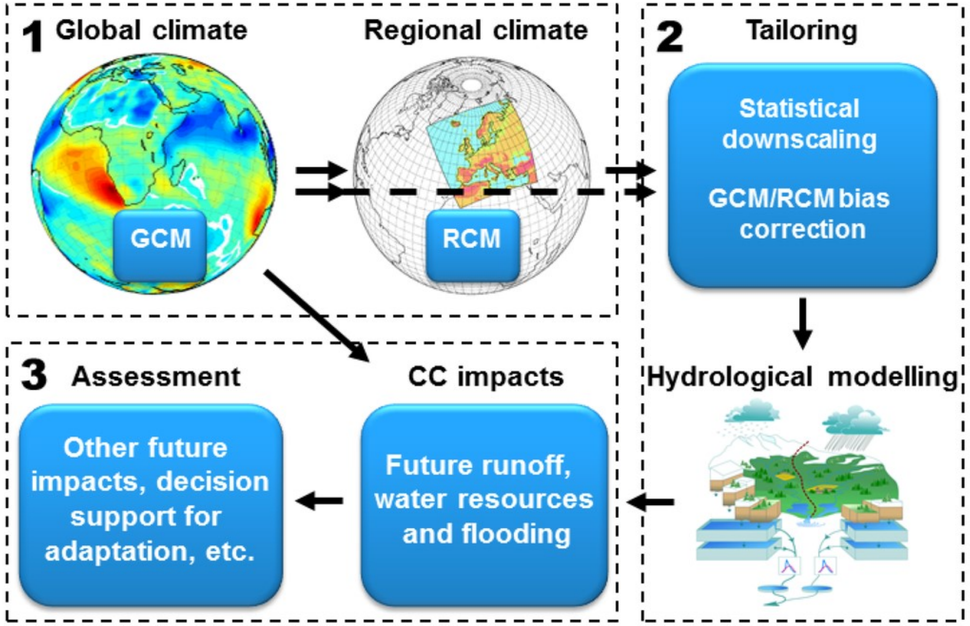
Deep learning for climate downscaling

Set up of a flexible deep learning framework for downscaling different climate variables on different temporal scales

Tailored forecasts for the use-case modelling on drought (WP4.6)



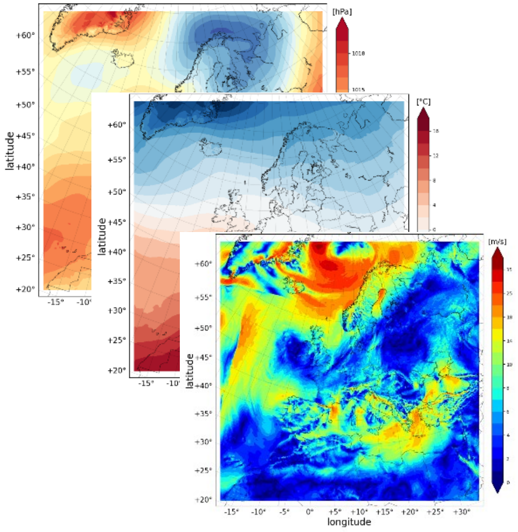
Improved assessment of future climate change and impacts of extreme events (WP4.7, WP7.4)



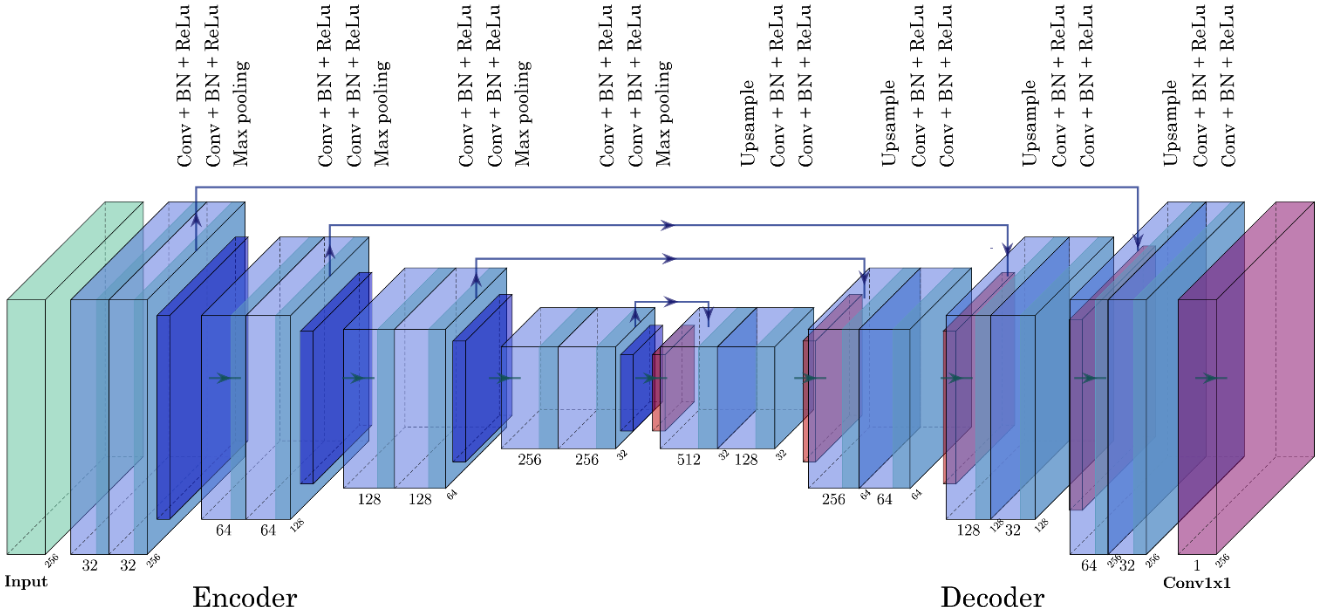
Olsson et al. (2016)

