Check the presentation recording on the Vimeo vEGU21 channel

Modeling the discharge behavior of an alpine karst spring influenced by seasonal snow accumulation and melting based on a deep-learning approach

Tanja Liesch[1], **Andreas Wunsch[1]**, Zhao Chen[2], Nico Goldscheider[1]

[1]KIT, [2]ERM

Pictures: Goldscheider

KARMA Project

The KARMA Project

Karst **A**quifer **R**esources availability and quality in the **M**editerranean **A**rea

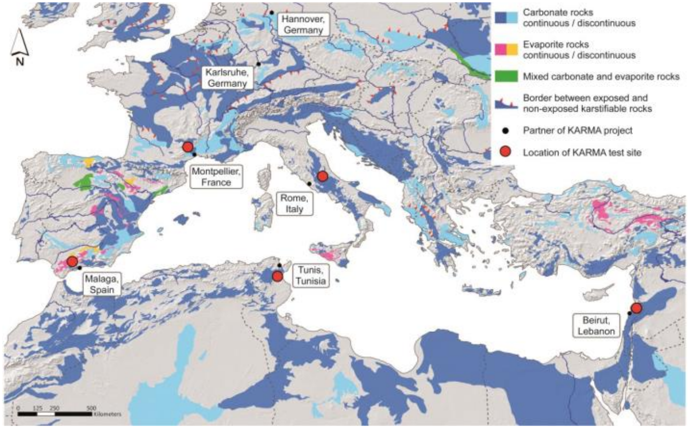
Karlsruhe Institute of Technology

- Karstified carbonate rocks: 21.6 % of the European land surface
- Essential for the freshwater supply of most Mediterranean countries

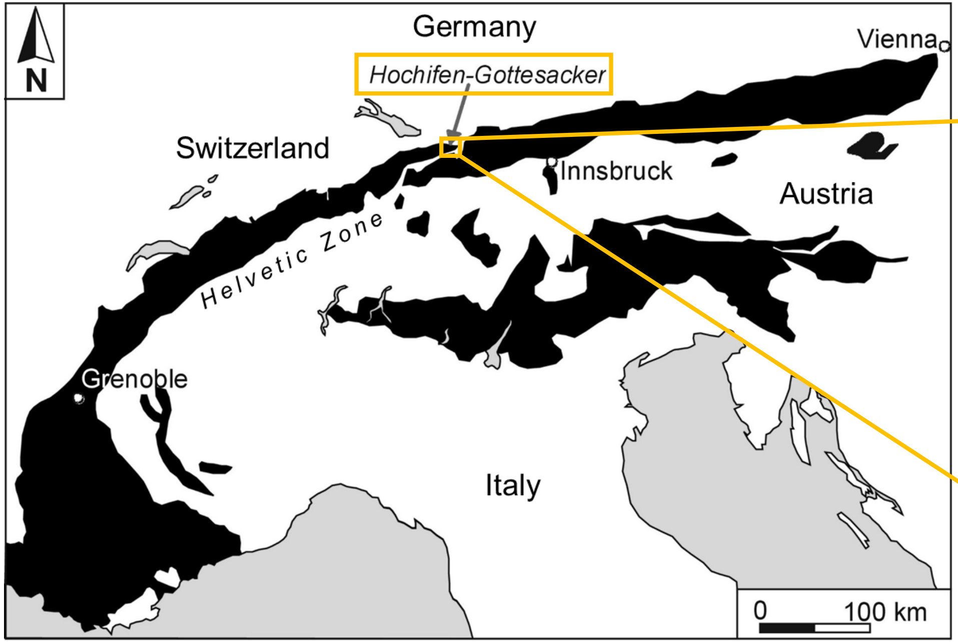
→Hydrogeological understanding

→Sustainable management

→Development of modelling tools

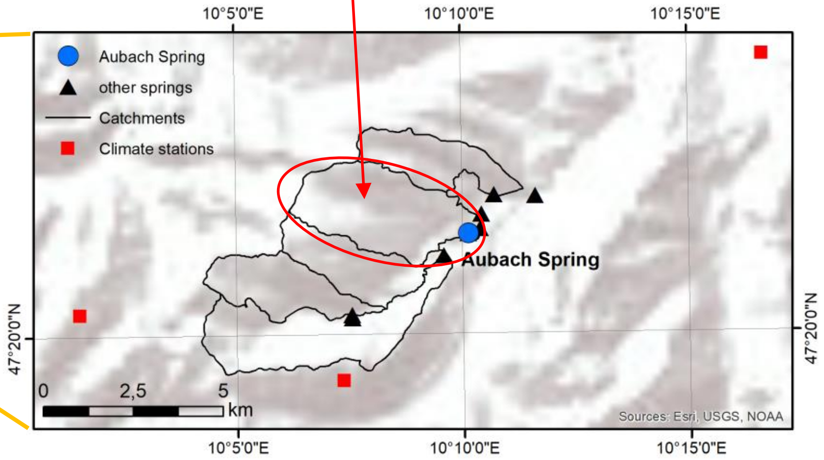


Study area: Hochifen-Gottesacker

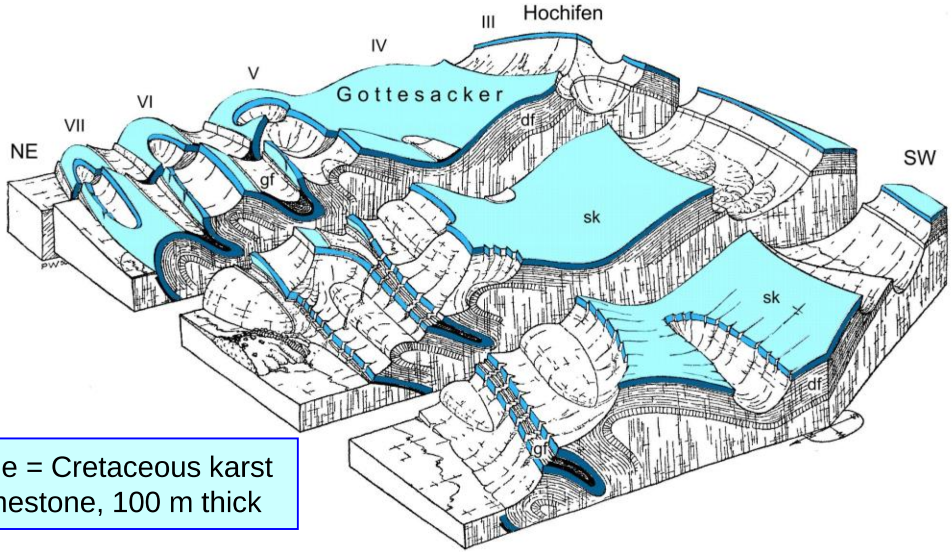


Goldscheider

primary catchment of Aubach Spring



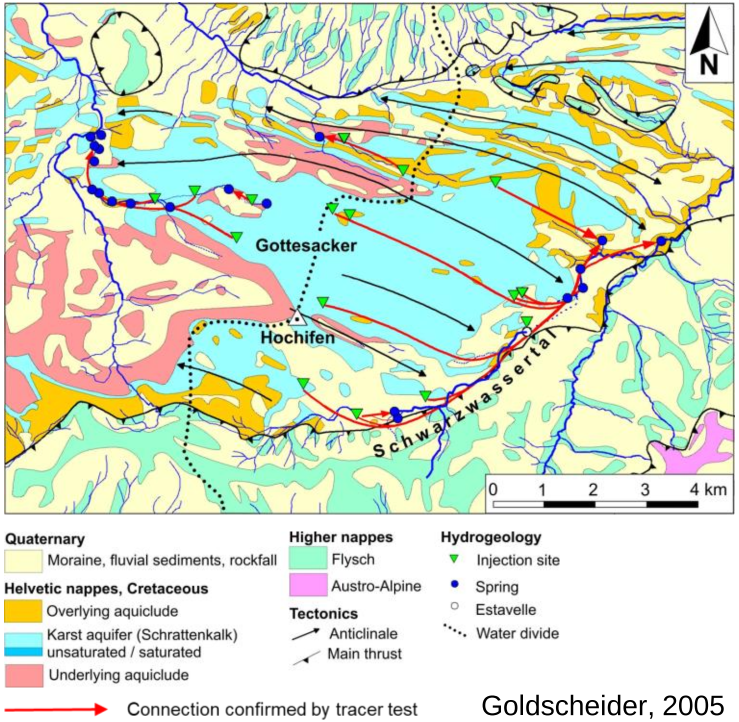
Study area: Hochifen-Gottesacker



Blue = Cretaceous karst limestone, 100 m thick

Synclines form individual sub-catchments

Modified by Goldscheider after Wagner (1950)