Deep learning for climate downscaling

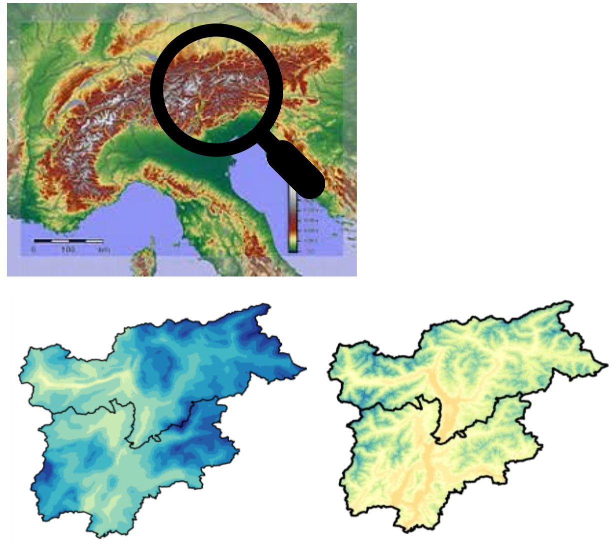
Atmospheric + additional predictors



Deep Learning Network



High-resolution fields of meteorological variables



Input data

- Predictors (depending on application):
  ERA5/SEAS5/CMIP (30-100 km)
  DEM
- Reference: Copernicus European Regional ReAnalysis (CERRA, 5.5 km)

DL Architecture

- Optimized feature selection
- Optimized DL scheme for specific variable
- Comparison with benchmarking schemes
- Transferability, Reproducibility, Interpretability

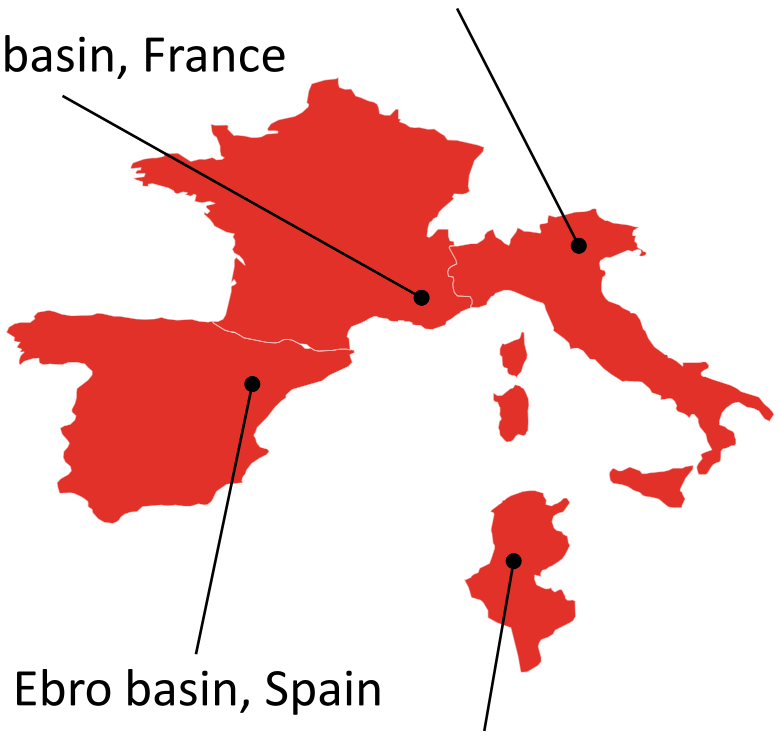
Output data

- Temperature, precipitation, wind speed, …
- Integration in OpenEO
- Validation of mean and extreme values

“Observations”: High resolution evapotranspiration

➢ ET estimation from ESA Copernicus data by the Two-source Energy Balance Model

- **daily**
- **100 m**
- **2017-2021**



sentinel-3	sentinel-2	ECMWF
SLSTR 1 km	MSI 20(10) m	ERA5 31 km
Land Surface Temperature	***Vegetation***	***Meteo***

SNAP **gpt**

Thank you for your attention

EODC Forum
2023