Goldscheider, 2005

ANN Model + Data

Deep Learning Technique: <u>Convolutional Neural Networks</u>[1] (CNNs)

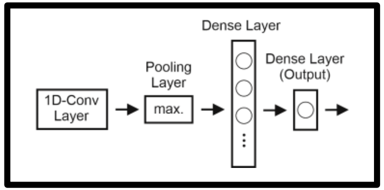
- Fast and reliable for GWL prediction[2]
- Model ensemble + Probabilistic approach (Monte Carlo dropout) → model uncertainty
- 8 years of hourly data between 2012 and 2020

Sequence(s) of Input Values

(climate variables)

→

1D-CNN



→

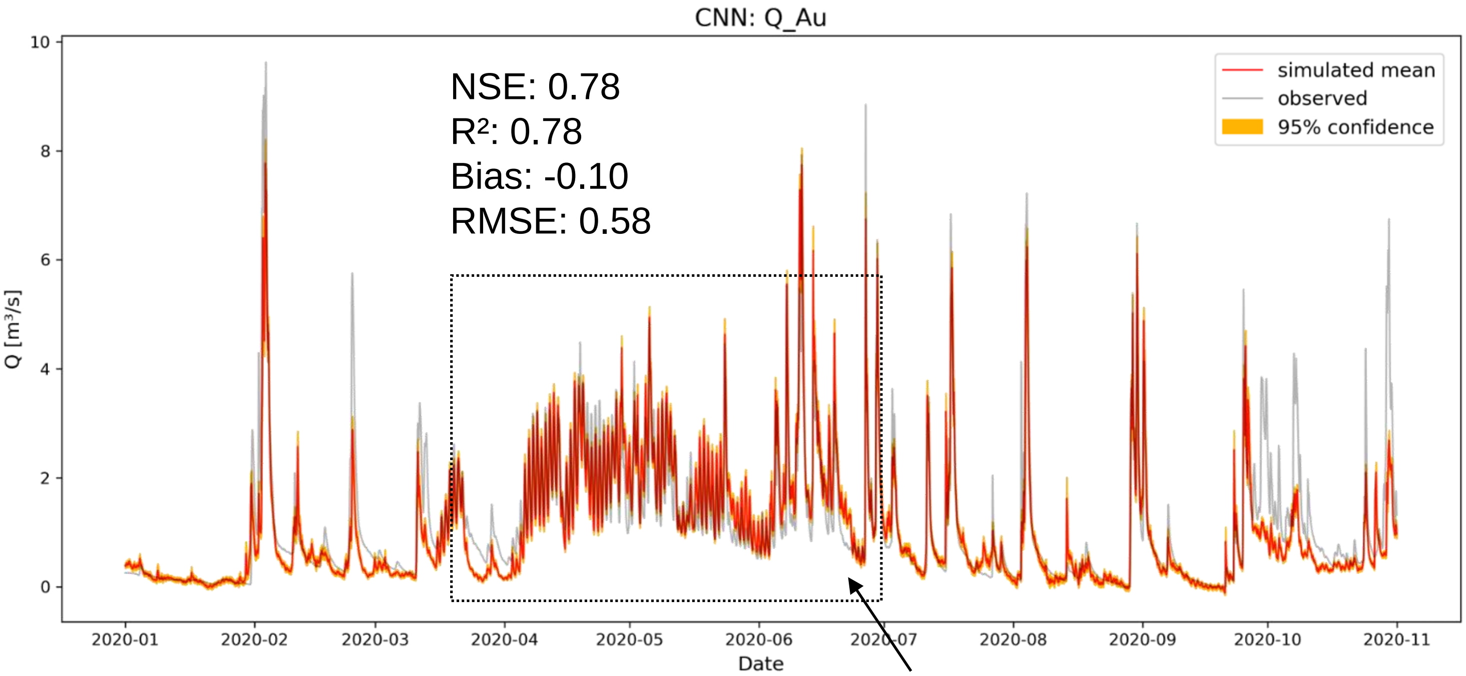
Single Q Value / Sequence of Q Values

<u>Evaluation:</u>

Training and Optimization	Testing (Prediction)
2012-2019	2020

[1]LeCun et al., 2015
[2]Wunsch et al., 2021:

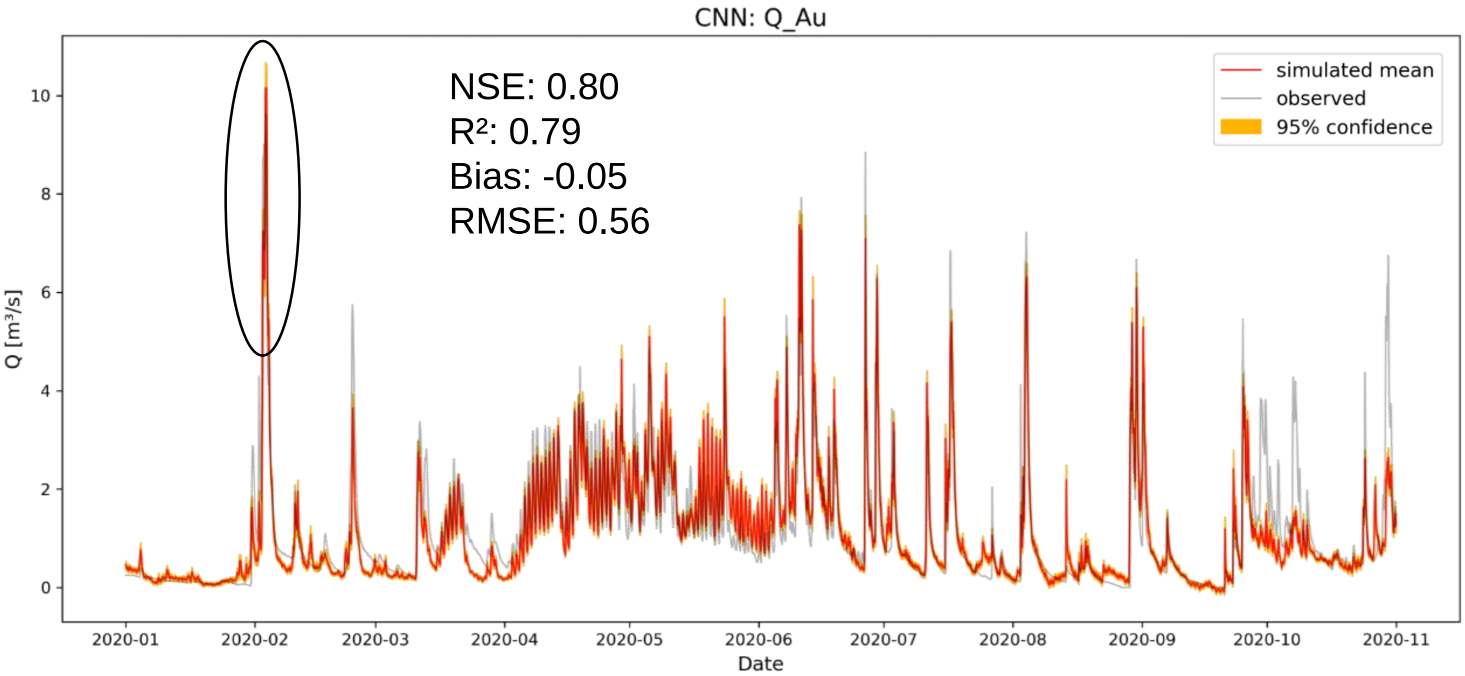
Results 1: Simple Simulation



strong snowmelt influence (increasing baseflow, daily variations)

- Input Data: (P, T, T_{sinus}) x 3 climate stations
- already quite satisfying results despite potentially large input errors

Results 2: Snow Routine Coupling



- Coupling with HBV Snow Routine

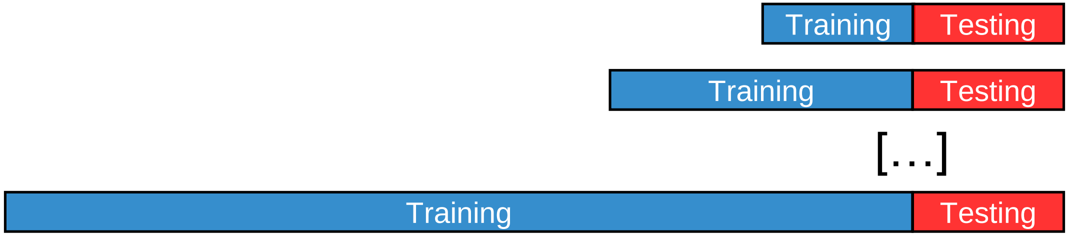
  → additional input: **WLSR** („water left snow routine")

- Only slight improvement

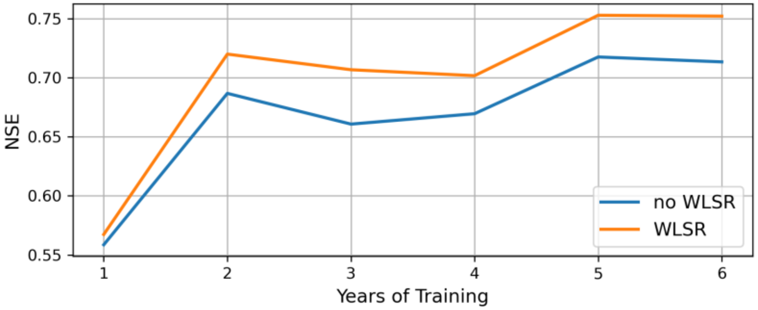
→ ANN model captures relationships already from original data

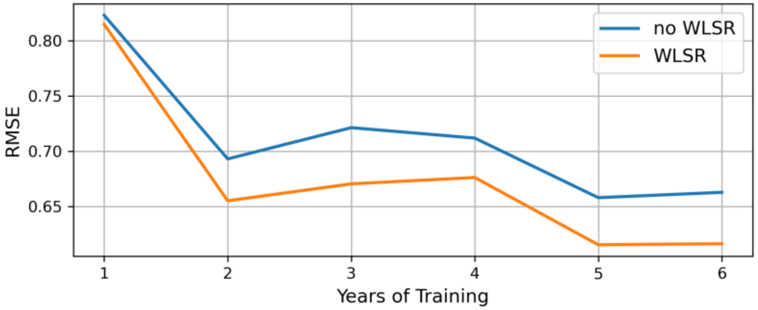
Does the Snow Routine allow shorter training?

- Experiment:
  - Fixed testset: 2020
  - Increase length of training data year by year (starting by 2018, until 2012)
    (2019 is used for early stopping to prevent overfitting)



Does the Snow Routine allow shorter training?





- Surprising: 2 years are already sufficient to learn major characteristics
- Snow Routine is always slightly better, but no fundamental difference

→ Answer is NO, <u>nevertheless,</u> putting additional effort into input data seems worth it (especially if the input data are short)

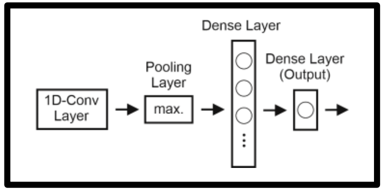
Sequence Forecasting

- „real“ forecasting, could be operationally applied
- we expect reasonable forecasts up to n = 5 hours (known average reaction time of the spring)

Sequence(s) of **m** Input Values

[P(t-m), …, P(t)]
[T(t-m), …, T(t)]
…
[Q(t-m), …, Q(t)]

1D-CNN

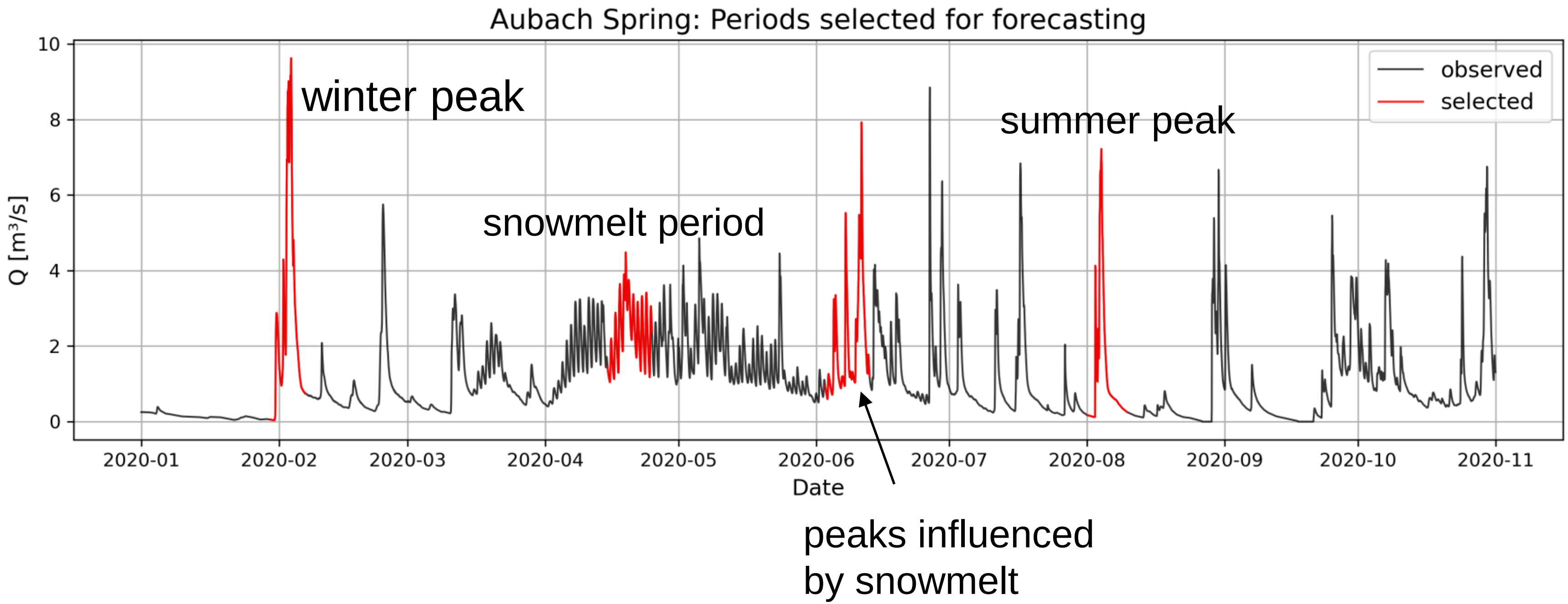


Sequence of **n** Q Values

[Q(t+1), …, Q(t+n)]

Now we use also discharge from the present and the past as inputs.

Sequence Forecasting: Test Periods



Sequence Forecasting: Evaluation

- Most error measures are not suited to:
  - judge every aspect of a time series
  - are dependent on sequence length
  - …

- 1-2h forecast: satisfying = better than Q(t) (naive model)
- ≥3h forcasts:

OR conditions

1. Better than naive model AND high Pearson r ($r \geq 0.8$)
2. very low RMSE (< 0.05)
3. high Pearson r ($r \geq 0.8$) AND low RMSE (< 0.05)

} trial and error conditions

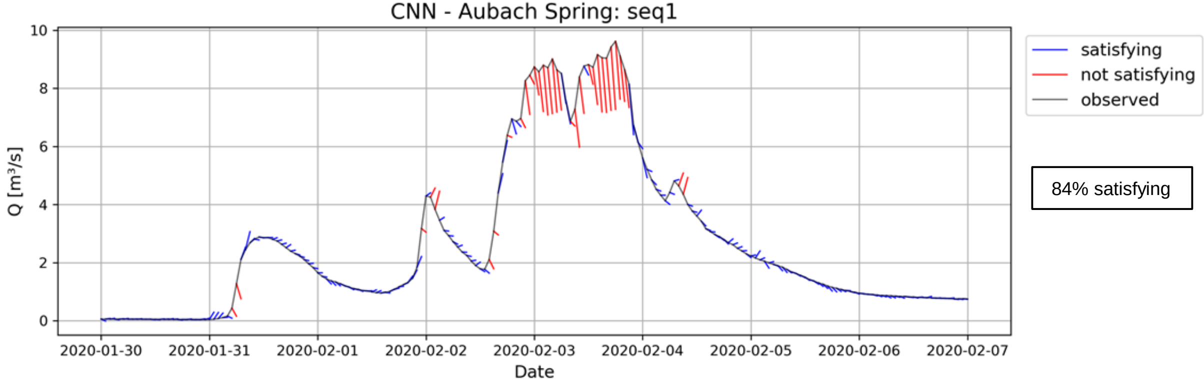
Sequence Forecasting: Winter Peak

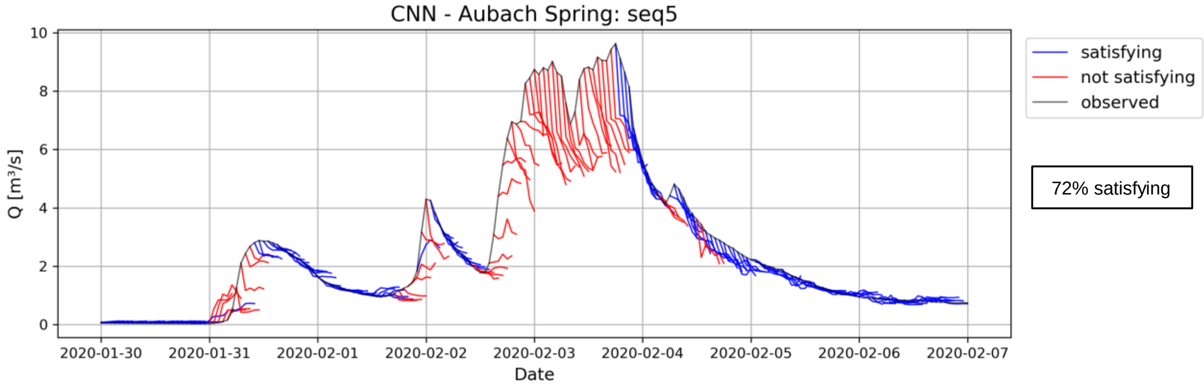
- model can capture declines quite well

  (BUT somehow always forecasts declines)

- severe problems with inclines

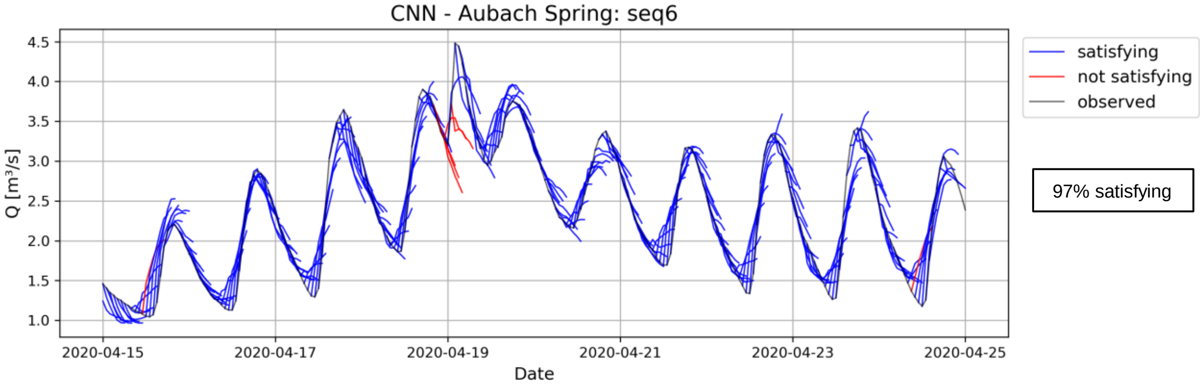
→ Winter peak is hard to forecast



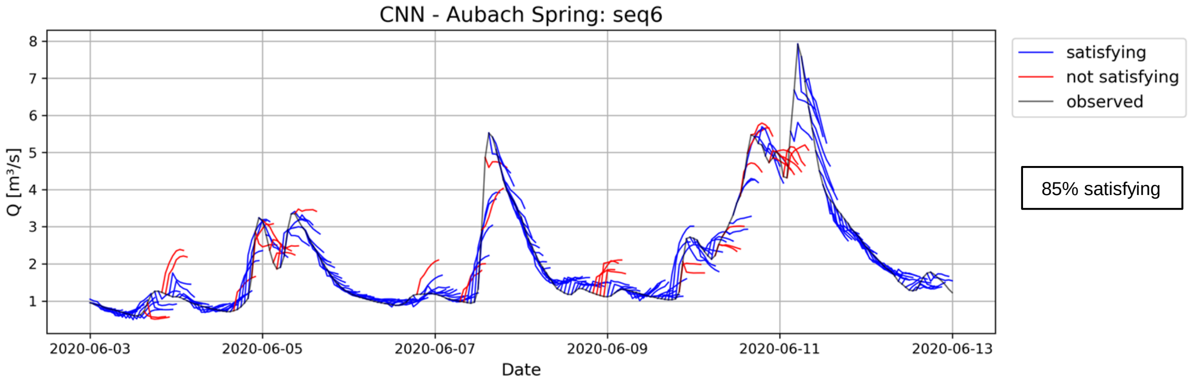


Sequence Forecasting: Snowmelt Period + Snowmelt Peak

- way better forecast up to 6h than for winter peak
- comparably easy to forecast
- >6h: short term events are not captured



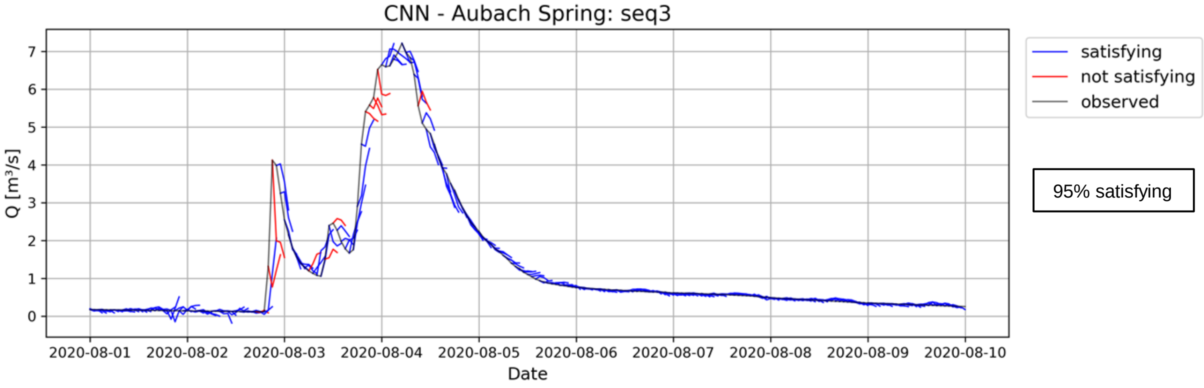
97% satisfying



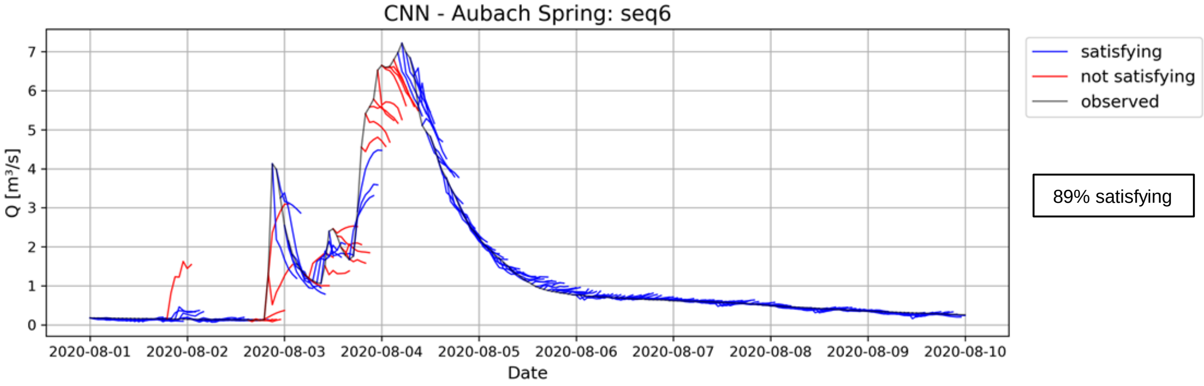
85% satisfying

Sequence Forecasting: Summer Peak

- Very good forecasts up to three hours
- Known problems emerge increasingly
- Better captured than winter peak



95% satisfying



89% satisfying

Summary

- CNNs are well suited to simulate karst spring discharge
- Putting effort into input data (e.g. by implementing a snow routine) is probably worth it (esp. for few data)

- Sequence forecasts are possible, quality depends on time of the year
- Better input data might improve this step reasonably

  (main error source is probably the input data)

Outlook

- Replace input data (ERA5, RADOLAN, …)
- Transfer and apply approach to mediterranian areas as part of the KARMA project
- Use 2D-Input to delineate catchments

Check also: http://karma-project.org/

The KARMA Project **K**arst **A**quifer **R**esources availability and quality in the **M**editerranean **A**rea

Thank you

Find and contact me:

https://github.com/AndreasWunsch

https://www.linkedin.com/in/andreaswunsch/

https://hydro.agw.kit.edu/21_172.php

https://www.researchgate.net/profile/Andreas-Wunsch

ORCID: 0000-0002-0585-9549

Email: **andreas.wunsch@kit.edu**